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Network analyses of emotion components: an exploratory application to the component process model of emotion

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Abstract
Emotion is an episode involving changes in multiple components, specifically subjective feelings, physiological arousal, expressivity, and action tendencies, all these driven by appraisal processes. However, very few attempts have been made to comprehensively model emotion episodes from this full componential perspective, given the statistical and methodological complexity involved. Recently, network analyses have been proposed in the field of emotion and cognition as an innovative theoretical and statistical framework able to integrate several properties of emotions. We therefore addressed the call for more multi-componential evidence by modeling the network of a comprehensive list of emotion components drawn from the Component Process Model of Emotion. Five-hundred students were confronted with mildly ambiguous scenarios from everyday life, and reported on their situational appraisals and emotion responses. Network analyses were applied to the emotion components related to a positive and a negative scenario to explore 1) how the components organize themselves into networks and dimensions; 2) which components are the most central within networks and dimensions; and 3) the patterns of components relation between and within dimensions. A three-dimensional solution emerged in both scenarios. Additionally, some appraisals and responses appeared to be differentially relevant and related to each other in both scenarios, highlighting the importance of context in shaping the strength of emotion component relations. Overall, we enriched the field of affective science by exploring the connections between emotion components in three novel ways: by using network analyses, by integrating them into a multi-componential framework, and by providing context to our emotion components. Our results can also potentially inform applied research, where understanding the interconnections and the centrality of components could aid the personalization of interventions.

Keywords Cognitive appraisal · Component Process Model · Emotion · Networks

In emotion research, it is generally accepted that an emotion has a componential nature: that is, what we call emotion is the byproduct of the interaction of several components, namely subjective evaluations, feelings, physiological arousal, expressivity, and action tendencies (Lange et al., 2020). Several emotion theories coexist, and differ in their conceptualizations of how and which of these components are most central. However, they converge on the necessity of an antecedent event for an emotion to occur – that is, a situation that will then be appraised (Scherer & Moors, 2019).

The Component Process Model (CPM) of emotion by Scherer (2009) has established itself as one of the most authoritative modern appraisal theories thanks to its dynamic and functional architecture. In the CPM, an emotion is a synchronized, multi-componential episode initiated by cognitive appraisal of an emotionally charged situation (e.g., an external event such as a friend not greeting back, or an internal event such as an upsetting memory). Compared to other emotion theories, the CPM assigns a special gate-keeper role to appraisal. Indeed, as a result of phylogenetic processes, appraisal is a highly sophisticated cognitive tool that allows us to navigate safely through complex and ambiguous situations. In other words, appraisals serve an evolutionary function, that the CPM has the merit of organizing into an increasingly differentiated, sequential

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architecture. For example, within a situational appraisal, early Stimulus Evaluation Checks (SECs) act as orienting responses to novelty, followed by evaluations of pleasantness, and of personal goal relevance. These first SECs fall under the functional category of Relevance detection, which is also found in non-human species and in simple organisms (Ellsworth & Scherer, 2003). It is theorized that if these basic checks are not present, an emotion episode cannot be elicited. Then, more "costly" cognitive checks are endorsed. The functional category of Implications regroups those checks that assess the personal consequences that might result from the situation, for example depending on who caused it, whether it is still conducive to personal goals, and what the probability of the desired outcome is. Then, the functional category of Coping Potential regroups those checks that determine the individual's ability to cope with and/or adjust to the situation. Finally, the functional category of Normative Significance assesses the compatibility of the situation to personal and external norms. In the CPM, the result of this multilevel appraisal process causally leads to the differentiation and modification of emotion responses, i.e., the experiential (e.g., frustration), somatic (e.g., feeling hot), expressive (e.g., frowning), and motivational (e.g., repair instinct) components of an emotion episode. Finally, the event is represented centrally as nonverbal feelings, and the emergent emotion (e.g., sadness) is categorized and labeled (Fig. S1). Importantly, in the CPM, emotion components activation is theorized to have a recursive effect on the other components: that is, once an emotion episode is initiated, a dynamic update of the system takes place continuously, always with an adaptive function (Scherer, 2009).

Despite the agreement on the multi-componential nature of emotion episodes, virtually no attempts have been made to model them comprehensively under a full componential perspective, mainly for two reasons. The first concerns the overwhelming amount of research dedicated to the investigation of what is considered as the "real" outcome of an emotion episode, that is, a categorical emotion (e.g., guilt, pride). Early appraisal theory aimed to identify the fixed patterns of component activation that would lead to the experience of these prototypical emotions, usually by applying self-report measures in a deductive-semantic fashion (Gentsch et al., 2018). In such cases, participants are presented with an emotion term, followed by a list of emotion components to be matched to the emotion based on their beliefs and experience. This procedure has however been heavily criticized for eliciting culturally-based and/or stereotypical assumptions about emotions (Scherer & Moors, 2019). Modern appraisal theorists have also now acknowledged the pervasive "impurity" and complexity of the emotion experience, proving that the existence of pure emotions is the exception rather than the rule (Scherer & Meuleman, 2013; Scherer & Moors, 2019). This has led appraisal research to shift from the identification of categorical emotions as outcomes of the emotion chain to the study of the interconnections between the five components: however, paradigm shifts are slow to be implemented in practice. Indeed, the most prolific contemporary strand of appraisal research is known as bi-componential, that is, concerned with exploring relations between component pairs (Meuleman et al., 2019). Scherer and Moors (2019) recently provided a summary of such evidence: overall, novel and goal-relevant stimuli elicit pre-attentive appraisals, which are linked to automatic action tendencies such as approach or avoidance tendencies, depending on the stimuli valence. When a stimulus is negatively valenced and externally caused, or general control/power over the situation is high, action tendencies are more aggressive in nature. Regarding the relation between appraisal and physiological reactions, evidence suggests that novel and goal-relevant stimuli re-orient attention and induce physiological changes in parameters such as muscular tone, electrodermal and respiratory activity, as well as pupil dilation, with negative and positive valence inducing differential reactions. A higher vascular reactivity and sympathetic arousal have also been associated with low prospective control. Finally, fewer experimental evidence is available for the appraisal-expressivity relationship: the strongest results concern the intrinsic pleasantness appraisal affecting frowning (corrugator muscles activity) and smiling (zygomatic muscles activity), and the power and control appraisals affecting vocal expressivity (Scherer & Moors, 2019).

The second reason for the scarcity of multi-componential modeling is pragmatic: attempting to model a large number of components involves great statistical and methodological complexity (Meuleman et al., 2019). Examples of these multi-componential attempts are rare, but two are noteworthy for their innovation. Within the CPM framework, Meuleman et al. (2019) used machine learning algorithms to explore the relationships between 18 appraisals and the emotion responses factors. They found that factors within the same emotion component, as well as appraisals factors and response factors, were mostly uncorrelated. Only the appraisal of goal compatibility and of suddenness were strongly related to physiological and expressive responses, respectively. More recently, Lange et al. (2020) proposed the network approach to model emotion components, which postulates how, for instance, the emotion of anger actually emerges from the interaction of beliefs, motivations, expressive behaviors and bodily reactions. Inspired by the theoretical proposition of Lange et al. (2020), we believe that networks could similarly advance modern appraisal research by allowing a comprehensive exploration of multi-componential relations.

Applied to many scientific fields in the last decade, network modeling has also grown exponentially in psychology (Borsboom et al., 2021). Its widespread popularity across disciplines lies in its foundational assumption that phenomena between and within individuals– from human genes and mental health to relational or social media transactions– are dynamic, complex systems, and thus exhibit complex behavior (Barabási, 2012). Because systems entail a structural organization—a network– of their components, it is often fruitless to study their functioning in isolation (Barabási, 2012; Borsboom et al., 2021). This is especially true when components interact with each other to give life to a phenomenon, which in turn can influence the functioning of the same components through feedback loops – a property known as bi-directionality (Dalege et al., 2016; Lewis, 2005). The simplicity with which networks visually convey very complex relationships between system components is another reason why they have become so popular (Hevey, 2018). Components, called nodes, are connected via edges that convey the magnitude and direction of their association. For example, thicker and green (or blue) edges signal a strong and positive (excitatory) relation, while thinner and red edges a weak and negative (inhibitory) relation (Borsboom et al., 2021; Dalege et al., 2016). Moreover, nodes can a) be more important (central) to the network, by being more strongly connected to all the other nodes; b) cluster into communities– i.e., groups of more densely connected nodes; and c) bridge different communities (Borsboom et al., 2021).

In psychology, these network properties have led to important theoretical and empirical advances through the modeling of affects, cognitions, and behaviors. For instance, network approaches have allowed the subfield of clinical psychology to move away from the long-standing essentialist, biologically-based view of mental disorders, and to explore how syndromes may actually be the byproducts of causal and dynamic interconnections of symptoms, such as negative cognitive schemas (Bringmann et al., 2022; Robinaugh et al., 2020). For example, in a sample of American psychology college students, Collins et al. (2023) investigated the moderating influence of depressive symptoms on the network of negative self-schemas associated with fear of happiness. They found that more depressed students reported stronger and positive links between nodes representing avoidance and devaluation of positivity. Similarly, Tao et al. (2022) explored the association between anxiety, depression and sleep disturbance symptoms in a large convenience sample of Chinese university students. The authors found that the symptoms of guilt, irritability, restlessness, fear, and sleep disturbance bridged the three disorders, meaning that once these symptoms are activated, they would in turn activate the entire network. This knowledge opens the possibility of improving the whole mental health network by acting on a single symptom (Jones et al., 2021). In cognitive psychology, networks have allowed to easily visualize how and with what intensity nodes are connected (or not), as well as their centrality, across groups. For example, Neubeck et al. (2022b) modelled cognitive performance components in young and old individuals and showed how the fluid intelligence component was more central, and the link between intelligence and working memory stronger, in the old group compared to the young one, while the accelerated attention component was most central in the latter. Similarly, Neubeck et al. (2022a) found that self-regulation and executive control functions were more strongly interconnected in older than in younger individuals, possibly due to a stronger effect of cognitive decline on overall regulatory processes. In the field of emotion psychology, Mattsson et al. (2020) explored the interconnection of academic-related positive and negative emotions in a sample of 241 Finnish university students, highlighting how self-efficacy beliefs emerged as the most central node and therefore targetable. More recently, Lange and Zickfeld (2021, 2023) confirmed the utility of the network approach by demonstrating that components are indeed shared between similarly valenced emotions, such as awe, admiration, and gratitude, guilt and shame, or awe and *kama muta* ("being moved").

Strikingly, emotion episodes were already being discussed as complex systems of component interactions almost 20 years ago (Lewis, 2005; Sander et al., 2005). The CPM itself relies on dynamic system principles, in particular that of recursiveness (i.e., bi-directionality; Moors, 2022; Sander et al., 2005), according to which "the emotion process is considered as a continuously fluctuating pattern of change in several organismic subsystems that become integrated into coherence clusters and thus yields an extraordinarily large number of different emotional qualities" (Scherer, 2009, p. 1320). The application of networks to the modeling of CPM emotion components is thus a natural step, if not *the* required step, to focus on the mechanisms underlying an emotion episode and move beyond standard emotion labels as outcomes (Scherer & Moors, 2019). Moreover, as suggested by Lange et al. (2020), the application of networks to emotion components and emotions has the potential to achieve the integration needed in emotion research, by serving as an alternative psychometric model to perhaps the most explicitly (and implicitly) applied one in the field: the reflective latent-variable model. Its theorization of what constitutes an emotion episode coincides with the lay notion of an unobserved (i.e., latent) construct, whose symptoms (i.e., indicators) are instead observable (Lange et al., 2020). These indicators are thus causally dependent on the latent variable and causally independent of each other, implying that: 1) an emotion episode is separable from its components; 2) these components have a fixed and universal pattern of activation that leads only to the experience of a particular emotion; and 3) they are correlated to the latent variable but not causally interacting between each other (Lange et al., 2020). However, empirical evidence contradicts the reflective latent-variable model of emotion: components are routinely manipulated to assess the target emotion (Mauss & Robinson, 2009); individuals vary in their situational appraisals, and in the intensity with which these appraisals affect emotion reactivity (Kuppens & Tong, 2010); appraisals exert a causal effect on other components of emotion (Meuleman et al., 2019), and some components are known to be more correlated than others (Lange et al., 2020; Scherer & Moors, 2019); and, finally, mixed emotions are the norm rather than the exception (Israel & Schönbrodt, 2021; Scherer & Meuleman, 2013).

Thus, inspired by the theoretical and methodological proposal by Lange et al. (2020), we aimed to explore the network of a comprehensive list of emotion components in slightly ambiguous, positive and negative daily life situations, without deductive prompt of emotion terms (Gentsch et al., 2018). This was done to explore what is referred to as an emotion episode in the CPM (Scherer & Moors, 2019). As noted in the findings reported above, bi-componential research points to few but stable relations between appraisal and emotion responses, while multi-componential evidence is so far sparse and heterogeneous. Therefore, we had several goals with this work.

Our first research question was to explore how the five emotion components organized themselves into a network and into dimensions. This would provide important information regarding the influence of context on component inter-connections and clustering. Emotion components in the CPM are theorized to be organized at a higher-order level, which comprises a four-factor structure of Valence, Arousal, Power, and Novelty (Fontaine et al., 2013). Recently, Fontaine et al. (2022) provided even more nuanced results concerning the relations between these four dimensions as negative and positive emotion terms turned out to be strongly distributed across a dimensional space consisting of the first two dimensions. The meaning of these terms was then further contextually refined by the dimensions of Power and Novelty. For example, the authors found a strong relation between Valence and Power dimensions in positive emotion terms, which did not hold for negative ones. The authors explained this finding by arguing that positive valence already captures substantial variance in power-related components (i.e., having power over a situation is generally perceived as positive). Based on this evidence, Fontaine et al. (2022) formulated specific predictions concerning the emergence of a distinct Power dimension, depending on the proportion of positive versus negative emotion terms. Translating their predictions to scenarios, we thus hypothesized that, in a positive one, appraisals belonging to the Coping Potential category would be more connected to or clustered with clearly valenced appraisals, such as the appraisal of pleasantness and of consequences, resulting in a blend of power and valence appraisals; and that, in a negative scenario, a Power dimension would emerge more clearly. Moreover, the authors show that when Novelty was higher, more Arousal and less Power were reported in emotion terms, respectively: we therefore hypothesized that the appraisals of suddenness, predictability, urgency, and immediateness, theoretically related to the higher-order Novelty dimension, would be more strongly associated to, or clustered with, either Arousal-related emotion components, or appraisals of Coping Potential, depending on the perceived situational novelty.

Our second research question concerned the assessment of components centrality: that is, we aimed at evaluating which component(s) appeared to be the most central (i.e., important) in the network and in the assigned dimensions. By estimating centrality indices, nodes that play a pivotal role in network activation and in their assigned dimensions can be identified. Given the strong evolutionary implication of the appraisals of pleasantness and of goal conduciveness in emotion emergence (Ellsworth & Scherer, 2003), we hypothesized that these will emerge as more central in the networks and in their assigned dimensions than other appraisals, regardless of the contextual valence. We further hypothesized that SECs related to the Coping Potential category will also emerge as central in the networks, given the theoretical and the empirical implications of these appraisals in valenced situations (Scherer, 2020; Scherer et al., 2022). Indeed, this hypothesis would also align with the finding by Mattsson et al. (2020) of self-efficacy beliefs emerging as the most central node in a network of positive and negative academic emotions.

Finally, our third research question concerned the formal testing of the between- and within-dimension component relations, following the recent contribution by Lange and Zickfeld (2023). This test permits to highlight the interrelation of components within the CPM. Given that previous research on emotion coherence has generally found stronger associations between elements within each component than across components (Lange et al., 2020; Mauss & Robinson, 2009), we hypothesized that emotion components within the same dimension would be more strongly connected to each other than across dimensions, an empirically proven property known as "small-world" (Borsboom et al., 2021; Dalege et al., 2016).

All in all, to the best of our knowledge, this is the first contextual application of network models within the CPM framework, aiming at providing complex modeling of specific emotion episodes.

Method

Participants

We began by recruiting first-year psychology students at our host institution, who received compensation in the form of course credits. In a second round of recruitment via social media, we then extended the study to students at other Swiss educational institutions at the Bachelor, Master, and occasionally doctoral level, if deemed appropriate. These participants were rewarded with a voucher. Inclusion criteria were being between 18 and 45 years old, being in good health, and having sufficient proficiency in French. The former age inclusion criterion was dictated by the known physiological and hormonal changes occurring after the age of 45 (Crandall et al., 2023; McKinlay, 1996; Rymer & Morris, 2000). Exclusion criteria were medical treatment, regular use of drugs or medication, and diagnosis of a psychiatric disorder, as these factors are known to influence emotional and physiological processes at both the self-report and objective levels (Clark & Beck, 2010; Edgar et al., 2007; Kin et al., 2007; Wirth & Gaffey, 2013). Concerning sample size, guidelines for network models in psychology are still in their infancy (Hevey, 2018). However, a sample size of 250 for approximately 25 nodes is generally recommended based on simulations (Dalege et al., 2017). Given that several research questions were to be answered by this database, we aimed at the largest possible sample. The final sample consisted of 500 participants, of whom 212 (42.4%) were rewarded with vouchers and 288 (57.6%) with credits. In total, the sample included 412 females (83%) and had a mean age of 22.41 years (SD = 3.23), with 78% of the participants being native French speakers. The predominant educational level was bachelor's degree (90% of the sample), with psychology being the most common subject (72% of the sample). The sample size obtained was considered adequate for network analyses.

Stimuli

As appraisals and emotion responses are specifically about situations, contextualization of our measures had to be performed. To explore emotion components, participants were thus administered four emotionally loaded scenarios (contexts) that were pre-tested in a pilot study. The first criterion for selecting the scenarios was that the scenario content had to be relevant to a student population. In the context of the CPM, emotionally charged autobiographical or written scenarios have been used extensively with student samples similar to ours (Gentsch et al., 2018; Pivetti et al., 2016; Scherer et al., 2022). The second selection criterion was that the scenario had to include some ambiguity in their formulation, as early pioneers in emotion research stated the important role of ambiguity in amplifying individual differences in appraisal processes (Lazarus & Folkman, 1984). Indeed, recent evidence shows that presenting stimuli with unambiguous valence increases the likelihood of obtaining floor or ceiling effects (Neta & Brock, 2021).

In the present work, analyses were conducted on the emotion components embedded in daily life situations. Specifically, out of the four scenarios, we employed the positive one, describing a birthday party - hereafter, Positive Scenario, adapted from Farrell et al. (2015) and Rohrbacher and Reinecke (2014) – and one of two negative scenarios, concerning social rejection. The scenario retained in the present work– hereafter, Social Rejection Scenario, adapted from Zimmer-Gembeck and Nesdale (2013) – reports an incident of ambiguous rejection around a group of close friends. Previous studies on emotion coherence have focused on situations that could activate the four emotion component systems, like anger or surprise situations (Evers et al., 2014; Reisenzein, 2000): we thus deemed this type of scenario appropriate to maximise a differentiated response in terms of valence and arousal, given the unexpectedness and negativity of the event. The Positive Scenario was tested for comparison purposes, as routinely done in affective science (e.g., Mauss & Robinson, 2009; Mauss et al., 2005). The other two scenarios, depicting an ambiguous, more active - overt - rejection incident and a neutral situation, are to be employed in a separate study on emotional processing and maladaptive personality, given the cognitive interpretation biases exhibited by individuals with pathological traits in these contexts (An et al., 2023; Grynberg et al., 2012; Priebe et al., 2022). Therefore, these two additional scenarios are not reported here. Nonetheless, the text of all scenarios, along with their corresponding French translations for the selected ones, are reported in supplementary Table S1.

Measures

Within the CPM, the five emotion components (appraisal, physiological reaction, expressivity, experience, and action tendency) were operationalized using a psycholinguistic instrument called GRID (Fontaine et al., 2013). The GRID was originally designed to assess semantic profiles of emotions at a componential level with 142 features (i.e., items). Later, the GRID has been applied to emotionally charged situations, such as scenarios (Scherer, 2020; Schlegel & Scherer, 2018) and video-clips (Mohammadi & Vuilleumier, 2020). Due to its length, two shorter versions were derived from the GRID (Scherer et al., 2013): the CoreGRID (63 features) and the MiniGRID (14 features).

The GRID, and derivatively the CoreGRID and MiniGRID, are organized at a higher-order level, which comprises a four-factor structure, and a lower-order level (see Table 1, "Higher Order Factor Assignment", and "Lower Order Factor Assignment"; Fontaine et al., 2013). For the current project, as a trade-off between comprehensiveness and parsimony, we integrated the MiniGRID with the Appraisal component of the CoreGRID to have better coverage of appraisals categories and content.

Appraisal measures As described in Scherer et al. (2013), 21 appraisals were derived from the French version of the Appraisal component of the CoreGRID instrument. Appraisals are categorized into the four main SEC functional categories of Relevance, Implications, Coping Potential, and Normative Significance (Fig. S1; Table 1). Participants rated each of the 21 items for each scenario on a 9-point scale ranging from 1 (not at all) to 9 (completely).

Emotion responses Emotional reactivity was assessed using the French version of the MiniGRID instrument (Scherer et al., 2013), with two items tapping the feeling component, four tapping the physiological component, four tapping the expressive component, and two tapping the action tendency component (Table 1).

Other measures For other projects, additional measures were administered which will not be discussed in depth as not part of the current study. Briefly, participants were asked to rate the intensity of nine categorical emotions experienced in the scenarios on a scale from 0 to 100, and to fill the following individual differences batteries: the Toronto Alexithymia Scale (TAS; Bagby et al., 1994), the Difficulties in Emotion Regulation Scale (DERS-F; Dan-Glauser & Scherer, 2013), the NEO Five-Factor Inventory (NEO-FFI; Costa & McCrae, 1992), the Personality Inventory for DSM-5 (PID-5; Maples et al., 2015), the 4-item Patient-Health Questionnaire (PHQ-4; Kroenke et al., 2009), the Berkeley Expressivity Questionnaire (BEQ; Gross & John, 1997); and the Positive and Negative Affective Schedule (PANAS; Watson et al., 1988).

Procedure

The entire study was conducted on LimeSurvey (https://www.limesurvey.org/fr), an online survey platform accessible from smartphones and laptops. All data were anonymized. The study was approved by the Ethics Committee of the University of Lausanne (protocol number: C-SSP-042020-00001).

At the beginning of the online study, students were greeted and given general information about the content of the study. After signing the consent form, they answered general demographic questions. The study was divided in two parts, a scenario part, and a questionnaire part, which were randomized to avoid order effect. Before being confronted with the two scenarios, participants were given a brief instruction based on that of Smith and Lazarus (1993), encouraging them to imagine themselves in the scenario and to immerse themselves in the emotions, feelings, and thoughts they elicited. Each of the two scenarios started with a description of the scene over a few lines. For each scenario, participants had to answer the selected CoreGRID and MiniGRID items and complete the emotion category questions. At the end of the study, a detailed debriefing on the research questions was provided. The study lasted between 50 and 90 min.

Analyses

Data processing

Analyses were performed in the R environment (R Development Core Team, 2020). For each of the two scenarios, we followed the same steps. Based on Cronbach's alpha calculations, the CoreGRID Appraisal component and MiniGRID items were reversed to obtain coherent response scores. We then transformed our data to ensure that the multivariate normality assumption was met (Epskamp et al., 2018). Deidentified data, R scripts for all analyses, and supplementary material - including code source and acknowledgments - can be found at our OSF link at https://osf.io/t9f43/.

Network and dimensionality estimation

To address our first research question, we endorsed the Exploratory Graph Analysis (EGA) framework (Golino & Christensen, 2024; Golino & Epskamp, 2017). Within this framework, we applied to our transformed data the standard psychometric network model - known as the Gaussian graphical model (GGM; Lauritzen, 1996) - in combination with a clustering algorithm– known as the Walktrap community detection algorithm (Pons & Latapy, 2005). The GGM estimates partial correlation coefficients that are plotted as edges connecting two nodes (Borsboom et al., 2021; Epskamp et al., 2018). Edge weights (connection strength) are depicted in the networks, along with their magnitude - thin or thick line - and direction - red for negative and green or blue for positive (Epskamp et al., 2018). GGM was used in conjunction with the extended Bayesian Information

Table 1 CoreGRID appraisal component and MiniGRID items, SECs and factors of assignment, and English translation

CoreGRID Appraisal (code starting with A) and MiniGRID Emotion Response (code starting with R) Items		SEC functional and emotion response categories	Lower Order Factor Assignment[a]	Higher Order Factor Assignment[a]
AR1	The event occurred suddenly	Relevance	Unexpected/Chance	NOVELTY
AR2	The event was important for and relevant to the person's goals or needs	Relevance	Goal Relevance	VALENCE
AR3	The event was pleasant for the person	Relevance	Valence (Valence Supra-Factor)	VALENCE
AR4	The event was important for and relevant to the goals or needs of somebody else	Relevance	Goal Relevance	VALENCE
AI1	The event had consequences that were predictable	Implications	Expected/Familiar	VALENCE
AI2	The event had negative, undesirable consequences for the person	Implications	Valence (Valence Supra-Factor)	VALENCE
AI3	The event happened by chance	Implications	Unexpected/Chance	NOVELTY
AI4	The event required an immediate response	Implications	Unexpected/Chance	NOVELTY
AI5	The event was caused by somebody else's behavior	Implications	Self vs Other Causation	NOVELTY
AI6	The event was unpredictable	Implications	Unexpected/Chance	NOVELTY
AI7	There was no urgency in the situation	Implications	–	AROUSAL
AI8	The event was caused by the person's own behavior	Implications	Self vs Other Causation	VALENCE
AI9	The event confirmed the expectations of the person	Implications	Expected/Familiar	VALENCE
AC1	The event was uncontrollable	Coping Potential	Coping Ability	POWER
AC2	The person could control the consequences of the event	Coping Potential	Coping Ability	POWER
AC3	The person had a dominant position in the situation	Coping Potential	Coping Ability	POWER
AC4	The person had power over the consequences of the event	Coping Potential	Coping Ability	POWER
AC5	The person was powerless in the situation	Coping Potential	Coping Ability	POWER
AC6	The person could live with the consequences of the event	Coping Potential	Coping Ability	VALENCE
AN1	The event involved the violation of laws or socially accepted norms	Normative Significance	Norm Violation	VALENCE
AN2	The event was inconsistent with the person's own standards and ideals	Normative Significance	Norm Violation	VALENCE
RF1	You felt the emotion very intensely	Feeling	Intensity	AROUSAL
RF2	You felt the emotion for a long time	Feeling	Duration	NOVELTY, VALENCE
RA1	You felt weak limbs (feeling weak limbs)	Autonomic Arousal[b]	Distress Symptoms	POWER
RA2	You felt your heart beating faster (rapid heart rate)	Autonomic Arousal	Autonomic Arousal	AROUSAL
RA3	You started breathing faster (rapid breathing)	Autonomic Arousal	Autonomic Arousal	AROUSAL
RA4	You felt you started sweating (sweating)	Autonomic Arousal	Autonomic Arousal	AROUSAL
RE1	You felt your jaw dropping	Expression	Jaw Drop	NOVELTY
RE2	You frowned your eyebrows	Expression	Frown vs Smile	VALENCE
RE3	You closed your eyes	Expression	Eyes Closed	POWER
RE4	You spoke more loudly	Expression	Vocal Energy	POWER
RT1	You wanted to tackle the situation	Action Tendency	Disengagement vs Intervention	POWER
RT2	You wanted to sing and dance	Action Tendency	Defensive vs Appetitive	VALENCE

Note: SEC= Stimulus Evaluation Check. To ease comprehension and results interpretability, we labelled the emotion components items as follows. The CoreGRID Appraisal component items were labelled with an "A" (i.e., "Appraisal") followed by a letter indicating their respective SEC category (i.e., "R" for Relevance, "I" for Implication, and so on). These two letters are then followed by a number, which indicates the respective item within the SEC. The same rationale applies to the MiniGRID: items are labelled with a "R" which stands for "Response", followed by a second letter indicating their related component, and a number indicating the within-component specific item. For example, RT1 represents the first item of the Action Tendency component of the MiniGRID emotion responses

[a] Based on Scherer et al. (2013)

[b] In the GRID (Scherer et al., 2013), this component is called Bodily Reaction Component, as it regroups different somatic activations along with autonomic arousal, such as body temperature and distress symptoms. Since the MiniGRID essentially entails all the autonomic arousal items, we renamed the component as such to ease interpretation of the labels.

Criteria (EBIC; Chen & Chen, 2008) - graphic least absolute shrinkage and selection operator (lasso; Tibshirani, 1996) approach, which shrinks partial correlation coefficients to zero to retain only those truly different from zero (Epskamp et al., 2018). The Walktrap community detection algorithm allows the identification of dimensions – or communities – by grouping nodes that are more strongly interconnected in the network (Golino & Epskamp, 2017).

We then performed a variable redundancy check. Local dependence – i.e., strong correlations – among items can lead to network instability: we therefore applied Unique Variable Analysis (UVA; Christensen et al., 2023), an approach that detects highly correlated items. For the current work, UVA is particularly useful since the Appraisal component of the CoreGRID and the MiniGRID were designed as semantic emotion analysis tools, and high intercorrelations between the items are thus expected. UVA reports the extent to which nodes overlap and share nearly the same relationships with other nodes in terms of edge strength and positive/negative direction via a measure called weighted topological overlap (wTO; Christensen et al., 2023). Based on recent guidelines and implementations (Christensen et al., 2023; Maertens et al., 2023), we implemented a wTO threshold of 0.20, and for each pair of items flagged as redundant, we retained the one with the higher ratio of main network loadings to cross-loadings, to obtain higher dimension stability. Developed within the EGA framework, network loadings have been shown to be equivalent to factor analytic loadings, with values of 0.15, 0.25, and 0.35 indicating low, moderate, and high magnitude, respectively (Christensen & Golino, 2021b). Indeed, as in factor analytic methods, items that cross-load heavily on dimensions other than the assigned one can lead to model misfit and instability (Christensen et al., 2023; Maertens et al., 2023).

After network structures and dimensions were retrieved in the empirical data, and redundant items removed, the stability and consistency of these dimensions was inspected with Bootstrapped EGA (bootEGA; Christensen & Golino, 2021a). Briefly, it is important to inspect if the number of dimensions retrieved by bootEGA is a recurrent solution, or if other dimension solutions are also found. Notably, the more frequently a dimension solution is retrieved, the more stable it is. Perfect stability is reached when the dimension solution is found 100% of time in the bootstrapped replicated samples. An item stability plot is then run to visualize how items are loading on their respective dimensions, and to identify possibly unstable items. Item stability values below the threshold of 0.75 and with network loadings lower than 0.15 signal instability (Christensen et al., 2023; Maertens et al., 2023). It is recommended to remove such items. The dimensionality and structural consistency of the network is then reassessed in an iterative fashion, until an optimal and stable solution is found (Christensen & Golino, 2021a).

Following this procedure, we were then able to robustly retrieve the underlying structural and dimensional organization of the CoreGRID Appraisals and MiniGRID components in both scenarios.

Network centrality indices estimation

To address our second research question, we followed the guidelines by Epskamp et al. (2018). We computed the centrality metrics of Node Strength and Expected Influence, and evaluated their stability. Centrality indices are measures of node importance and indicate which node plays a pivotal role in the network. Node Strength indicates how strongly a node is directly connected to all the other nodes in the network. Expected Influence centrality, on the other hand, is a measure of positive connectivity (Epskamp et al., 2018). The larger these parameters, the more influential a given node is in the network. To evaluate the stability of these aforementioned centrality indices, we applied the *case-dropping subset bootstrap* (Epskamp et al., 2018). This method verifies if centrality indices, after iteratively dropping a predefined percentage of cases (i.e., observations) from the dataset, are still stably correlated with the centrality indices of the original dataset. Their stability is measured by a parameter called the *correlation-stability (CS) coefficient* (Epskamp et al., 2018): values above 0.25 indicate acceptable stability, and values above 0.5 indicate optimal stability. Following Epskamp et al. (2018) guidelines, we also estimated the trustworthiness of edge weights via bootstrapped confidence intervals and via bootstrapped difference tests, which are reported in details in the Supplementary Material. Given that centrality indices are estimated in relation to the network and not to the retrieved dimensions, we also report the results from network loadings: the highest the network loading for a given node is, the most central this node is to its assigned dimension (Christensen & Golino, 2021b).

Within-dimension and between-dimension mean edge weight comparison

To address our third goal, we followed the procedure recently outlined by Lange and Zickfeld (2023). Even though dimensionality estimation can provide a visual understanding of emotion components connections, a formal test is needed and was hence conducted. Specifically, the first formal test assesses if edges between the retrieved EGA dimensions are different from zero. This would confirm the utility of using networks to model emotion components: otherwise, emotion components would be perfectly independent and separable, which is against the CPM. The second test assesses if within-dimension edges are stronger than between-dimension edges, which would provide additional insight into coherence among the CPM emotion components. Bootstrapping techniques were used, in conjunction with an adapted version of an equivalence test based on the 95% bias-corrected and accelerated (BCa) confidence intervals and Holm correction for statistical significance testing. We refer the reader to the original publication and script by Lange and Zickfeld (2023) for further analytical details.

Further exploratory testing

Recently, in a multi-sample study, Schlegel and Scherer (2018) found an age effect on Emotion Knowledge, that is, the ability to understand and recognize the emotions of others from a componential perspective. Subjects were presented with the five emotion components described in the CPM and had to select those that best represented a given emotional episode. The authors found that emotion understanding increased with age until reaching a plateau in middle and late adulthood, with women scoring slightly higher on the construct. However, to the best of our knowledge, studies examining these demographic differences in age and gender on *each and all* the five CPM components are virtually absent. The only exception is the recent study by Young and Mikels (2020) who tested if age differences in the appraisal of personal, other- or circumstantial control over the consequences of ambiguous social and non-social situations emerged in a sample of 50 older adults ($M_{Age}=62.8$; $SD=5.2$) and 50 younger adults ($M_{Age}=22.8$; $SD=2.1$). Interestingly, older adults appraised situations higher in terms of personal control, and lower in terms of negativity (but similar in terms of positivity), compared to younger adults (Young & Mikels, 2020). Given this recent evidence, we deemed appropriate to control for the effects of age (above or below the median age in years; for a similar approach, see McCormick et al., 2023) on all CPM components through the metric invariance analyses with permutation tests developed by Jamison et al. (2022) in the EGA framework. For the sake of comprehensiveness, we also tested for metric invariance for incentive groups (Group 1 versus Group 2) and for gender. While the former test is not expected to yield significant results, gender differences may appear spuriously due to the unbalanced nature of our sample (83% females). We report these exploratory results in detail in the Supplementary Material retrievable at our OSF link. In both scenarios, metric invariance analyses on the CoreGRID Appraisal and MiniGRID items retained in the final EGA models showed no significant differences in network loadings for median age, sex and group belonging as the grouping variables (Table S7-S9 for the negative scenario and Table S10-12 for the positive scenario). Since none of these testings resulted significant, the variables age, gender and groups were not considered further in the modelling process.

Results

The descriptive statistics of the untransformed variables after reversing the marked items are shown in Table 2 (see Table S2 in the Supplementary Material for the descriptive statistics of the transformed variables). For the sake of clarity, in the network analyses, an "S" and "P" prefixes were added to the appraisals and emotional reactivity items from Table 1 to distinguish between those belonging to the Social Rejection and to the Positive scenarios, respectively. The reader can thus refer to Table 1 for variables content.

Social rejection scenario

Network and dimensionality estimation

To answer our first research question regarding the Social Rejection Scenario, after applying the default EGA approach to all 33 transformed CoreGRID Appraisal and MiniGRID items, we first checked for local dependence issues. UVA identified three pairs of redundant items (see Table 1 for items content): SAC2 and SAC4 (wTO = 0.293); SRF1 and SRF2 (wTO = 0.400); and SRA2 and SRA3 (wTO = 0.505). The ratio of network loadings (main/cross-loadings) were as follows: SAC2 = Inf (i.e., perfect loading on assigned dimension) versus SAC4 = 54.289; SRF1 = 2.405 versus SRF2 = 1.712; SRA2 = 2.405 versus SRA3 = 6.416. Therefore, only SAC2, SRF1 and SRA3 were retained in the subsequent analyses.

To explore structural consistency and replicability of the dimensions emerging from these locally reduced data, bootEGA was then performed. The median number of dimensions found via bootEGA in the reduced dataset was 3, with acceptable confidence intervals (95% CI [1.41, 4.59]). However, their structural consistency was very low (0.390, 0.334, and 0.194 for dimension 1,2, and 3, respectively), with item stability indices varying between 25 and 100%, indicating overall instability (Fig. S2, left panel): as recommended, we therefore removed items with items stability indices below 75% (Christensen & Golino, 2021a), ending up with 23 nodes. We then repeated the bootEGA procedure, now obtaining satisfactory structural consistency (0.808, 0.952, and 0.996 for dimension 1,2, and 3, respectively) and item stability range (between 91 and 100%). Following existing guidelines, and to further strengthen the structural consistency of our dimensions, we did not retain items with network loadings lower than 0.15, as this denotes weak

Table 2 Descriptive statistics of the untransformed CoreGRID appraisal component and MiniGRID items in the two scenarios

	Social Rejection Scenario						Positive Scenario					
Variable	mean	standard deviation	min	max	skew	kurtosis	mean	standard deviation	min	max	skew	kurtosis
AR1	6.15	2.16	1	9	-0.63	-0.32	8.15	1.68	1	9	-2.31	4.95
AR2	4.70	2.60	1	9	-0.02	-1.22	6.62	2.27	1	9	-1.07	0.36
AR3	7.62	1.82	1	9	-1.51	1.83	7.92	1.47	1	9	-1.96	4.50
AR4	3.72	2.33	1	9	0.42	-0.86	3.93	2.35	1	9	0.27	-1.03
AI1	6.00	2.32	1	9	-0.32	-0.80	6.06	2.07	1	9	-0.64	0.02
AI2	6.02	2.23	1	9	-0.74	-0.16	8.16	1.32	1	9	-2.23	5.80
AI3	5.24	2.31	1	9	-0.09	-0.82	8.47	1.34	1	9	-3.33	11.91
AI4	4.58	2.50	1	9	0.15	-1.10	6.28	2.66	1	9	-0.49	-1.09
AI5	6.37	2.33	1	9	-0.76	-0.28	7.17	2.29	1	9	-1.02	-0.15
AI6	6.15	2.19	1	9	-0.55	-0.40	6.58	2.17	1	9	-0.56	-0.66
AI7	4.91	2.77	1	9	0.03	-1.30	5.53	3.03	1	9	-0.28	-1.46
AI8	4.21	2.20	1	9	0.16	-0.78	7.22	2.01	1	9	-1.49	1.84
AI9	7.29	1.91	1	9	-1.09	0.51	7.04	1.82	1	9	-1.27	1.70
AC1	6.06	2.36	1	9	-0.56	-0.63	6.95	2.04	1	9	-0.85	-0.10
AC2	5.84	2.25	1	9	-0.33	-0.84	6.08	1.96	1	9	-0.49	-0.13
AC3	7.64	1.81	1	9	-1.44	1.47	7.10	1.71	1	9	-0.99	0.72
AC4	5.76	2.36	1	9	-0.21	-1.03	6.42	1.92	1	9	-0.80	0.36
AC5	6.54	2.33	1	9	-0.88	-0.16	7.61	1.82	1	9	-1.44	1.35
AC6	3.64	2.30	1	9	0.46	-0.87	8.12	1.41	1	9	-2.02	4.51
AN1	3.65	2.43	1	9	0.46	-1.01	8.50	1.49	1	9	-3.44	11.49
AN2	5.61	2.71	1	9	-0.45	-1.09	8.09	1.88	1	9	-2.30	4.50
RF1	5.68	2.30	1	9	-0.40	-0.74	5.74	2.33	1	9	-0.54	-0.60
RF2	4.84	2.60	1	9	0.01	-1.24	4.77	2.54	1	9	-0.08	-1.18
RA1	2.61	2.29	1	9	1.25	0.33	8.27	1.52	1	9	-2.48	5.74
RA2	4.11	2.70	1	9	0.21	-1.39	4.13	2.65	1	9	0.12	-1.42
RA3	3.49	2.57	1	9	0.57	-1.06	3.07	2.38	1	9	0.73	-0.94
RA4	2.63	2.32	1	9	1.26	0.32	2.26	2.01	1	9	1.49	0.94
RE1	2.31	1.99	1	9	1.50	1.32	1.74	1.62	1	9	2.50	5.73
RE2	4.63	2.81	1	9	0.03	-1.39	7.99	1.91	1	9	-2.02	3.19
RE3	1.86	1.67	1	9	2.33	5.14	8.27	1.73	1	9	-2.72	6.71
RE4	2.00	1.81	1	9	1.89	2.67	3.16	2.65	1	9	0.70	-1.12
RT1	4.89	2.90	1	9	-0.05	-1.44	2.89	2.53	1	9	0.99	-0.45
RT2	1.20	0.90	1	9	5.72	36.94	5.04	3.13	1	9	-0.16	-1.57

dimensional belonging (Christensen et al., 2023; Maertens et al., 2023). With this procedure, two appraisals were discarded: SAI7 (urgency) and SAI8 (personal agency).

The final reduced structure included 21 items from the CoreGRID and MiniGRID**,** and 90 non-zero edges. The median number of dimensions extracted by bootEGA was 3, with optimal confidence intervals (95% CI [2.55, 3.45]) and even better structural consistency (0.966, 0.972, and 0.984 for dimension 1,2, and 3, respectively) and item stability range (between 97 and 100%; Fig. S2, right panel). Figure 1 shows the structural and dimensional organization of CPM emotion components in the Social Rejection Scenario.

On dimension 1, labelled "Valence/Relevance", loaded the following items: SAR2 (relevance of personal goal); SAR3 (unpleasantness); SAI2 (negative consequences); SAI4 (need for immediate response); SAC6 (inability to live with consequences); SAN1 (violation of socially accepted norms); SAN2 (violation of personal norms); SRF1 (intensity of emotions); and SRT1 (wanting to tackle the situation). On dimension 2, labelled "Unexpectedness/Coping", loaded the following items: SAR1 (suddenness); SAI6 (unpredictability); SAC1 (uncontrollability); SAC2 (no control of consequences); SAC3 (no dominance); SAC4 (no power over consequences); SAC5 (powerlessness). Finally, on dimension 3, labelled "Arousal/Expressivity", loaded the following MiniGRID items: SRA1 (felt weak limbs); SRA3 (breathing faster); SRA4 (sweating); SRE1 (dropped jaw); SRE3 (closed eyes); and SRE4 (speaking more loudly).

Network centrality indices estimation

To answer our second research question, again focusing on the Social Rejection scenario, we computed the centrality indices of Strength and Expected Influence of the network (Fig. 2).

We then investigated the stability of the centrality indices via the *case-dropping subset bootstrap approach* (Epskamp et al., 2018). The *CS*-coefficients of Strength ($CS(\text{cor}=0.7)=0.672$), and Expected Influence ($CS(\text{cor}=0.7)=0.672$) were all above the cutoff of 0.5. Overall, we can be confident about the interpretation of these centrality metrics (Fig. S3).

Results from the edge-weight bootstrapped confidence intervals and bootstrapped difference tests supported the findings that edges were stable, and that the strongest and weakest edges were significantly different from each other (see Figs. S4, S5, and Table S3). SAI2, SRF1, SRA3, SAC5, and SRA1 were therefore robustly confirmed to be central to the network, in order of magnitude (see Fig, S5, bottom panels).

Table S4 reports the network loadings for the three dimensions in the Social Rejection Scenario. The results are quite similar to the centrality indices reported in Fig. 2: SAI2 also emerged as the node with the highest network loading (0.39) within the Valence/Relevance dimension. While SRA1 emerged as the node with the highest network loading (0.39) within the Arousal/Expressivity dimension, SRA3 emerged as slightly more central to the entire network. Similarly, SAC1 emerged as the node with the highest network loading (0.35) within the Unexpectedness/Coping

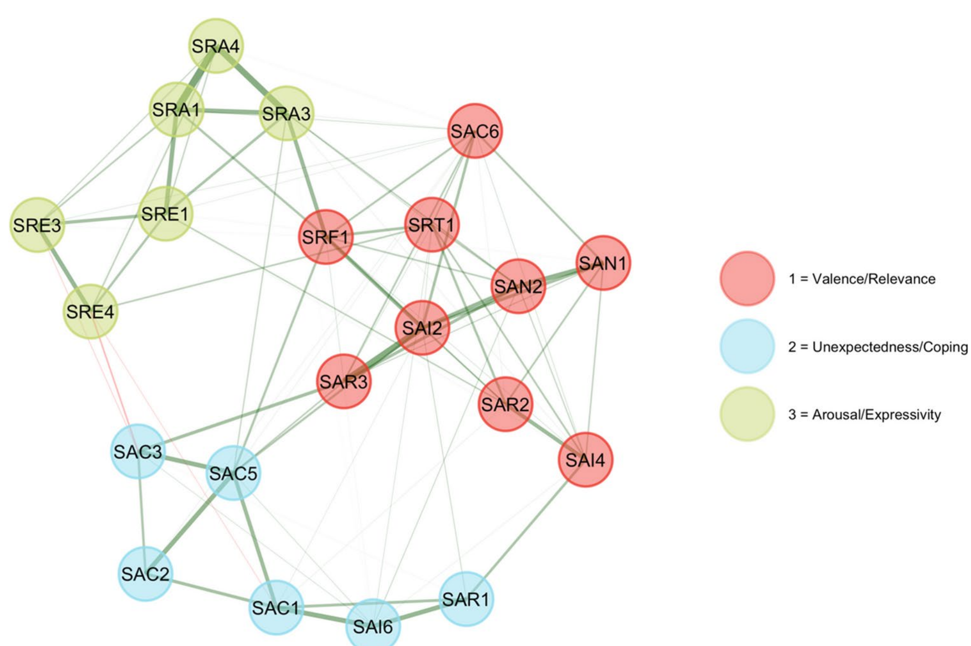


Fig. 1 Estimated network structure and dimensionality results for EGA for the final reduced data set, with unstable items removed. Items labels start with an "S", denoting their belonging to the Social Rejection Scenario. Connection strength between nodes is represented by lines thickness. Red and green lines indicate negative and positive relations, respectively.

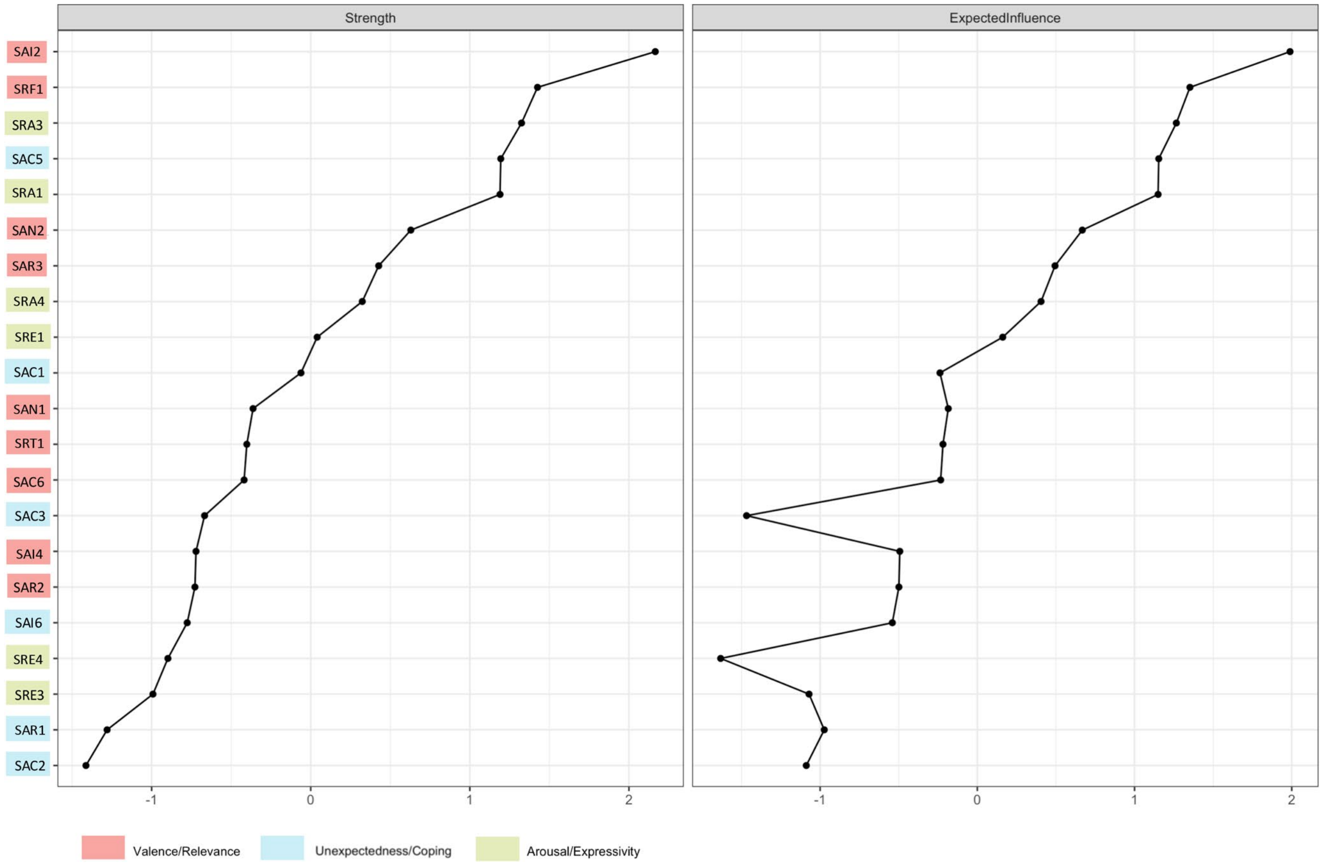


Fig. 2 Centrality indices (z-scores) of the CoreGRID Appraisal Component and MiniGRID in the Social Rejection Scenario. Respective communities are indicated

Table 3 Results of the within versus between-dimension mean edge weight differences for the Social Rejection Scenario

Dimensions	Average between-dimension edge M(SE), 95% CI_{Bca}, *p*-value	Difference of average within- and between-dimension edges ΔM(SE), 95% CI_{Bca}, *p*-value
Valence/Relevance vs Unexpectedness/Coping	0.017(0.003), [0.013, 0.023], $p<0.001$	Valence/Relevance: 0.066(0.004), [0.059, 0.074], $p<0.001$ Unexpectedness/Coping: 0.088(0.008), [0.072, 0.101], $p<0.001$
Valence/Relevance vs Arousal/Expressivity	0.016(0.002), [0.012,0.020], $p<0.001$	Valence/Relevance: 0.067(0.004), [0.059, 0.075], $p<0.001$ Arousal/Expressivity: 0.117(0.006), [0.105, 0.128], $p<0.001$
Unexpectedness/Coping vs Arousal/Expressivity	0.009(0.003), [0.004, 0.015], $p<0.01$	Unexpectedness/Coping: 0.096(0.007), [0.080, 0.108], $p<0.001$ Arousal/Expressivity: 0.124(0.006), [0.112, 0.134], $p<0.001$

Note: Valence/Relevance: Dimension 1; Unexpectedness/Coping: Dimension 2; Arousal/Expressivity: Dimension 3; SE = standard error; 95% CI_{Bca} = 95% bias-corrected and accelerated confidence interval.

dimension: however, it was not the most central to the entire network, which appeared to be SAC5 instead.

Within-dimension and between-dimension mean edge weight comparison

Finally, to answer our third research question for the Social Rejection scenario, the bootstrapped analyses results following Lange and Zickfeld (2023) procedure are reported in Table 3. Overall, the average edge between all dimension contrasts were statistically and significantly different from zero (at $p<0.001$ and $p<0.01$), meaning that dimensions were not independent from each other. This is visually evident from Fig. 1 from the dense interconnections between nodes across dimensions.

All the tests concerning the differences of average within- and between-dimension edges were significantly different from zero ($p < 0.001$), meaning that within-dimension edges were stronger than between-dimension edges, for each set of dimension comparisons.

Positive scenario

Network and dimensionality estimation

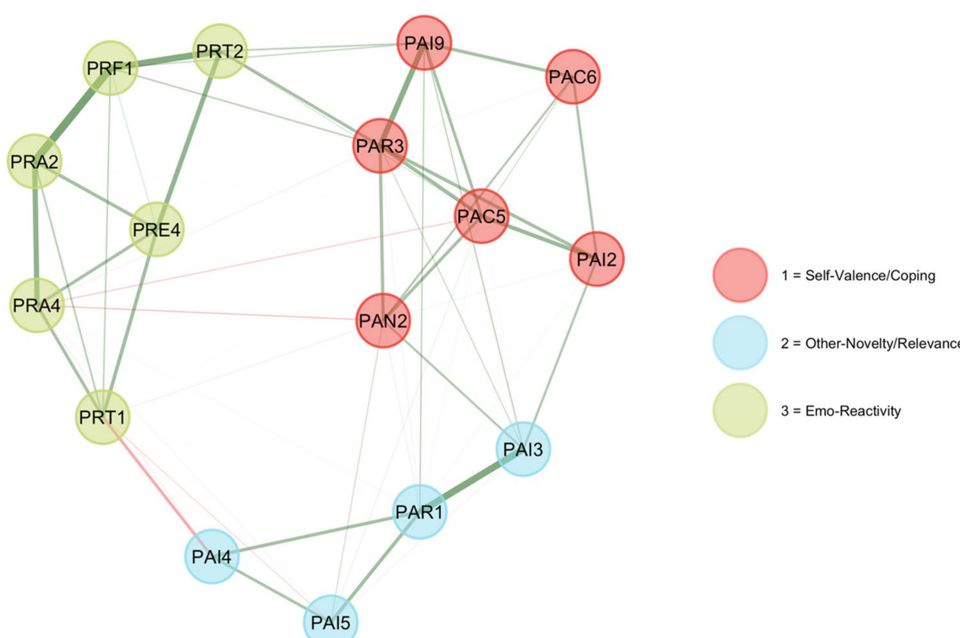
To answer our first research question regarding the Positive scenario, and after applying the default EGA approach to all 33 transformed CoreGRID Appraisal and MiniGRID items, we first checked for local dependence issues. UVA identified two pairs of redundant items (see Table 1 for item content): PRF1 and PRF2 (wTO = 0.505), as well as PRA2 and PRA3 (wTO = 0.466). The ratio of network loadings (main/cross-loadings) were as follows: PRF1 = 7.134 versus PRF2 = 6.221; PRA2 = 12.505 versus PRA3 = 2.151. Therefore, PRF1 and PRA2 were retained in the subsequent analyses.

To explore structural consistency and replicability of the dimensions emerging from these locally reduced data, bootEGA was then performed. The median number of dimensions found via bootEGA in the reduced dataset was 4, with acceptable confidence intervals (95% CI [2.06, 5.93]). However, their structural consistency was very low (0.282, 0.350, 0.436 and 0.950 for dimension 1, 2, 3, and 4, respectively), with the appearance of other residual dimensions. Item stability indices varied between 19 and 100%, indicating overall instability (Fig. S6, left panel). As recommended, we thus removed items with item stability indices below 75% (Christensen & Golino, 2021a), ending up with 18 nodes. We then repeated the bootEGA procedure, obtaining acceptable– but not satisfactory– structural consistency (0.524, 0.720, and 0.968 for dimension 1, 2, and 3, respectively) and item stability range (between 53 and 100%). Following existing guidelines, and to further strengthen the structural consistency of our dimensions, we did not retain items with network loadings lower than 0.15, as this denotes weak dimensional belonging (Christensen et al., 2023; Maertens et al., 2023). With this procedure, two appraisals were discarded: PAR2 (personal relevance) and PAR4 (other relevance).

The final reduced structure included 16 items from the CoreGRID Appraisal component and MiniGRID**,** and 58 non-zero edges. The median number of dimensions extracted by bootEGA was 3, with optimal confidence intervals (95% CI [2.79, 3.21]), and satisfactory structural consistency (0.984, 0.868, and 0.990 for dimension 1, 2, and 3, respectively) and item stability range (between 90 and 100%; Fig. S6, right panel). Figure 3 shows the structural and dimensional organization of CPM emotion components in the Positive Scenario.

On dimension 1, labelled "Self-Valence/Coping", loaded the following items: PAR3 (pleasantness); PAI2 (reversed; original formulation: negative consequences); PAI9 (expectations confirmed); PAC5 (reversed; original formulation: powerless); PAC6 (reversed; original formulation: inability to live with consequences); and PAN2 (reversed; original formulation: violation of personal norms). On dimension 2, labelled "Other-Novelty/Relevance", loaded: PAR1 (suddenness); PAI3 (reversed; original formulation: chance-caused); PAI4 (reversed; original formulation: need for

Fig. 3 Estimated network structure and dimensionality results for EGA for the final reduced data set, with unstable items removed. Items labels start with an "P", denoting their belonging to the Positive Scenario. Connection strength between nodes is represented by lines thickness. Red and green lines indicate negative and positive relations, respectively



immediate response); and PAI5 (reversed; original formulation: other-agency). On dimension 3, labelled "Emo-Reactivity", loaded all the MiniGRID items: PRF1 (intensity of emotion state); PRA2 (heartbeat getting faster); PRA4 (sweating); PRE4 (speaking more loudly); PRT1 (wanted to tackle the situation), and PRT2 (wanted to sing and dance).

Network centrality indices estimation

To answer our second research question, still on the Positive scenario, we computed the centrality indices of Strength and Expected Influence of the network (Fig. 4).

The *CS*-coefficients of Strength (*CS*(cor = 0.7) = 0.672) and Expected Influence (*CS*(cor = 0.7) = 0.672) were all above the cutoff of 0.5 (Fig. S7). Similarly to the Social Rejection scenario, results from the edge-weight bootstrapped confidence intervals and bootstrapped difference tests supported the findings that edges were stable, and that the strongest and weakest edges were significantly different from each other (see Figs. S8, S9 and Table S5). PAR3 and PRF1were confirmed to be the most central to the entire network, followed by PRA2, PAI9, and PRT2, albeit less robustly (see Fig, S9, bottom panels).

Table S6 reports the network loadings for the three dimensions in the Positive Scenario. The results are quite similar to the centrality indices reported in Fig. 4: PAR3 emerged as the node with the highest network loading (0.37) within the Self-Valence/Coping dimension. PRF1 emerged as the node with the second highest network loading (0.37) within the Emo-Reactivity dimension, preceded by PRA2, and it was the most central to the entire network. PAR1 emerged as the node with the highest network loading (0.43) within the Other-Novelty/Relevance dimension: however, it was not the most central to the entire network, possibly due to the small size of this dimension.

Within-dimension and between-dimension mean edge weight comparison

Finally, to answer our third research question regarding the Positive scenario, the bootstrapped analyses results following Lange and Zickfeld (2023) procedure are reported in Table 4. Overall, the average edge between all dimension contrasts were statistically and significantly different from zero (at $p < 0.001$ and $p < 0.01$), meaning that dimensions were not independent from each other. This is visually

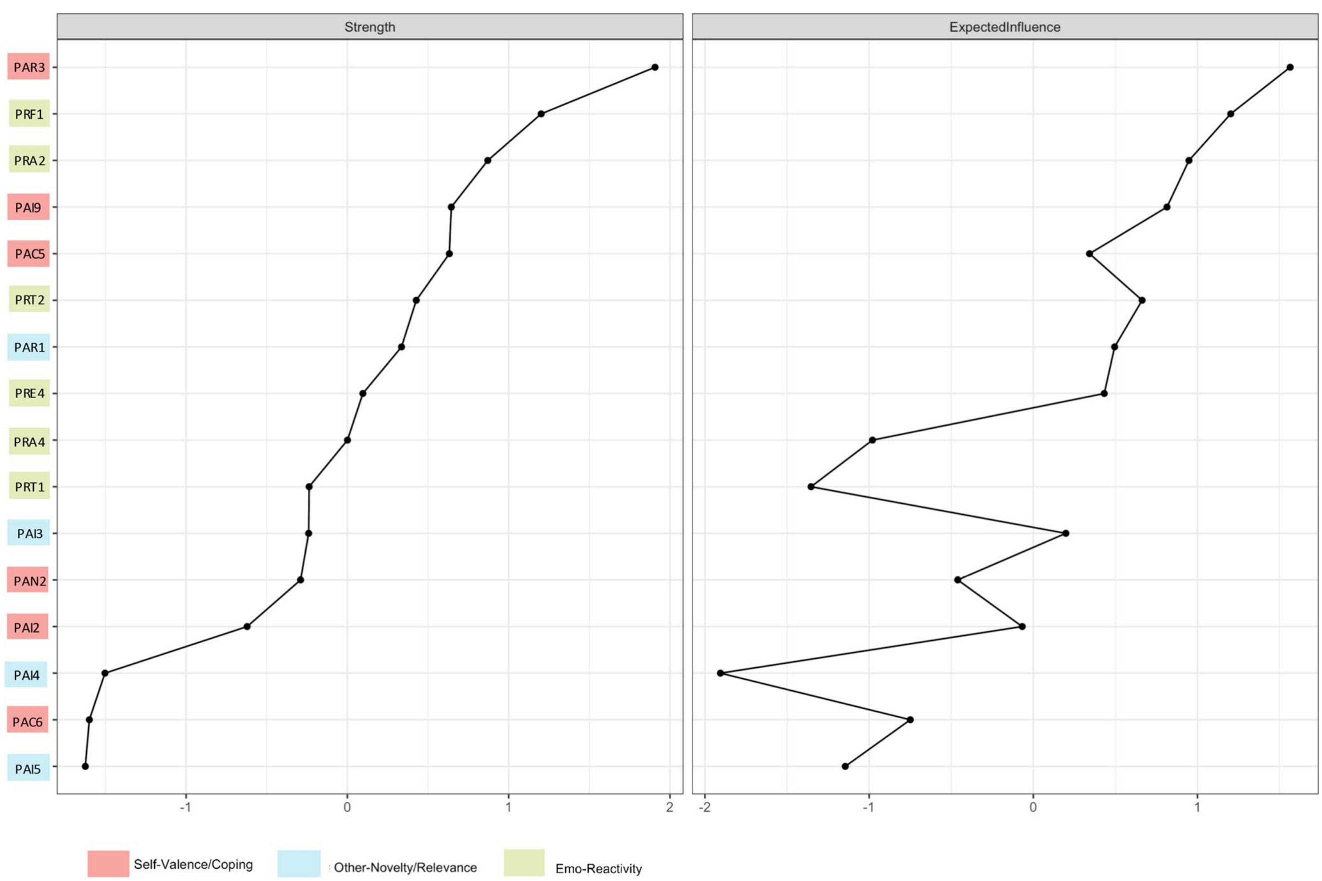


Fig. 4 Centrality indices (z-scores) of the CoreGRID Appraisal Component and MiniGRID in the Positive Scenario. Respective communities are indicated

Table 4 Results of the within versus between-dimension mean edge weight differences for the Positive Scenario

Dimensions	Average between-dimension edge M(SE), 95% CI_{BCa}, *p*-value	Difference of average within- and between-dimension edges ΔM(SE), 95% CI_{Bca}, *p*-value
Self-Valence/Coping vs Other-Novelty/Relevance	0.027(0.005), [0.019, 0.037], $p < 0.001$	Self-Valence/Coping: 0.090(0.008), [0.074, 0.104], $p < 0.001$ Other-Novelty/Relevance: 0.115(0.013), [0.088, 0.137], $p < 0.001$
Self-Valence/Coping vs Emo-Reactivity	0.023(0.004), [0.015, 0.031], $p < 0.001$	Self-Valence/Coping: 0.094(0.007), [0.081, 0.107], $p < 0.001$ Emo-Reactivity: 0.117(0.005), [0.108, 0.127], $p < 0.001$
Other-Novelty/Relevance vs Emo-Reactivity	0.016(0.005), [0.008, 0.028], $p < 0.01$	Other-Novelty/Relevance: 0.126(0.013), [0.099, 0.149], $p < 0.001$ Emo-Reactivity: 0.124(0.005), [0.113, 0.133], $p < 0.001$

Note: Self-Valence/Coping: Dimension 1; Other-Novelty/Relevance: Dimension 2; Emo-Reactivity: Dimension 3; SE = standard error; 95% CI_{Bca} = 95% bias-corrected and accelerated confidence interval

evident from Fig. 3 from the dense interconnections between nodes across dimensions.

All the tests concerning the differences of average within- and between-dimension edges were significantly different from zero ($p < 0.001$), meaning that within-dimension edges were stronger than between-dimension edges, for each set of dimension comparisons.

Discussion

With this study, we aimed to contribute to the existing heterogeneous and sparse multi-componential literature on emotion components using network analysis.

Our first goal was to uncover the structural and dimensional organization of emotion components within the CPM framework in different contexts. Overall, we found densely interconnected networks, with nodes clustering into three dimensions in each scenario. Within their assigned dimensions, some appraisals and emotion responses were unstable and were removed from the models. This is consistent with a variable-set approach to appraisal theories (Fernando et al., 2017). Indeed, not all appraisals and emotion responses might be salient in all situations, as cues to make a certain appraisal might be missing. Moreover, an emotion state could be present without the need for a certain appraisal (Fernando et al., 2017). To the best of our knowledge, only one other study investigated the influence of context on the semantic meaning of emotion terms within the CPM. Gentsch et al. (2018) similarly found that appraisal was the least stable component when embedded in an achievement versus a generalised context. In our study, the three-dimensional structure differed in two interesting ways. First, whereas in the negative scenario the focus was on the subjects' goals, needs, consequences, and coping, in the positive scenario, there was a clearly distinguished self- and other-oriented dimensions. Studies of the appraisal profiles of several positive emotions (Yih et al., 2020) have similarly shown the presence of an "other" orientation component. Second, the experiential and action tendency components loaded onto the "Valence/Relevance" and the "Emo-Reactivity" dimensions for the negative and positive scenarios, respectively. One explanation for this finding could lie in the scenario contents themselves. In other words, the negative context could push the responses towards a Valence/Relevance dimension given the unexpectedness feature of the scenario and the need to restore the situation by acting out, something that is not needed in the positive scenario. Similar to our results, Gentsch et al. (2018) also found that the experiential component qualitatively changed following appraisal changes depending on the context.

Additionally, we replicated the findings by Fontaine et al. (2022) by retrieving the two stable and transversal dimensions of Valence and Arousal in both scenarios. As further hypothesized, we found that a clearly separated Power dimension emerged in the negative scenario, which we labelled Unexpectedness/Coping, and which included the four Coping Potential appraisals. This Power dimension did not emerge in the positive scenario, where these types of appraisals were less numerous and clustered with Valence-related appraisals, again in line with Fontaine et al. (2022). We also found their hypothesized patterns of Novelty– Power– Arousal relations. In the positive scenario, the appraisal of immediateness (belonging to the Other-Novelty/Relevance dimension) was moderately and negatively connected to the Action Tendency (behavioral response) component item "Wanted to tackle the situation". In the negative scenario, the appraisals of suddenness and unpredictability (belonging to the Unexpectedness/Coping dimension) were moderately and strongly connected to the appraisal of uncontrollability (belonging to the Unexpectedness/Coping dimension), respectively. In other words, the higher the Novelty, the lower the Power. In our networks, we found virtually no evidence for the Novelty-Arousal direct relation, only very marginally in the positive scenario, in the direction hypothesized by Fontaine et al. (2022). The appraisal of suddenness (belonging to the Self-Valence/Coping dimension) was negatively and very weakly correlated with arousal symptoms of sweating (belonging to the Emotion Reactivity dimension). Finally, we found evidence for the Power-Arousal relationship. In the positive scenario, the appraisal of power over the situation (belonging to the Self-Valence/Coping dimension) was negatively correlated with arousal symptoms of sweating (belonging to the Emo-Reactivity dimension). Similarly, in the negative scenario, the appraisal of powerlessness (belonging to the Unexpectedness/Coping dimension) was positively and weakly correlated with arousal symptoms of increased breathing (belonging to the Arousal/Expressivity dimension).

From the above results, a differentiated componential organization emerges as a function of the context, which was also confirmed by the centrality metrics. Indeed, our second goal was to identify the most important node(s) within each network among a truly context relevant pool of features, and within each dimension. Given the similarity of findings, we focus here on the Expected Influence parameter, given its extended use in network research (Robinaugh et al., 2016). In the negative scenario, the Expected Influence parameter reported that the appraisal of negative consequences, the current emotion intensity, the appraisal of powerlessness, as well as the autonomic responses of distress (i.e., feeling the limbs weak) and arousal (i.e., breathing faster) were the nodes that, when activated, were responsible for the subsequent activation of the whole network and activation persistence. Similarly, in the positive scenario, the appraisals of situational pleasantness and the intensity state were the nodes with the highest Expected Influence value. The differentiated component patterns tell an interesting story: while in both scenarios the experiential component plays an important role in the network, in a negative context, appraising its consequences and recruiting physical resources as in a fight or flight situation are more central than in the positive context, where the focus seems to be more on the "here and now" in terms of valence and feelings. These findings are consistent with an evolutionary perspective of appraisal, whose paramount goal is to ensure personal well-being in adverse conditions (Ellsworth & Scherer, 2003). Moreover, the fact that the appraisal of powerlessness emerged as one of the most central node in the negative scenario is consistent with the attention it has received in appraisal research as a plausible cause for the onset of emotion disorders (Mehu & Scherer, 2015). This has recently been shown to be the case when the appraisal of personal coping potential is chronically underestimated, leading to appraisal biases that can impact healthy affectivity in the long run (Scherer et al., 2022).

Inspired by the recent work of Lange and Zickfeld (2023), our third goal was to investigate the relations of emotion components between and within dimensions, and to test if they significantly differ from zero. Overall, we showed, visually and via formal testing, that features within the same emotion components (e.g., appraisal) were more connected to each other than across emotion components, a sign of emotion coherence (Lange et al., 2020). For example, within the same appraisal dimension, we found strong relations among valence-oriented features (i.e., appraisal of negative/positive consequences) and unpleasantness/pleasantness of situation. Similarly, within an emotion response dimension, we also found strong relations among emotion response components, such as the distress symptoms of limb weakness and sweating and the autonomic arousal feature of respiration acceleration in the Social Rejection Scenario, or the intensity of the emotion state, the action tendency of wanting to sing and dance, and the arousal response of heart beating faster in the Positive Scenario. This is consistent with Lange and Zickfeld (2021), who found that the powerlessness/coping potential-related items were more strongly interconnected than with other appraisal categories; and that physiological reactions items also showed thicker edges between them.

Interestingly, when considering the dimensional shift of the experiential component in the two scenarios (i.e., clustering with appraisal in the Social Rejection Scenario, and with emotion responses in the Positive Scenario), we witnessed something similar to Mauss et al. (2005). After administering an emotionally salient film clip, alternating amusing and sadness scenes, the authors found that the intensity of the experience of amusement correlated with the concordance of physiological and behavioural components, while this was not the case at higher levels of sadness experience. Mauss et al. (2005) argue that the intensity of the experience of sadness could be decoupled from the other emotion responses because of social pressure, requiring hence to be controlled. This rationale also appears to apply well to the findings in our negative scenario.

Focusing on the CPM, similarly to Meuleman et al. (2019), we found strong correlations between emotion response components, a sign of emotion coherence. For example, in the positive scenario, we replicated Meuleman et al. (2019)'s positive correlations between the expressive response of "Spoke more loudly" and the action tendency responses of "Wanted to sing and dance" and "Wanted to tackle the situation", as well as the arousal-related emotion responses of faster heartbeat and sweating, although with some differences in magnitude. Similarly, in the negative scenario, we replicated the positive correlation between the expressive responses of "Jaw drop" and "Spoke more loudly", and between the latter and the action tendency response of "Wanted to tackle the situation", and the arousal-related emotion response of sweating, although again with some differences in magnitude. We however also noticed several discrepancies. For example, concerning appraisal-emotion response relations, we found in our Social Rejection Scenario that the appraisal of personal goal relevance was only slightly positively associated with the action tendency component of "Wanting to tackle the situation". The opposite is true for Meuleman et al. (2019). In our study, the appraisal of suddenness was not directly related to any emotion response variables, while in Meuleman et al. (2019) it was moderately and positively correlated with the expressivity factor of "Jaw drop". Overall, we believe that the standing discrepancies between our results and previous componential literature may be due to the estimation of conditional dependencies, i.e., controlling for all other variables in the network, which may have led to weaker/absent correlations between certain nodes in our study. Another explanation could lie in the estimation of composite scores via principal component analysis in Meuleman et al. (2019), which might have led to more parsimonious but less nuanced models. Finally, we could argue that Lange and Zickfeld (2021) have a preponderance of feeling components at the expense of the other components.

From a theoretical standpoint, we provided evidence for the utility of a variable-set conceptualisation of multicomponential emotional episodes (Fernando et al., 2017). This approach has been recently proposed as an alternative to early approaches in appraisal theories focused on finding fixed and prototypical patterns of components (Moors, 2024). In a data-driven way, we showed that not all appraisals were indeed relevant to a specific context and emotional episode. In other words, we were able to identify the variability in appraisal-emotion response relations across situations (Fernando et al., 2017). Moreover, we provided evidence for the interconnection of a comprehensive spectrum of emotion components with advanced and refined analyses, urged within the CPM framework by Scherer and Moors (2019), extending beyond employing pairs of appraisals (e.g., pleasantness, relevance, and goal conduciveness; Aue & Scherer, 2008; Kreibig et al., 2012; van Reekum et al., 2004) or a limited number of appraisals (Menétrey et al., 2022), or appraisal clusters (Meuleman et al., 2019). With the present study, we showed how emotion components cluster and cohere differently in different contexts, contributing to a conversation in the field on the topic of emotion coherence which has been long debated (Constantinou et al., 2023; Gentsch et al., 2014; Sznycer & Cohen, 2021). Interestingly, in line with recent evidence (Lange, 2023; Lohani et al., 2018), we found stronger coherence of emotion components in a negatively salient context, marked by a denser network and a higher number of non-zero edges compared to a positively salient context, which generally speaking is also less researched upon.

From a practical standpoint, the knowledge produced can subsequently inform studies on real-life structural organisation of emotion components and their reciprocal influences (Fontaine et al., 2022; Scherer, 2019), spurring the field towards the application of networks to ecological momentary assessment of emotion components. This will honour the dynamic system approach roots of emotional episodes as theorised in the CPM (Lewis, 2005; Sander et al., 2005). More importantly though, we have confirmed the centrality in a negative context of the appraisal of powerlessness, which resonates with recent evidence on the role of the broader Coping Potential appraisal category in predicting the frequency of negative emotions and emotional disturbances (Mehu & Scherer, 2015; Scherer, 2020, 2022). Urgency in addressing cognitive biases within this category in young people has thus been strongly vocalized in the field (Scherer et al., 2022), as affective disturbances appear to be potentially triggered or worsened by transitioning to university (Duffy et al., 2019). Thus, our findings can guide educators, university counsellors and psychologists in the tailoring of existing psychoeducational programs to specifically young students by promoting empowered appraisal along with the strengthening of coping skills (Anderson et al., 2024; Compas et al., 2017) in the face of daily, ambiguous social situations. Psychologists and university counsellors should also collaborate with policymakers in raising public awareness on mental health well-being in this young population, which appears to have increasingly worsened in the last decade (Arakelyan et al., 2023) and in securing a place for the aforementioned psychoeducational interventions in educational curricula across colleges and universities. In turn, policymakers should ensure the allocation of resources for professional developmental programs to train educators, counsellors and teachers, as well as for the optimal implementation and delivery of these interventions.

Finally, regarding the generalizability of our findings, although the validation and application of the GRID instrument have been carried out cross-culturally (Fontaine et al., 2013, 2022), appraisal profiles of positive (Cong et al., 2022) and negative (Roseman et al., 1995) emotions appear to be modulated by cultural belonging. Thus, emotion components clusters and coherence could also differ across cultures (Lange et al., 2020; Mesquita & Ellsworth, 2001; Zickfeld et al., 2019). Moreover, the young age of our sample prevents generalization of our findings to older populations, as age differences in appraisal processes have been recently showed by Young and Mikels (2020), although in a small sample. Thus, future studies should tackle these empirical questions, and attempt replication of our findings in larger samples, diversified for culture of belonging and age.

Limitation and future directions

Our study has several limitations. First of all, as we found some evidence of items multi-dimensionality (i.e., item cross-loadings on other dimensions; see Tables S4 and S6), future studies could conduct hierarchical network analysis, a method recently proposed (Jiménez et al., 2023). This approach would allow disentangling the variance accounted for in the CoreGRID Appraisal component and MiniGRID items by the four identified higher order factors and replicating the lower-order factors, as in Fontaine et al. (2013), and explore in a more nuanced way the hypotheses set by Fontaine et al. (2022). Second, psychometric network analysis does not provide information about the degree of variable endorsement (Lange et al., 2020). Hence, we cannot claim that the edges connecting the emotion components in this study apply similarly to everyone. This will require further personalized evidence using techniques such as network comparison tests (van Borkulo et al., 2022) or moderated networks (Haslbeck et al., 2021). Moreover, network models cannot convey information about causal relationships between nodes as the edges are partial correlation coefficients. In other words, the directionality of effects between two nodes cannot be established (Lange & Zickfeld, 2021). Finally, as discussed above, we acknowledge the non-generalizability of our findings, given the employment of only two scenarios, and the exploratory modelling of CPM components, whose dynamic and sequentiality assumptions cannot be met in cross-correlational network models (Lange et al., 2020). However, we believe that our work can inspire future researchers to apply network models to emotion components embedded in more diverse contexts, with varying degrees of ambiguity and potentially inform further ecological momentary assessment studies of appraisals and emotional response in everyday life situations.

Conclusion

Overall, this study explored the relationships between emotion components in three novel ways: 1) by using networks, 2) by embedding these in a multi-componential framework, and 3) by providing context to emotion components. Our results can be informative for applied research, such as in educational settings, where understanding the interconnections and centrality of components could aid the personalization of interventions.

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Data availability De-identified data, analyses code and supplementary material are available at https://osf.io/t9f43/

Declarations

Ethics approval This work was approved by the CER-SSP-UNIL Ethic committee (C-SSP-042020-00001).

Informed consent Informed consent was obtained from all individual participants included in the study.

Conflict of interests The authors declare no competing interests.

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