Social anxiety and concordance in emotional responses across levels of evaluative threat

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Abstract

Objective: Cognitive-behavioral theories of emotional disorders assert that emotional responding comprises concordant responses (e.g., co-occurring subjective distress and physiological arousal), but this is often not observed in practice. We investigated whether concordance would be greater when social threat is higher. ***Method:*** $N = 46$ socially anxious participants underwent experiences involving varying degrees of social interaction and evaluative threat. Affect, cognitions, behaviors, and physiological responses were assessed repeatedly. We used a network modeling approach to explore the associations among emotion response components that are typically associated with trait social anxiety. After estimating contemporaneous partial-τ networks for each condition, we identified the optimal modularity statistic with absolute thresholding. Permutation testing was used to investigate hypotheses tied to absolute and relative concordance. Concordance was defined as a lack of community structure as measured by a non-significant modularity statistic, indicating a unidimensional anxiety response. ***Results:*** Contrary to hypotheses, absolute concordance was not observed in any of the conditions involving social-evaluative threat but was observed in the non-social control network. Additionally, no significant differences in relative concordance emerged when comparing explicit evaluation vs. non-explicit evaluation or social vs. non-social networks. ***Conclusion:*** Our findings align with the extant literature suggesting that concordance is not a necessary or common feature of emotional episodes and has implications for our theoretical understanding of social anxiety. Future work should explore individual differences in concordance and interactions among components across different timescales.

Keywords: emotional concordance, network analysis, social anxiety

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Socially anxious individuals share common fears of negative evaluation, but their emotional response patterns in the face of social threat can differ across persons and within persons across contexts. While talking to unfamiliar people at a party, a socially anxious person might exhibit physiological arousal (e.g., racing heart), anxious behaviors (e.g., avoiding eye contact), and negative thoughts (e.g., “no one likes me”), all of which are believed to interact and heighten the affective experience of social anxiety (Clark & Wells, 1995; Rapee & Heimberg, 1997; subsequently updated by Heimberg et al., 2010, 2014). In a conversation with colleagues, that same person might experience some physiological discomfort without accompanying anxious thoughts or behaviors and, consequently, feel less anxious.

What causes these different responses in the face of ostensibly similar situations involving social interaction? Predominant theories of social anxiety suggest that the activation and interaction across multiple responses occurs when a social situation is perceived to be dangerous or threatening (Clark & Wells, 1995; Rapee & Heimberg, 1997; Heimberg et al., 2010, 2014). This conceptualization of social anxiety as a multicomponent response to socially threatening stimuli aligns with adaptationist (e.g., Ekman, 1992; Izard, 1992; Tomkins, 1962) and some appraisal theories (e.g., Lazarus, 1991; Scherer, 2001) of emotion. Together, they argue that emotions like anxiety are comprised of a set of *concordant* (i.e., strongly associated) cognitions, behaviors, physiological responses, and subjective affective experiences that are synchronized to prompt action in response to situational demands. Intuitive as this conceptualization may seem, years of research have produced limited empirical support for concordance among components of emotional responses, both in the case of social anxiety and emotions more broadly (Hollenstein & Lanteigne, 2014; Lougheed et al., 2021). To better understand concordance (or the lack thereof) in social anxiety, the current study examines *if* and *how* theoretically important social anxiety responses are associated across different levels of experimentally manipulated social-evaluative threat.

Theoretical Concordance in Social Anxiety

Prevailing theories of social anxiety disorder either imply or overtly state that concordance among components of the anxiety/fear response during perceived or imagined social-evaluative threat is a core feature of the disorder. Clark and Wells' (1995) cognitive model argues that, within the context of a social interaction, maladaptive beliefs that social situations are dangerous trigger an “anxiety program” comprised of cognitive, physiological, affective, and behavioral responses. Once activated, these responses interact in a positive feedback loop; for example, heightened physiological responses are interpreted negatively, contributing to greater anxiety and observable anxious behaviors which, in turn, elicit negative feedback from others and further increase anxiety. Similarly, Rapee and Heimberg's (1997; subsequently updated by Heimberg et al., 2010, 2014) cognitive-behavioral model posits that socially anxious individuals exhibit a distorted mental representation of themselves as viewed by others that both influences and is influenced by a multicomponent anxiety response comprised of affective (e.g., subjective distress), behavioral (e.g., avoidance; safety behaviors), physiological (e.g., sweating; blushing), and cognitive (e.g., self-criticism; catastrophizing) responses. This model also implicates a positive feedback loop in the maintenance of social anxiety disorder, generated by the mutually reinforcing interactions among components of the anxiety response. Thus, the “anxiety response” or “anxiety program” proposed by these theories mirrors emotion theories that assume response concordance.

Empirical Concordance in Social Anxiety

Despite the fact that many theories of emotion and psychological disorders assume concordance among the elements of an emotional response, the reality is that these components tend to be either loosely coupled (Bradley & Lang, 2000; Lang, 1968) or, in some cases, discordant (i.e., negatively associated or not significantly associated; Hollenstein & Lanteigne, 2014; Lougheed et al., 2021; Mauss & Robinson, 2009). For social anxiety in particular, findings have been mixed. Among studies that report concordant reactions to social threat, the observed associations among emotional response indicators tend to be modest (Borkovec et al., 1974; Calvo & Miguel-Tobal, 1998; Constantinou et al., 2021; Moscovitch et al., 2010). In some cases, the pattern of results observed among socially anxious individuals are suggestive of concordance but the analytic approach precludes this conclusion. For instance, in an imagery task, individuals with social anxiety disorder rated socially threatening imagery as less pleasant and more arousing than individuals with other anxiety disorders and exhibited significant fear potentiation, but the relationships *among* these variables (i.e., the key within-person associations) were not specifically analyzed (Cuthbert et al., 2003; see also Beidel et al., 1985). When concordance is observed, it is most often among self-reported indicators of anxiety (e.g., cognitions, perceived arousal), whereas discordance is the norm when examining objective physiological indicators of anxiety (see Eckman & Shean, 1997; Edelmann & Baker, 2002; Mauss et al., 2004).

A number of studies suggest that emotion response patterns vary substantially based on situational context, under certain conditions, or among particular types of anxiety responses but not others. In an empirical investigation of group differences in responding during social and non-social fearful imagery, McTeague et al. (2009) found that individuals diagnosed with social anxiety disorder reported that imagining feared social situations was more aversive, unpleasant, and arousing, and exhibited greater physiological arousal and stronger startle responses as compared to non-anxious control participants. However, these anxiety group differences did not emerge when participants imagined more generally threatening situations (e.g., physical attacks that would pose a threat to one's life). Although concordance was not directly tested, these findings suggest that group differences (consistent with a pattern of concordance) may be more likely to occur in situations that are perceived as particularly relevant and threatening to socially anxious individuals. Studies that specifically test for concordance by examining the associations among emotion components have yielded similar results. Within social-evaluative contexts, the intensity of social threat or the level of demand (i.e., performance expectations) present in the situation may also influence concordance. In one study, individuals high in speech anxiety were assigned to either a low-demand speech task in which they were told to try their best and stop at any point or a high-demand speech task in which they were told that it was important to continue speaking for as long as possible. Significant associations among systolic blood pressure and cognitive anxiety responses were observed in the high-demand condition whereas no associations between physiological and cognitive anxiety responses were found in the low-demand condition (Matias & Turner, 1986). There is also evidence to suggest that concordance may be more likely to be observed among variables measuring the same component of an emotional response (e.g., self-reported anxious cognitions) than among those measuring different components of the emotional response (e.g., self-reported anxious cognitions and objectively measured physiological reactivity; Calvo & Miguel-Tobal, 1998; Matias & Turner, 1986).

Factors Influencing Concordance

Social Threat Context

A number of contextual factors have been hypothesized to influence whether or not concordance occurs, such as situational context (e.g., in-lab vs. natural environment; social vs.

non-social), emotion elicitation procedure (e.g., imagery vs. in-vivo), intensity of emotional response, or level of threat present in environment (Cacioppo et al., 2000; Hollenstein & Lanteigne, 2014; Lougheed et al., 2021). Taken further, constructivist emotion theories (e.g., Barrett, 2006a, 2006b; Russell, 2003) have emphasized that concordance is neither central nor necessary to the experience of emotion, arguing that there is no single type of situation that elicits fear, nor a single "fear response" comprised of the same synchronized components. Emotions manifest differently across individuals, contexts, and time (Quigley & Barrett, 2014). Proponents of concordance have argued that an emotion must reach a certain level of intensity before concordance among the components of that emotion are observed (Davidson, 1992; Hodgson & Rachman, 1974), although this may differ depending on the emotion under study (e.g., amusement vs. sadness; Mauss et al., 2005). Intense emotions are presumed to be associated with concordance in part because they can overwhelm a person such that they struggle to regulate their emotional response (Hollenstein & Lanteigne, 2014; Lougheed et al., 2021). For socially anxious individuals, anxiety is theorized to be more intense in the presence of others (vs. alone) and in situations involving clear social evaluation given these situations raise opportunities for rejection and embarrassment (e.g., Moscovitch, 2009). To test these ideas, the current study examines concordance among emotion response indicators across contexts involving different levels of social-evaluative threat.

Examining Multiple Components of the Emotional Response

Methodological limitations may partly explain the mixed findings in the emotional concordance literature. Many early studies of concordance chose a single observable indicator of each emotion component and selected different indicators across studies (e.g., either skin conductance or heart rate was used as the sole indicator of physiological arousal). Additionally, most research has not included indicators of each component of the emotional response (i.e., affective, cognitive, behavioral, and physiological), instead focusing on a smaller number of components (e.g., physiological arousal and self-reported affect; Cacioppo et al., 2000; Mauss et al., 2005; Mauss & Robinson, 2009). In reality, emotions are complex and the experience of emotion varies widely; accordingly, our understanding of concordance will be improved by focusing on many components of an emotional response and including multiple observable indicators of those components. Thus, in the current study, multiple indicators of affect, cognitions, behaviors, and physiology are included to evaluate concordance.

The analytic approach used to estimate concordance among emotional response channels is also likely to impact results. First, concordance as a phenomenon has been operationalized inconsistently. Some have defined concordance as a pattern of within-person associations between different response indicators thought to be relevant to the emotion(s) under study, whereas others have used the term to characterize group differences across individuals low and high in trait social anxiety. For example, significant differences between socially anxious and control individuals on self-report but not physiological measures of arousal have been interpreted as evidence of discordance between perceived and actual arousal in social anxiety (e.g., Anderson & Hope, 2009; Klumbies et al., 2014; Lang et al., 1983). Here, we define concordance as within-person associations and consider the group comparison approach to be characteristic of inconsistent responding between groups rather than discordance within a given person's emotional response components. Second, research on emotional response patterns in social anxiety has typically used bivariate correlations to examine concordance among pairs of variables rather than considering multiple components of an emotional response simultaneously. Newer and more complex analytic techniques (e.g., multivariate approaches) have the potential to offer new insights into emotional concordance. For example, Friedman et al. (2014) used redundancy analysis to account for the associations among physiological variables and self-reported affective variables before calculating the associations between the variable sets, finding a stronger correlation between the two sets of variables than has been previously reported between pairs of variables (e.g., 0.52-0.53 vs. 0.30).

A Network Approach to Concordance

The *network* or *complex systems* approach, a rapidly growing area of research that has been used to study the symptoms of mental disorders (Robinaugh et al., 2020), offers one promising method by which to study emotional concordance. The network approach to psychopathology argues that, rather than latent mental disorders causing observed psychological symptoms (e.g., a person fears negative evaluation and avoids social situations because they have an underlying social anxiety disorder), it is the mutually reinforcing interactions among these symptoms themselves that cause them to hang together as a recognizable syndrome (Borsboom, 2017). In the case of concordance, a network approach can be used to study the interacting affective, cognitive, physiological, and behavioral responses hypothesized to comprise an emotion such as anxiety. One approach to modeling and visualizing psychological networks has been to estimate partial correlation networks from cross-sectional data. Although this contemporaneous approach cannot be used to determine the causal relationships among the components of an emotional response, it can be a helpful tool to begin identifying the associations that may exist among conceptually related components (Robinaugh et al., 2020).

Further, it is possible to use a measure referred to as *modularity* to investigate whether a network exhibits *community structure*; that is, whether a network is characterized by densely connected groups of nodes (i.e., components of an emotional response) with weak connections between different groups (Newman, 2006). If there are distinct groups of nodes (i.e., the network exhibits community structure), this would suggest discordance because there are separate clusters of indicators that do not connect strongly to one another, rather than a concordant single cluster of indicators. The modularity statistic generated by this method can be either positive or negative, with larger positive values indicating possible community structure and values closer to one indicating strong community structure. This method is relevant to understanding emotional concordance as it can provide valuable information about if and how components of an emotional response are associated. The present study thus takes a network approach and tests how strongly key affective, cognitive, behavioral, and physiological emotional responses tied to social anxiety cluster together under differing levels of social-evaluative threat with the goal of improving our understanding of when emotional concordance occurs.

Overview and Hypotheses

Individuals high in trait social anxiety symptoms completed a non-social control task alone and a series of conversations with strangers in dyads or groups at different levels of experimenter-manipulated social-evaluative threat (i.e., when given specific instructions that conversation partners would be evaluating one another or not). Physiological indicators of anxiety were assessed passively and continuously throughout the study session via wristband sensors. Self-reported affective and cognitive indicators tied to state social anxiety were assessed via a brief survey immediately following each experience. Participants' anxious behaviors during each of the social interactions were video recorded and later coded by the study team.

All hypotheses[1] and plans for analysis were pre-registered via the Open Science

[1] The present study focuses on a subset of the hypotheses presented in the preregistered materials, which cover more components of the parent study.

Framework (https://osf.io/tdc38) and prior preliminary analyses conducted with these data are also listed there (note, changes to preregistered variables and plans for analysis can be found in the Supplementary Material). We operationalized emotional response concordance in two different ways depending on whether we were assessing *absolute* concordance (i.e., whether each network was concordant *in and of itself*) or *relative* concordance (i.e., whether network X was more or less concordant *relative to* network Y). Concordance was defined as a *lack* of community structure arising from highly interconnected components of the anxiety response. Tests of absolute concordance were included to contextualize any relative concordance findings, as it would be less meaningful to conclude that one network was more concordant relative to another if we did not know whether that network was itself concordant.

Regarding *absolute concordance,* we hypothesized that each *social* experience network (i.e., any combination of experiences involving social interaction) would exhibit absolute concordance (**Hypothesis 1a**). Theories of emotion and social anxiety predict that emotions will be stronger under greater perceived threat, and that strong emotional responses are characterized by a set of affective, cognitive, physiological, and behavioral components that are all strongly associated with each other. Accordingly, we expected to see concordance (i.e., a lack of community structure due to interrelationships among all components of the anxiety response) under conditions involving *any* potential for social-evaluative threat (i.e., being in any social situation vs. being alone). By contrast, we hypothesized that the non-social, alone experience network would exhibit discordance (i.e., significant community structure arising from associations among some but not all components of the anxiety response; **Hypothesis 1b**). Importantly, we hypothesized that this network would exhibit significant community structure rather than it being completely disconnected; specifically, different indicators within the same response channel (i.e., different cognitions) were expected to be associated due to conceptual and often methodological overlap.

In terms of *relative concordance*, we hypothesized that experiences involving greater social-evaluative threat would be more concordant relative to those involving less social-evaluative threat. We operationalized social-evaluative threat in two different ways: (1) whether the situation involves *any* risk of being socially evaluated (i.e., social vs. non-social context) and (2) within a social situation, *how much* risk there is of being socially evaluated (i.e., explicitly evaluative vs. non-explicitly evaluative social context). Accordingly, we hypothesized that there would be greater concordance under explicitly evaluative conditions as compared to non-explicitly evaluative conditions **(Hypothesis 2a)** and that there would be greater concordance during the social experiences as compared to the non-social, alone experience (**Hypothesis 2b**)[2]. Taken together, this study aims to advance our understanding of emotional responses to social threat by investigating whether greater social threat can help explain when concordance occurs among multiple affective, cognitive, behavioral, and physiological components of social anxiety.

Method

Participants

Participants (*N* = 46) were recruited via the University of Virginia undergraduate participant pool and consented to participate for course credit. Prospective participants were screened using the Social Interaction Anxiety Scale (SIAS; Mattick & Clarke, 1998). The SIAS ranges from 0 to 80, with higher scores indicating greater social anxiety symptom severity. Participants were deemed eligible if they had a score of 34 or above, which is suggestive of

[2] This comparison was based on a more limited set of variables given not all questions asked during the social conditions applied for the alone condition.

moderate to severe social anxiety (Mattick & Clarke, 1998).[3] Participants completed the SIAS at two time points: once prior to enrolling, and again on the day of their study session approximately one to three months later. Accordingly, we expected some participants' self-reported anxiety about social interactions to change during the study period. We elected to include all participants identified as being high in trait social anxiety at the first SIAS administration in our analyses because they are known to be vulnerable to perceiving social interactions as threatening even if their social anxiety symptoms fluctuate over time.

Given that a key component of this study involved passively sensing participants' psychophysiological reactivity, participants eligible based on the SIAS were further screened for factors that can influence psychophysiological reactivity and measurement. Following feedback received about best practices for screening from psychophysiology experts on the listserv of The Society for a Science of Clinical Psychology (SSCP), participants were excluded if they endorsed routine use of benzodiazepines, stimulants, antipsychotics, mood stabilizers, beta-blockers, monoamine oxidase inhibitors (MAOIs), medications that cross the blood-brain barrier, or medications used for pain management. Participants were also excluded if they endorsed a diagnosis of cardiovascular disease or high blood pressure. Those found eligible based on these criteria were also asked to abstain from benzodiazepines, stimulants, caffeine, nicotine, vigorous physical exercise, and marijuana for at least two hours prior to the start of their scheduled study session, and alcohol and illicit drugs for at least 24 hours prior to their study session. Two participants in the high social anxiety group were allowed to participate despite taking

[3] For the broader parent study, $N = 54$ participants were recruited, 9 of whom were low in social anxiety symptom severity as determined by a SIAS score of 10 or below. For the present study, we focus on the high social anxiety group ($N = 46$) considering the small sample size of the low social anxiety group ($N = 9$) and our goal of characterizing anxious responding to social threat.

exclusionary medications (stimulants and medications that cross the blood-brain barrier), but these participants refrained from taking their medication for at least two hours prior to the start of their study session. See Table 1 for detailed demographic information.

Procedure

Participants were scheduled in groups of four to six to participate in a virtual session conducted via Zoom videoconference by two to three trained undergraduate research assistants and/or clinical psychology graduate students. During the session, participants underwent five experiences (though in some cases, there was insufficient time to complete all five experiences): one by themselves, two in a dyad, and two with the full group of four to six participants. The experience completed alone was always first, and the subsequent dyadic and group experiences were presented in an order that was completely randomized. During the non-social experience completed alone, each participant was randomly assigned to watch one of three preselected videos, all of which involved colorful moving shapes, for two minutes. (A preliminary set of analyses conducted by the study team found that, among an mTurk sample N = 75, affect during the three videos was comparable and did not differ significantly from baseline.) During the dyadic and group experiences, participants were assigned to discuss one of four predetermined conversation topics (e.g., "If you won a million dollars, what would you do with the money and why?") for either four minutes (dyadic experiences) or six minutes (group experiences). The longer time for the group experiences was to allow more opportunities for all participants to speak. The order of the conversation topics and social experiences were randomized to minimize order effects. For each of the two group and dyadic experiences, one was designed to elicit a heightened sense of social-evaluative threat by telling participants they would be rated by interaction partners on the basis of their likeability and conversational skills. For the other two (not explicitly evaluative) experiences, participants were instructed to discuss the assigned conversation topic but were told that they would not be rated by their partner(s)[4] at the end of the conversation.

A brief questionnaire that inquired about affective and cognitive symptoms of social anxiety was administered to participants at four timepoints during each of the five experiences: prior to learning about the upcoming experience (to capture baseline data before/between experiences), after hearing an explanation of the upcoming experience and being instructed to think for two minutes about how the experience might go (to capture anticipatory anxiety), immediately following the experience (to capture in-the-moment reactions to the experience), and after being instructed to reflect for two minutes about how the previous experience went (to capture post-event processing). For the purposes of this study, analyses focus only on the questionnaire administered immediately following each experience. Additionally, throughout the session, psychophysiological reactivity was assessed continuously via an Empatica E4 wristband and Huawei Watch 2 Android smartwatch. Participant behaviors were recorded via Zoom. At the end of the session, participants completed trait anxiety and demographics questionnaires.

Variables

Trait Variables

Social Interaction Anxiety Scale (SIAS). The SIAS (Mattick & Clarke, 1998) is a 20-item scale that assesses anxiety in the context of social interactions. We used a validated non-heteronormative adaptation of the scale (Lindner et al., 2013), which rephrases item 14 (“I have difficulty talking to attractive persons of the opposite sex”) to be more inclusive of sexual

[4] For the two dyadic experiences, participant pairings were random but preassigned and remained the same for both of the experiences. In the event that an odd number of participants attended the Zoom session, one of the undergraduate RAs or graduate students served as a conversation partner to the unpaired participant.

minorities (“I have difficulty talking to attractive persons of the sex/sexes that I am interested in”). Items on the SIAS are rated from 0 (not at all characteristic of me) to 4 (extremely characteristic of me), and a total score is obtained by reverse-coding three positively-worded items and calculating the sum of all 20 items.

State Variables

To capture different components of emotional responding to social threat, we selected three to five state variables to serve as indicators of affective, cognitive, physiological, and behavioral components of anxiety.

Affective Variables

Subjective Anxiety. Participants rated their state anxiety during each experience by responding to the prompt “When my feelings were most intense during the last experience, I felt…” on a five-point Likert scale from very calm (1) to very anxious (5).

Subjective Arousal. Participants rated their state arousal during each experience by responding to the prompt “When my feelings were most intense during the last experience, I felt…” on a five-point Likert scale from very relaxed (1) to very worked up (5).

Affective Valence. Participants rated their affective valence during each experience by responding to the prompt “When my feelings were most intense during the last experience, I felt…” on a five-point Likert scale from very positive (1) to very negative (5).

Cognitive Variables

Fear of Negative Evaluation. Fear of negative evaluation is at the core of social anxiety and is one of the criteria used to diagnose social anxiety disorder (American Psychiatric Association, 2022). Participants rated their fear of negative evaluation during each experience by responding to the prompt, “During the last experience, I was ____ about what the people I was interacting with would think of me" on a five-point Likert scale from not at all worried (1) to very worried (5). Note that the fear of negative evaluation item was not administered during the non-social experience (i.e., watching a video alone) given that the item was not relevant to that experience.

Self-Appraisal. Low self-esteem is positively associated with symptoms of social anxiety (Iancu et al., 2015). Accordingly, we asked participants to rate how they felt about themselves during each experience by responding to the prompt, "During the last experience, I felt good about myself" on a five-point Likert scale from disagree completely (1) to agree completely (5). Prior to conducting analyses, responses to this variable were reverse-coded given that the direction of the Likert scale (i.e., disagree completely to agree completely) was opposite that of most other questions.

Social Performance Concerns. Socially anxious individuals are often concerned about doing something "wrong" or "stupid," particularly during activities involving skilled social interaction (e.g., conversations; Moscovitch, 2009). Participants thus rated their concerns about making mistakes during each experience by responding to the prompt, "During the last experience, I was worried that I was saying or doing the wrong things" on a five-point Likert scale from disagree completely (1) to agree completely (5).

Satisfaction with Performance. In addition to exhibiting low self-esteem, individuals high in trait social anxiety tend to be highly self-critical (Iancu et al., 2015; Werner et al., 2019). Accordingly, participants rated their satisfaction with their performance during each experience by responding to the prompt, "I felt ____ with how I did during the last experience" on a scale from very unsatisfied (1) to very satisfied (5). Prior to conducting analyses, responses to this variable were reverse-coded given that the direction of the Likert scale (i.e., very unsatisfied to very satisfied) was opposite that of most other questions.

Physiological Variables

Skin Conductance Level (SCL). Participants' electrodermal activity (EDA) was assessed continuously with the Empatica E4 wristband (https://www.empatica.com/research/e4/) via dry, snap-on silver (Ag) plated electrodes placed on the ventral (inner) wrist. The E4 EDA sensor has a sampling frequency of 4Hz, uses an alternating current with 8Hz frequency, and has a range of 0.01-100 µSiemens and a max peak to peak value of 100 µAmps at 100 µSiemens. EDA (i.e., skin conductance) can be broadly decomposed into the gradually changing tonic level of electrical conductivity of the skin (i.e., skin conductance level; SCL) and rapidly-changing phasic skin conductance responses (SCRs; Dawson et al., 2017). We focused on tonic SCL as a measure of sympathetic nervous system activity (Cacioppo et al., 2000) based on findings linking increased SCL to fear and anxiety (Kreibig, 2010) and due to the fact that the E4's 4Hz sampling rate may be too slow to accurately detect SCRs in the data (Braithwaite et al., 2013). Tonic SCL was calculated using FLIRT (Föll et al., 2021), a program designed to extract features from wearable physiological data such as that collected by the Empatica E4 wristband, using its default settings. The timeseries extracted from FLIRT presented the mean tonic SCL at a rate of once per second.

Skin Temperature. Participants' skin temperature was assessed continuously with the Empatica E4 via an infrared thermopile with a sampling frequency of 4Hz and a range of -40 to 115°C and a resolution of 0.02°C. Skin temperature was included among the psychophysiological variables based on research that has used skin temperature to accurately classify individuals into high- vs. low-stress groups (Sano et al., 2018). The raw skin temperature timeseries used in this study included temperature readings in Celsius every 0.25 seconds.

Heart Rate. Participants' heart rate (HR) was assessed continuously via the SWear app (Boukhechba & Barnes, 2020) installed on a Huawei Watch 2 Android smartwatch. HR was measured via a photoplethysmography (PPG) sensor, which uses light to measure fluctuations in blood flow under the skin. Increased HR frequently occurs in the context of fear and anxiety and is reflective of a combination of sympathetic and parasympathetic nervous system activity (Cacioppo et al., 2000; Kreibig, 2010). The raw HR timeseries, which presents HR in beats per minute (bpm) approximately once per second, was obtained directly from the Android watch.

Behavioral Variables

Participants' observable anxious behaviors were coded using the Social Performance Rating Scale (SPRS; Fydrich et al., 1998), which was developed to assess anxious behaviors during videotaped or live conversations. Behaviors are coded on a five-point Likert scale from 1 (*Very Poor*) to 5 (*Very Good*) based on five behavioral anchors: conversation flow, voice quality, conversation length, gaze, and discomfort. A rating was assigned for each of the five behavioral indicators for every two-minute segment of the four social interactions, resulting in two ratings per indicator for the four-minute dyadic interactions and three ratings per indicator for the six-minute group interactions. Subsequently, following Gorlin and Teachman (2015), the two to three ratings for each of the five behavioral indicators within an experience were averaged to obtain an average behavioral indicator score for that experience. Thus, for each social experience, a participant had an average score for conversation flow, another for voice quality, and so on. Ratings were reverse-coded prior to conducting analyses so that the direction of the

Likert scale matched that of the affective and cognitive variables (i.e., *Very Good* to *Very Poor* as opposed to *Very Poor* to *Very Good*).

Coding Procedure and Reliability. Recordings from study sessions conducted via Zoom were uploaded into the EUDICO Linguistic Annotator (ELAN; *ELAN*, 2021), a free, open-source tool that allows for textual annotation of audiovisual data. A group of undergraduate research assistants, led by the graduate student first author, were trained to use the SPRS coding system. The coding team was oriented to the SPRS and ELAN as a group, and then independently coded a set of recordings, and then discussed ratings as a group until discrepancies were resolved. For the dyadic experiences, training proceeded until, across raters, none of the ratings based on any of the five behavioral anchors had a difference of more than one rating point. The group experiences were coded by the full team until there was a difference of no more than two rating points on a single behavioral anchor during one (out of three total) two-minute section of the conversation. Subsequently, the coding team independently coded each of the video recordings of the dyadic and group conversations. Coding assignments were distributed in such a way as to minimize repeated coding of any one participant by the same research assistant to reduce potential bias.[5]

Data Processing and Cleaning Plan

Affective, Cognitive, and Behavioral Variables

For each network, participant scores on each of the cognitive and affective variables were extracted from the relevant survey timepoint and averaged across the conditions included in that network. For example, the explicitly evaluative network included data from both the group explicitly evaluative and the dyadic explicitly evaluative experiences. If a participant rated their

[5] Note that the graduate student lead author (ERT) coded the video data for all of the participants in the first session (p001-p004) due to a confidentiality issue.

state anxiety during the group explicitly evaluative experience at two and rated their state anxiety at four during the dyadic explicitly evaluative experience, their average state anxiety for the explicitly evaluative network would be three. Scores on the behavioral indicators were averaged in the same way after a total score for each behavioral indicator was calculated for all social experiences, as described above.

Psychophysiological Variables

In addition to the outlier and noise removal procedures implemented by Empatica and FLIRT, we visually inspected the physiological data and manually removed any remaining outliers (see Supplementary Material for detailed rationale for outlier detection and removal decisions). For **skin temperature,** we excluded data points below 24℃ or above 36℃. For **heart rate,** we excluded data points below 30bpm or above 200pm. We also excluded heart rate data from any experiences during which a participant experienced a sudden increase or decrease (i.e., over 60bpm) in heart rate over a period of less than two minutes. For **tonic SCL,** we excluded data points below 0.1μS or above 40μS. Additionally, recognizing that ambulatory psychophysiological research is a relatively new area and that there is a lack of established norms in regard to expected tonic SCL, we also conducted a separate sensitivity analysis with a more stringent outlier detection threshold (i.e., < 1μS) to examine how results of the concordance tests differed when only examining data from participants with stronger tonic SCL signals (see Supplementary Material).

Given the different sampling rates between the physiological data streams (i.e., sampled continuously throughout each experience) and the self-report data (i.e., sampled once immediately after each experience), the more frequently sampled physiological data were averaged to match the more infrequent self-report sampling rate. That is, for each experience, the average tonic SCL, average skin temperature, and average HR during that period were calculated for each participant. Subsequently, these values were then averaged again across conditions included in each network in the same manner as the cognitive, affective, and behavioral variables. Following these processing steps, variables from all emotional response categories (i.e., affective, cognitive, behavioral, physiological) were standardized to ensure that associations among components would be interpretable.

Analytic Approach

Network Estimation

All analyses were conducted in R version 4.2.0 (R Core Team, 2022). As many of the variables were not normally distributed, the *ppcor* package (Kim, 2015) was used to estimate Kendall's partial tau (partial-τ) networks (Kendall, 1962). Kendall's partial-τ is appropriate when one or more variables in a dataset do not meet the requirements of Pearson's partial correlation, and is particularly well-suited to small datasets with tied ranks (e.g., ordinal data; Akoglu, 2018). Given that *ppcor* cannot handle missing data, pairwise deletion was used such that participants' missing data for a specific network were removed from that network but were not excluded from analyses overall. If a participant was missing data for one of the experiences included in a network but not the other(s), they were included in the network with partial data (e.g., a participant who completed the dyadic explicitly evaluative experience but not the group explicitly evaluative experience would be included in the explicitly evaluative network with just the data from the dyadic experience). Accordingly, sample size varied across networks to maximize the data included in each network; Table 2 outlines which participants were included in each network. To investigate the extent to which our findings were influenced by this approach, we also conducted a set of supplementary analyses using listwise deletion (i.e., removing participants with any missing data from all analyses; see Supplementary Material).

The nodes (i.e., variables) included varied slightly by network based on data collection procedures (e.g., fear of negative evaluation was not assessed in the context of the non-social experience) and hypothesis type (e.g., to assess relative concordance, the two networks being compared must include the same nodes). To test our hypotheses, five partial-τ networks were estimated: (1) an explicit evaluation network comprising data from the "experience" timepoint during both dyadic and group explicitly evaluative conditions, (2) a non-explicit evaluation network comprising data from the "experience" timepoint during the dyadic and group non-explicitly evaluative conditions, (3) a network comprising data from the "experience" timepoint during all four conditions involving social interaction (i.e., group non-explicit evaluation, group explicit evaluation, dyad non-explicit evaluation, dyad explicit evaluation), and (4) a network comprising data from the "experience" timepoint during the one non-social experience (i.e., watching a video alone). Additionally, a reduced version of the social interaction network (5) that matched the structure of the non-social network (i.e., did not include behavioral nodes or the fear of negative evaluation cognitive node) was constructed to test **Hypothesis 2b.** The reduced social experience network was included because two networks must include the same nodes in order to be accurately compared. See Table 2 for an overview of the data included in each network.

Thresholding Procedure

After estimating each partial-τ network, a sensitivity analysis was performed using absolute thresholding. First, we took the absolute value of the partial-τ estimates for each network, which aids in modularity calculation and provides valuable information about which components covary without taking into account whether these associations are positive or negative. Subsequently, the sensitivity analysis was performed, which consists of removing (i.e., setting equal to 0) all partial-τ coefficients below a certain preset value. Starting with 0.05 as the minimum and setting 0.5 as the maximum partial-τ coefficient below which to exclude, absolute thresholding was applied in steps of 0.01 for each network. At each level of thresholding, the *walktrap* (Pons & Latapy, 2006) community detection algorithm was used to calculate the optimal modularity statistic.

Given that the data used to estimate the different networks come from the same set of subjects, we chose one threshold value that remained constant across all networks rather than choosing network-specific threshold values. The optimal threshold value was defined as the highest threshold value that, across all networks, produced a fully connected graph (i.e., none of the nodes were completely disconnected). Once this overall threshold value was applied, we probed around that threshold value within each network by increasing or decreasing the threshold value by 0.05 to determine whether changing the threshold substantially changed the modularity value for that network or whether it was reasonably consistent across levels of thresholding.

Accuracy and Stability of Edge Weight Estimates

After selecting the most appropriate threshold level and applying it to each network, we used the *bootnet* package (Epskamp et al., 2018) to conduct edge stability analyses on the thresholded networks using nonparametric bootstrapping with 1,000 bootstrap samples.

Network Visualization

Networks were visualized using the *qgraph* (Epskamp et al., 2012) and *networktools* (Jones, 2022) packages. For the absolute concordance tests, we used the *MDSnet* function to visualize each network with multidimensional scaling (MDS) with an ordinal configuration. MDS represents the associations among variables as distances between points in two-dimensional space; this technique is useful when visualizing networks because the distance between nodes is interpretable (i.e., the distance between nodes roughly corresponds to the strength of their association). For the relative concordance tests, we used the *PROCRUSTESnet* function to visualize pairs of networks side by side. This approach uses ordinal MDS to plot each network, then applies the Procrustes algorithm to bring the two networks into a similar visual space to aid in comparison (Jones et al., 2018).

Operationalization of Concordance and Permutation Testing Procedure

A permutation testing procedure was used to test each hypothesis. Absolute concordance was defined as a lack of community structure as measured by a non-significant modularity statistic. Statistically, a non-significant modularity statistic suggests that either: a) there are no associations between components of the anxiety response, so there are no communities (i.e., anxiety is not a cohesive concept), or b) components of the anxiety response are highly interconnected, so distinct communities cannot be detected because all components belong to the same cluster (i.e., there is a single dimension to the anxiety response). Given that the latter is consistent with the theoretical conceptualization of concordance whereas the former is not, concordance was more specifically defined as a lack of community structure arising from a unidimensional anxiety response. By contrast, discordance was defined as the presence of community structure as measured by a significant modularity statistic (i.e., an anxiety response characterized by multiple distinct dimensions). See Figure 1 for a visual depiction of concordance and discordance.

To determine whether each of the estimated networks exhibited absolute concordance (**Hypothesis 1a-b**), we simulated 1,000 random networks that were similar in structure to the observed network. Specifically, in each random network, the degree of each node was preserved and the strength of each node was highly correlated with the observed network, but the edges were randomly redistributed. This resulted in a sample of 1,000 random networks that were similar to the observed networks but had no community structure by definition. After the random networks were simulated, we used the *walktrap* algorithm to calculate the optimal modularity of each random network. Finally, we plotted the distribution of 1,000 modularity values of the random networks and examined where the optimal modularity of the observed network fell within that distribution. If the observed modularity was unlikely to arise from this null distribution (i.e., $p < .05$) due to being higher than the majority of modularity statistics in the null distribution, we concluded that there was significant community structure (i.e., discordance) in the observed network. If the observed modularity statistic of a given network was found to be likely to arise from the null distribution (i.e., $p > .05$, indicating a lack of community structure), the network was determined to exhibit concordance. Each network visualization was then qualitatively inspected to better understand the pattern of associations among emotion components under different levels of social threat.

Regarding relative concordance, a network X was said to be more concordant than network Y if the observed difference (i.e., X-Y) between the optimal modularity of the two networks was negative (i.e., network X had less modularity than Y) and that difference was unlikely to arise under the null hypothesis that both networks do not have a significant community structure. To test the questions tied to relative concordance (**Hypotheses 2a-b**), we compared the distributions of optimal modularity values for the random networks simulated to test Hypotheses 1a-b. For each observed network, we had 1,000 simulations of random networks and, by extension, 1,000 optimal modularity estimates. We examined the difference between the 1,000 simulated modularity values for each observed network by subtracting each of the 1,000 modularity estimates from network X from the 1,000 modularity estimates from network Y. This resulted in a distribution *D* of 1,000 difference scores for each comparison. Subsequently, we computed the observed difference between the observed modularities of network X and network Y (X-Y = D_{obs}). Finally, we examined where D_{obs} fell within the distribution *D*. If D_{obs} was unlikely to be from the distribution *D* (i.e., $p < .05$), then we concluded that the difference between the modularity of network X and network Y was not likely to arise under the assumption that both networks do not have a significant community structure (i.e., indicating a significant difference in concordance). We elected to take this permutation testing approach to examine relative concordance because, to our knowledge, it is more challenging to directly claim that one network has more or less of a community structure than another.

Given that our analysis plan involved running multiple tests, we managed the inflated Type I error rate with the Benjamini-Hochberg (BH) correction (Benjamini & Hochberg, 1995) using the *p.adjust* function in the *stats* package (R Core Team, 2022). Specifically, we applied the BH correction to the set of p-values obtained from the absolute concordance tests (Hypotheses 1a-b) and separately applied the correction to the set of p-values obtained from the relative concordance tests (Hypotheses 2a-b). The BH correction works by controlling for the false discovery rate and is less stringent than correcting for the family-wise error rate, thus making it more powerful. In this case, we set our false discovery rate to 5%.

Results

Social Anxiety Symptoms

Based on the pre-enrollment SIAS (M = 45.57; SD = 8.87; range = 34-69), all participants included in analyses reported experiencing moderate to severe symptoms of social anxiety (Mattick & Clarke, 1998). On average, participants endorsed similar levels of social anxiety symptoms on the SIAS that was administered at the time of their study session (M = 43.83; SD = 15.16; range = 10-76).[6]

Overall Network Characteristics

Table 2 presents the final composition of each network. Table 3 presents descriptive statistics for each of the variables included in each network. Based on the sensitivity analysis, a threshold level of 0.12 was selected because it was the highest threshold that still produced a fully connected graph across all networks.[7] Accordingly, all networks were thresholded such that partial-τ coefficients smaller than 0.12 were set to zero. Results of the edge stability analyses, as well as the results of the two sets of sensitivity analyses (i.e., listwise vs. pairwise deletion and stringent vs. lenient EDA outlier removal), can be found in the Supplementary Material. For all networks, the bootstrapped confidence intervals around the estimated edge weights were large and tended to overlap substantially; accordingly, the majority of edge weights within networks are unlikely to differ significantly and the order of edge weights should be interpreted with caution. Regarding the sensitivity analyses, the absolute concordance findings for the explicit evaluation and non-social networks were consistent with each other and the main analyses,

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[6] Eligibility was determined based on a pre-enrollment SIAS score > 34. Thus, although 13 out of 46 participants (28.26%) had day-of-session SIAS scores below our original cutoff value, they were included in analyses given that they are considered vulnerable to perceiving social situations as threatening.

[7] This threshold level was selected based off of the full set of 10 networks that were originally estimated before these analyses were split into two different projects (see Supplementary Material for detailed explanation). To maintain consistency across both projects using these networks, we elected to keep the threshold level at 0.12.

whereas the absolute concordance findings for the non-explicit evaluation and reduced social (i.e., fear of negative evaluation and behavioral variables excluded) networks were inconsistent with the main analyses. The absolute concordance findings for the full social network were consistent between the main analyses and the stringent EDA supplementary analyses, but inconsistent between the main analyses and the listwise deletion supplementary analyses. The relative concordance findings were consistent across all three sets of analyses. Characteristics specific to individual networks are presented below.

Which networks are concordant in and of themselves? (Hypotheses 1a-b)

Contrary to hypotheses, absolute concordance was not observed in any of the conditions involving social-evaluative threat but was observed in the non-social network. Among the discordant networks (i.e., those with significant community structure), components of the same response category (e.g., anxious behaviors) and self-reported components (i.e., affect and cognitions) tended to cluster together. See Figures 2-3 for network visualizations and Table 4 for statistics. See Supplementary Material for the full social experience network visualization.

Which networks are more or less concordant relative to each other? (Hypotheses 2a-b)

Contrary to hypotheses, no significant differences in concordance emerged when comparing the explicit evaluation vs. non-explicit evaluation or social vs. non-social networks. That is, for both of the comparisons, the observed difference in modularity between the two networks was likely to arise under the assumption that both networks do not have a significant community structure. See Figures 2-3 for a visual comparison of network structure and Table 5 for statistics. See Supplementary Material for a qualitative comparison of the full and reduced social experience networks; note that we are unable to make direct quantitative comparisons between these networks given that they are comprised of different nodes.

Discussion

This study sought to advance our understanding of emotional concordance by investigating whether concordance among multiple affective, cognitive, behavioral, and physiological components of social anxiety was greater when social threat was higher. With regard to absolute concordance (i.e., lack of community structure arising from a unidimensional anxiety response), we found no evidence of higher concordance under social threat. In fact, only the non-social, alone network exhibited concordance, whereas all of the networks involving some level of social threat were discordant. Further, there was no evidence that more socially threatening conditions were more concordant relative to less socially threatening conditions, regardless of whether this comparison was operationalized as social vs. non-social context or explicitly vs. non-explicitly socially evaluative context. Our findings contrast with predominant theories of emotion (e.g., Ekman, 1992; Scherer, 2001) and social anxiety (e.g., Clark & Wells, 1995; Heimberg et al., 2014) which assert that concordance among components is a central feature of emotional responding likely to be observed during periods of strong emotion (Davidson, 1992). However, the results of the present study are consistent with decades of empirical research that suggests concordance is not commonly found in practice (Hollenstein & Lanteigne, 2014; I. B. Mauss & Robinson, 2009).

The finding that socially threatening situations were characterized by discordance and a non-social, non-threatening situation by concordance is surprising and counter to all of our hypotheses, making interpretation challenging. One potential approach to understanding these findings involves reconsidering how concordance has been defined and studied. For one, we must consider what preconditions are required, if any, to say that concordance is occurring. Historically, concordance has been discussed and studied within the context of explicit emotional episodes; in this study, the non-social task that did not involve any clear emotional trigger or activation was characterized by concordance. This raises the question: can concordance occur in a state more akin to resting that does not include a clear emotional trigger? Clearly, people are not blank slates devoid of any activity while at rest, as evidenced by neuroscientific research on the default mode network (Raichle, 2015). Additionally, constructivist theories of emotion argue that people are continuously experiencing and evaluating their current neurophysiological state, deemed *core affect,* and attributing meaning to this internal state based on contextual cues (Russell, 2003). Future research should continue to assess emotional responding and explore concordance under conditions that do not involve explicit emotion elicitation to improve our understanding of when concordance occurs.

Additionally, it is necessary to determine what must be happening during an emotional episode to say that concordance is occurring. Whether explicitly stated or implied, theories of concordance have typically assumed that emotion response components must be both associated and activated, and that these processes occur at the same time across components (Bulteel et al., 2014). By contrast, we found a lack of *contemporaneous* concordance across emotion components during situations involving social-evaluative threat. However, it is still likely that there are important interdependent processes at play among the components despite them being weakly associated at one time point. For instance, the emotion components we assessed may operate on different timescales (e.g., skin conductance might quickly peak at the start of a social task whereas self-reported anxiety might remain high for the entirety of the task) or the rate of change of actual emotional processes may be faster than the rate at which we measured them and thus not accurately captured (Cacioppo et al., 2000; Lougheed et al., 2021; I. B. Mauss et al., 2005). Thus, when an emotion is elicited, components of the emotional response are likely changing at different rates and peaking at different times, resulting in different patterns of fluctuation over the course of an emotional episode. Lending support to the idea that the timescale on which a process occurs may impact concordance, Evers et al. (2014) proposed a dual-process perspective on concordance and found evidence for concordance within but not between relatively more automatic (more unconscious and fast) and reflective (more conscious and slow) processes in the context of an anger provocation task. Though important affective, cognitive, physiological, and behavioral components are likely to be interacting and influencing each other during emotional responding, these dynamic relationships are difficult, if not impossible, to capture with contemporaneous “snapshots” of emotional responding (Hollenstein, 2021). Moving forward, it will be important to identify the time scale on which different emotion components operate, develop approaches to accurately measure each component on its respective time scale, and use analytical approaches that allow for the modeling of time-dependent relationships among components (e.g., Yang et al., 2019).

Beyond these conceptual considerations, there are other possible explanations for our findings that are worth considering. Reviews of the concordance literature have consistently suggested that discordance may occur in cases where an elicited emotion is not sufficiently intense (Davidson, 1992; Hodgson & Rachman, 1974). It is possible that, in the present study, the social experiences did not elicit a strong enough social anxiety response for concordance to be observed. For example, the virtual nature of the social interactions may have led participants to perceive them as less threatening or enable them to more easily engage in avoidance behaviors (e.g., texting with friends, avoiding eye contact), which together could result in insufficiently intense emotional responses. Further, the repetitive nature of the self-report assessments could have also provided a distraction from anxiety, thereby reducing emotional intensity. However, if we keep the assumption that emotional intensity is a prerequisite for concordance, it would follow that the concordant, non-social experience must have elicited the highest emotional intensity relative to the discordant social experiences. This was not the case – the lowest average subjective arousal (*M* = 2.21, *SD* = 1.14) and subjective anxiety (*M* = 2.24, *SD* = 1.25) ratings were reported during the non-social experience (as we expected would occur). Accordingly, emotional intensity may not be the primary factor predicting when concordance is most likely to occur.

It is also possible that individual participants had different levels of concordance and discordance in their emotional responding, but the between-subjects analytic approach masked these individual differences. In both laboratory and daily life studies, emotional concordance has been found to vary substantially at the individual level (Bulteel et al., 2014; Ekman, 1992; Hollenstein & Lanteigne, 2014; P. Lang et al., 1993; Lougheed et al., 2021; I. B. Mauss et al., 2005). For example, in a 4-week study that used ambulatory physiological monitoring and ecological momentary assessment to examine emotion concordance in daily life, Van Doren et al. (2021) found that increased physiological arousal was strongly associated with greater self-reported arousal for some individuals but only weakly associated for others. In a study that modeled emotional responses to an anxiety-provoking speech task with intraindividual networks, substantial individual differences were found with respect to the dynamic patterns of associations among responses (e.g., positive vs. negative feedback loops; Yang et al., 2019). Taken together, it is clear that there are individual differences with regard to if, when, and how emotional concordance occurs; future work should explore these individual differences in the case of emotional responding to social threat. For example, it may be useful to explore trait emotion dysregulation as a possible predictor of concordance. Emotion regulation, particularly suppression, has been found to reduce emotional concordance among experiential, behavioral, and physiological responses to both negative and positive stimuli (Dan-Glauser & Gross, 2013), suggesting that discordance may be more likely when regulatory strategies can be successfully implemented (see also Hodgson & Rachman, 1974).

Patterns of Associations Among Components

In addition to testing questions tied to absolute and relative concordance, we also visualized and qualitatively inspected each network to better understand patterns of concordance and discordance in social anxiety. Across all networks, associations among emotion response components tended to be fairly weak, with average edge weights (i.e., partial-τ coefficients) ranging from 0.213 to 0.243. Among the discordant networks (i.e., social-evaluative networks), the strongest associations were often between variables within the same response channel that had conceptual overlap (e.g., subjective anxiety and subjective arousal; conversation length and conversation flow). Some commonalities also emerged in community structure in the discordant networks, namely that components from the same response channels or that were measured in the same way (e.g., self-reported affect and cognition) tended to form communities. This is consistent with a number of studies that have found concordance among self-reported symptoms of anxiety but not between self-reported and objectively measured indicators of anxiety (e.g., Eckman & Shean, 1997; Edelmann & Baker, 2002; I. Mauss et al., 2004). Taken together, these findings provide some tentative evidence for concordance *within* response channels in cases where the overall network did not exhibit absolute concordance. However, it is not clear whether this is due to actual concordance at a conceptual level, shared measurement variance, or some combination of the two

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Clinical Implications

The present findings need to be replicated and many open questions remain but the current results raise intriguing possible implications for clinical practice, particularly how we understand and explain emotional responding at the individual level. When taking a cognitive-behavioral approach to therapy, clients are typically provided with psychoeducation about the interactions among thoughts, feelings, and behaviors and how these interactions can intensify an emotional experience. However, the way this model of emotional responding is presented typically implies all-or-none action in that all response components (i.e., affective, cognitive, behavioral, physiological) are assumed to be relevant to all clients and occur concurrently. In reality, it is likely more beneficial to determine the components of emotions and the sequence in which those components occur at the individual level rather than assuming that all components are comparably activated for all clients. Beyond this, if we are to accept the notion that concordance is characterized by mutually reinforcing interactions among components that are activated and fluctuate on different timescales, this offers numerous opportunities for altering unhelpful emotional responses. A client is already likely to be offered different tools (e.g., mindfulness vs. cognitive restructuring) for managing different components of emotional responding (e.g., physiological arousal vs. negative thinking patterns); this framework suggests that it may also be useful to implement these strategies at different points in time depending on what the sequence of emotional responding looks like for that particular client. Of course, there are many cases in which these interactions occur rapidly and a clear sequence cannot be easily identified. Considering this, it is also critical for clients to learn tools for managing challenging emotions that are effective across response types and contexts (e.g., distress tolerance skills).

Limitations

The results of this study should be interpreted in light of its limitations. First, our sample size (i.e., N = 39 in the networks with the most observations) was relatively small compared to other cross-sectional network analyses. In a recent review of papers taking a network approach to psychopathology, 200 cross-sectional network analyses were identified with sample sizes ranging from N = 20 to N = 65,561, with a median sample size of 373.5 (Robinaugh et al., 2020). There are not clear benchmarks with respect to the minimum number of observations needed for cross-sectional network analyses, but current guidelines typically recommend conducting an a priori power analysis to determine the sample size needed for the expected network structure (Epskamp & Fried, 2018). Importantly, our sample size was determined based on power analyses for the parent study for which these data were collected; accordingly, a limitation of the present study is that we did not conduct an a priori power analysis specific to the analyses presented here. Thus, it is possible that our sample size resulted left us underpowered to detect true effects. Indeed, the ranges in modularity estimates across levels of thresholding were quite wide, and the results of the bootstrapped edge stability analyses indicated that most edge weights, with the exception of the strongest edges (e.g., between subjective arousal and subjective anxiety in the explicit evaluation network), were unstable. Together, these findings are suggestive of high sampling variability. Future work should test whether concordance is observed under social threat among larger samples of socially anxious individuals to test the replicability of our results.

Second, although participants were given clear instructions for the explicitly evaluative vs. non-explicitly evaluative threat conditions, we did not specifically assess whether participants internalized the instruction manipulation. To shed some light on the impact of the instructions, we did a secondary, post hoc analysis using a Wilcoxon rank sum test with continuity correction (given that the normality assumption was violated) to determine whether participants' self-reported fear of negative evaluation differed between the explicit evaluation (M = 3.19, SD = 1.29) and non-explicit evaluation conditions (M = 2.73, SD = 1.09). Although self-reported fear of negative evaluation was greater on average in the explicit evaluation conditions as compared to the non-explicit evaluation conditions, this difference did not reach statistical significance, p = 0.130, d = 0.382. Accordingly, a limitation of the current study is that the instruction manipulation may not have reliably increased perceived social threat in all participants.

Third, data were collected for two minutes during the non-social baseline condition, which is slightly shorter than the 5-10 minutes typically recommended when establishing a psychophysiological baseline (Boucsein et al., 2012; Quintana et al., 2016). Given that the non-social condition (i.e., watching a video alone) was always the first task that participants completed (whereas the subsequent conversations were randomized), it is possible that participants were anxious during this task because they were unfamiliar with the study procedures. However, this seems unlikely; as shown in Table 3, the non-social experience was frequently associated with the lowest scores on different indicators of anxiety (e.g., subjective arousal, subjective anxiety, performance concerns, heart rate) as compared to the experiences involving social threat.

Finally, there are limitations to consider with respect to the study sample. Though participants reported experiencing moderate to severe anxiety about social interactions, this was not a clinical sample with diagnosed social anxiety disorder. It is thus possible that patterns of concordance and discordance among emotional responses may be different among individuals who have a diagnosis of social anxiety disorder. Additionally, the sample was relatively homogenous in terms of age (M = 19.28, SD = 1.91), sex (76.1% female), race (71.7% White), and ethnicity (89.1% non-Latinx/Hispanic). There is reason to suspect that concordance may differ based on demographic characteristics; for example, one study found greater concordance in emotional responding among women versus men (Rattel et al., 2020). Additionally, important cultural differences in socially anxious responding have been identified; for instance, Asian-American individuals have been found to report elevated trait social anxiety symptoms compared to White Americans, but exhibit comparable nonverbal behaviors during a social-evaluative task (Okazaki et al., 2002). Though this reflects a group difference rather than a direct test of concordance, these findings suggest that behavioral and self-reported emotion components could be loosely coupled or discordant among Asian-American individuals under social threat. Future research should examine emotional concordance among more diverse samples under different levels of social-evaluative threat to clarify how concordance differs across contexts and cultures.

Despite these limitations, there are also numerous strengths to this study, most notably: (a) the assessment of multiple components of the anxiety response and multiple indicators for each response component, (b) an analytic approach that allowed us to examine associations between components while accounting for the other components under consideration, and (c) a study design that allowed us to operationalize social threat in two different ways (i.e., alone vs. with others and explicit vs. non-explicit evaluation), thereby advancing our understanding of which types of situations may be associated with concordance.

Conclusion

This study examined whether the presence of greater social-evaluative threat could help explain when emotional concordance occurs. Results unexpectedly showed that the non-social condition, but not any of the conditions ostensibly involving social threat, exhibited concordance and that emotional responses were not relatively more concordant during social threat relative to a non-social task. Qualitative inspection of the discordant networks indicated that conceptually similar components of social anxiety (e.g., different cognition indicators), as well as components assessed via the same response modality (e.g., self report), tended to form communities. Taken together, this study adds to the growing body of literature which suggests that contemporaneous concordance among response components is not an inherent or necessary aspect of an emotional episode.

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Tables

Table 1. Sample demographics

Variable	High SIAS (*n* = 46)
Age	*M* = 19.28
	SD = 1.91
Sex	
Female	35 (76.1%)
Male	11 (23.9%)
Other	0 (0%)
Race*	
Caucasian/White	38 (71.7%)
Asian	8 (15.1%)
African American	4 (7.5%)
Middle Eastern	2 (3.8%)
American Indian/Alaska Native	1 (1.9%)
Native Hawaiian/Pacific Islander	0 (0%)
Other	0 (0%)
Ethnicity	
Latinx/Hispanic	4 (8.7%)
Not Latinx/Hispanic	41 (89.1%)
Prefer not to answer/Other	1 (2.2%)

* = When self-reporting their race, participants were able to select all that apply; accordingly, the total number of races identified add up to more than the total sample size. In total, 7 participants endorsed more than one race.

Table 2. Network composition.

Network	**Experience(s) Included**	**Nodes Excluded**	**Total *N***
Explicit Evaluation	Dyadic Explicitly Evaluative; Group Explicitly Evaluative	None	35
Non-explicit Evaluation	Dyadic Non-explicitly Evaluative; Group Non-explicitly Evaluative	None	35
Full Social	Dyadic Explicitly Evaluative; Dyadic Non-explicitly Evaluative; Group Explicitly Evaluative; Group Non-explicitly Evaluative	None	39
Reduced Social	Dyadic Explicitly Evaluative; Dyadic Non-explicitly Evaluative; Group Explicitly Evaluative; Group Non-explicitly Evaluative	All Behavioral; Fear of Negative Evaluation (Cognitive)	39
Non-Social	Alone Video	All Behavioral; Fear of Negative Evaluation (Cognitive)	33

Table 3. Descriptive statistics by network.

Network	Variable													
	Affective						Cognitive							
	Subjective Arousal		Subjective Affect		Subjective Anxiety		Fear of Negative Eval		Self-Appraisal		Performance Concerns		Performance Satisfaction	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Explicit Evaluation	2.63	1.20	2.19	1.10	2.77	1.21	3.19	1.29	2.40	0.91	2.91	1.23	2.44	0.91
Non-explicit Evaluation	2.39	0.82	2.40	0.94	2.77	1.04	2.73	1.09	2.73	0.93	2.80	1.19	2.67	0.99
Full Social	2.55	0.93	2.34	0.91	2.78	1.01	3.04	1.09	2.62	0.85	2.91	1.10	2.62	0.84
Non-Social	2.21	1.14	2.48	0.80	2.24	1.25	-	-	2.70	0.85	1.94	1.30	2.55	1.00

Network	Variable (continued)															
	Behavioral										Physiological					
	Gaze		Vocal		Length		Discomfort		Flow		Tonic SCL		HR		Skin Temp	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Explicit Evaluation	1.76	0.88	1.85	0.84	2.20	0.77	2.33	0.74	2.32	0.89	2.01	4.33	79.40	11.09	31.17	2.27
Non-explicit Evaluation	2.07	0.83	2.14	0.92	2.29	0.80	2.44	0.76	2.60	0.81	1.35	3.19	80.54	8.78	31.05	2.03
Full Social	1.89	0.71	2.03	0.72	2.23	0.64	2.34	0.56	2.47	0.65	1.77	4.13	79.81	9.71	31.05	2.06
Non-Social	-	-	-	-	-	-	-	-	-	-	0.83	1.74	76.96	11.86	31.17	2.45

Note: Descriptive statistics not reported for the Reduced Social network as it is simply a version of the Full Social network with variables removed.
Tonic SCL = Tonic skin conductance level; HR = Heart Rate

Table 4. Absolute concordance results.

Network	Modularity	Range in Modularity*	Original *p*	BH-Adjusted *p***	Communities***
Explicit Evaluation	0.341	0.228-0.539	0.012	0.022	(1) Subjective Arousal, Subjective Anxiety, FNE, Performance Concerns; (2) Vocal, Length, Discomfort, Flow, Skin Temp; (3) Affect, Self-Appraisal, Performance Satisfaction, Gaze, Tonic SCL; (4) HR
Non-explicit Evaluation	0.390	0.182-0.421	0.013	0.022	(1) Gaze, Vocal, Length, Discomfort, Flow, Tonic SCL, HR; (2) Affect, FNE, Self-Appraisal, Performance Concerns, Performance Satisfaction; (3) Subjective Arousal, Subjective Anxiety, Skin Temp
Full Social	0.363	0.253-0.440	0.019	0.027	(1) Gaze, Vocal, Length, Discomfort, Flow; (2) HR, Skin Temperature; (3) Affect, Tonic SCL; (4) Subjective Arousal, Subjective Anxiety, Fear of Negative Evaluation, Performance Concerns; (5) Self-Appraisal, Performance Satisfaction.
Reduced Social	0.273	0.218-0.323	0.010	0.022	(1) HR, Skin Temp; (2) Affect, Self-Appraisal; Performance Satisfaction, Tonic SCL; (3) Subjective Arousal, Subjective Anxiety, Performance Concerns
Non-Social	0.113	0.078-0.130	0.107	0.119	--

Note: Tonic SCL = Tonic skin conductance level; HR = Heart Rate; FNE = Fear of negative evaluation
* = Range in modularity reflects the change in modularity statistic across levels of thresholding (i.e., 0.07-0.17) around the optimal threshold (i.e., 0.12). Larger ranges indicate that the amount of community structure observed in the network changes substantially based on the level of thresholding and should thus be interpreted with caution.
** = The BH-adjusted p-values reflect a correction for 10 tests rather than the five tests presented here. We chose to keep the correction at the same level because we already ran the planned full set of 10 absolute concordance tests (see preregistration) before ultimately deciding to reduce the scope of this paper and focus on only five of those tests.
*** = Communities were identified using the *walktrap* (Pons & Latapy, 2006) community detection algorithm with the number of steps set to 4.

Table 5. Relative concordance results.

Comparison	**Observed Difference in Modularity**	**Original *p***	**BH-Adjusted *p****
Explicit Evaluation vs. Non-explicit Evaluation	0.049	0.528	0.660
Social vs. Non-social	0.160	0.096	0.240

* = The BH-adjusted p-values reflect a correction for four tests rather than the two tests presented here. We chose to keep the correction at the same level because we already ran the planned full set of four relative concordance tests (see preregistration) before ultimately deciding to reduce the scope of this paper and focus on only two of those comparisons.

Figures

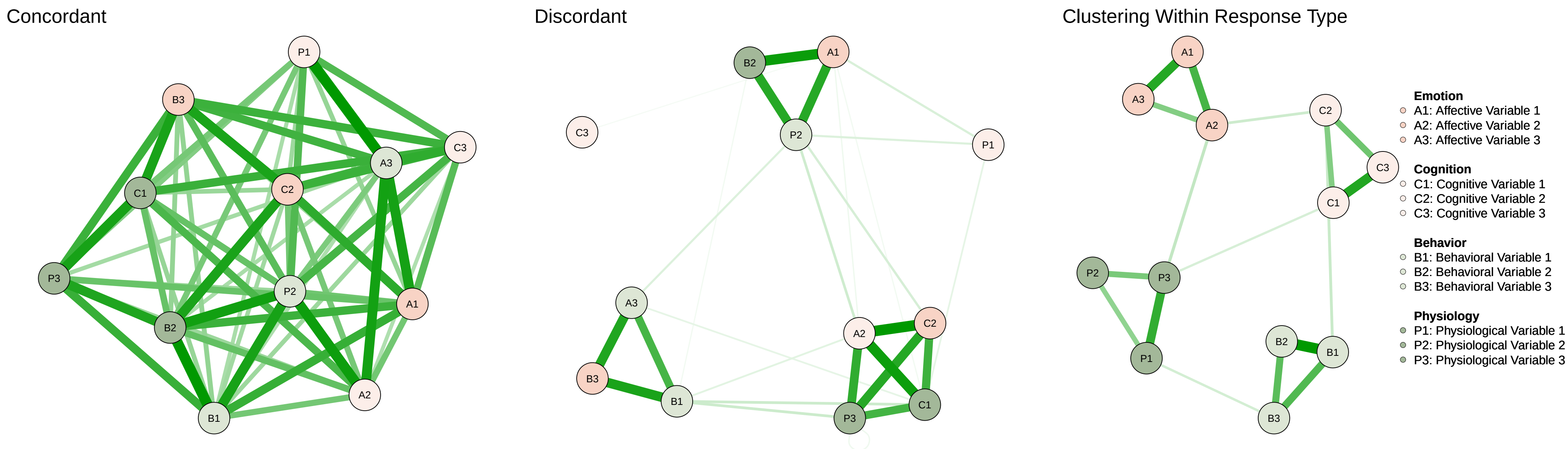

Figure 1. Theoretical representations of concordance (left), discordance (center), and clustering within emotion response categories (right). In the concordant network, all response components are highly interconnected and there is a lack of community structure. By contrast, there are distinct communities in the discordant network, with weak connections between communities. The within-response clustering network would statistically be identified as discordant given its strong community structure but differs from the center figure in that all of the indicators of a given emotional response type are associated with each other. In other words, there is potential evidence for concordance within but not between emotion response categories in the right-most figure.

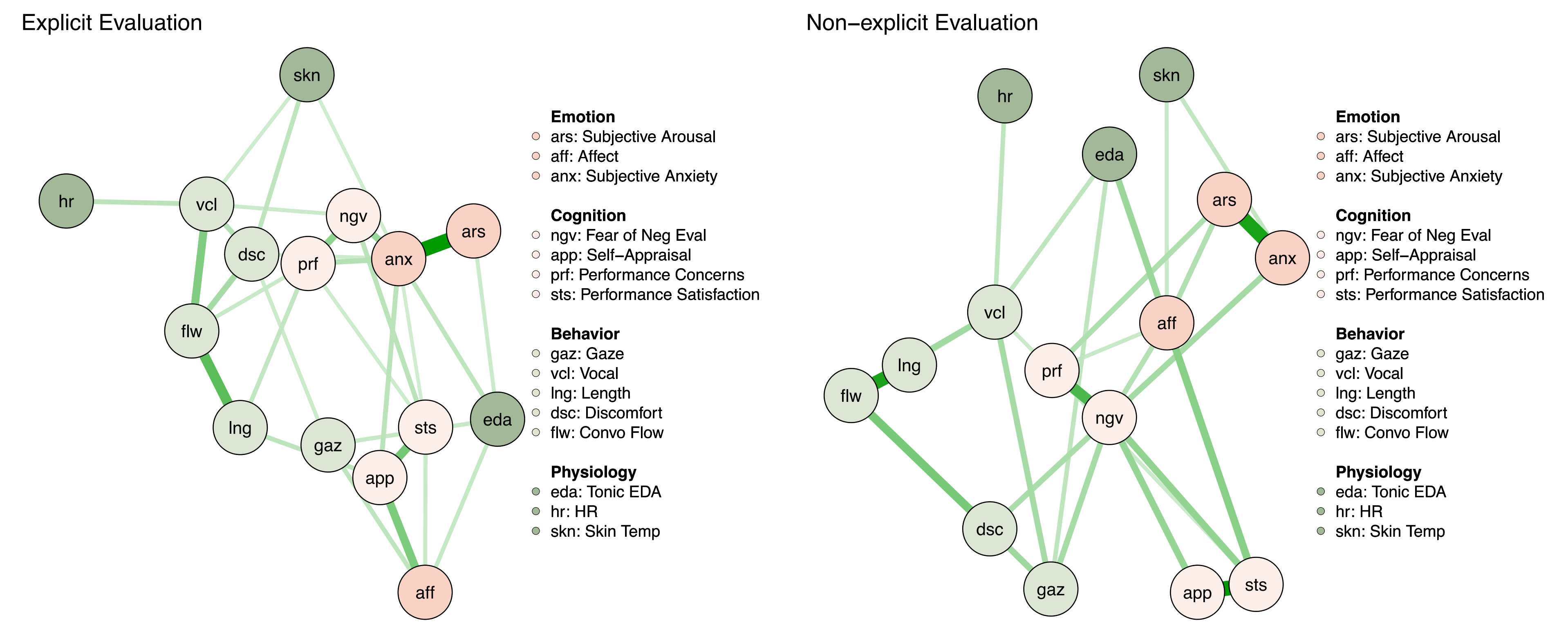

Figure 2. Partial-τ networks with absolute thresholding (0.12) for the explicit evaluation (left) and non-explicit evaluation (right) experiences. Edges represent partial rank correlations and nodes represent emotional response indicators. Thicker edges indicate stronger partial rank correlations. Node color corresponds to type of emotion response component (i.e., affective, cognitive, physiological, behavioral). See Supplementary Material for network visualization in which node color corresponds to *walktrap*-identified community membership. Networks are visualized using ordinal MDS with repulsion = 0.4 to minimize node overlap. Nodes that are closer together in space tend to be more strongly correlated than nodes that are farther apart. Edge weights in the explicit evaluation network ranged from 0.124 *(subjective anxiety – performance satisfaction)* to 0.671 *(subjective anxiety – subjective arousal)* and edge weights in the non-explicit evaluation network ranged from 0.122 *(performance concerns – performance satisfaction)* to 0.595 *(self-appraisal – performance satisfaction).*

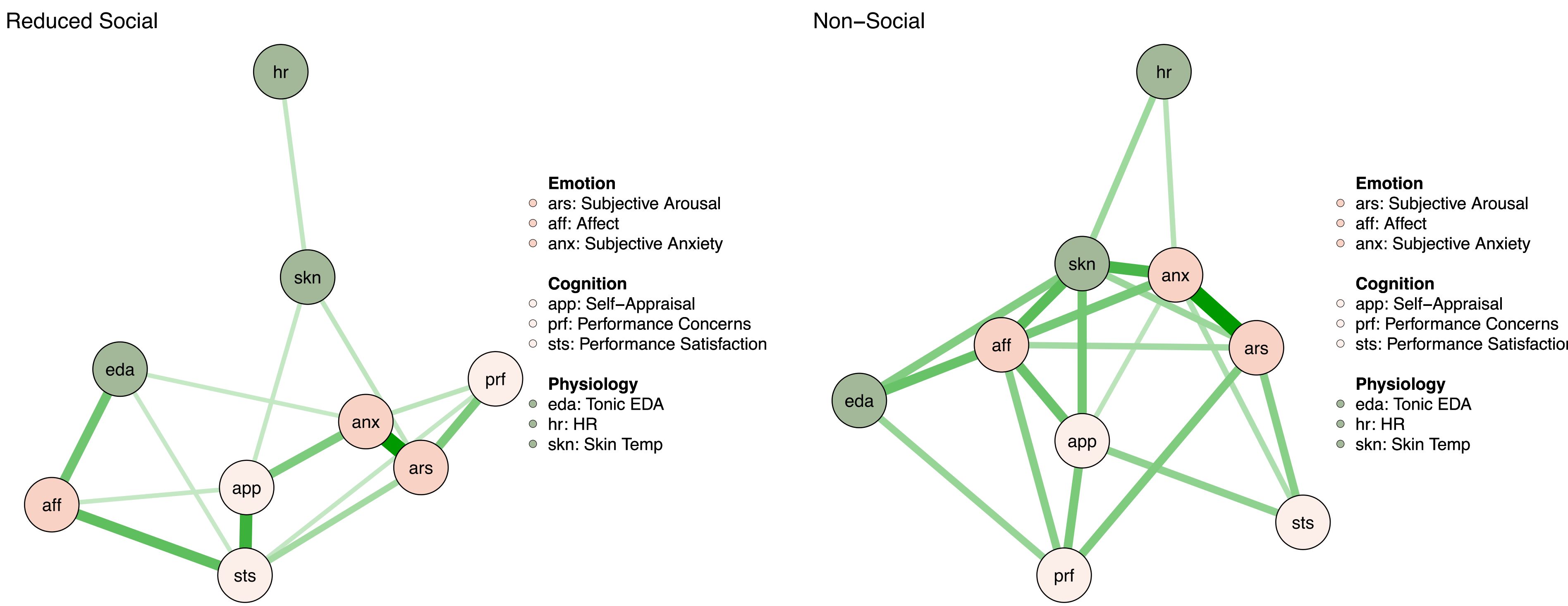

Figure 3. Partial-τ correlation networks with absolute thresholding (0.12) for the reduced social (left) and non-social (right) experiences. Behavioral nodes and the fear of negative evaluation cognitive node are excluded from these networks. Edges represent partial rank correlations and nodes represent emotional response indicators. Thicker edges indicate stronger partial rank correlations. Node color corresponds to type of emotion response component (i.e., affective, cognitive, physiological). See Supplementary Material for visualization of reduced social network in which node color corresponds to *walktrap*-identified community membership. A secondary visualization of the community structure of the non-social network is not provided as this network exhibited concordance. Networks are visualized using ordinal MDS with repulsion = 0.3 to minimize node overlap. Nodes that are closer together in space tend to be more strongly correlated than nodes that are farther apart. Edge weights in the reduced social network ranged from 0.123 *(performance satisfaction – tonic SCL)* to 0.546 *(subjective arousal – subjective anxiety)* and edge weights in the non-social network ranged from 0.130 *(subjective anxiety – self-appraisal)* to 0.489 *(subjective arousal – subjective anxiety).*