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Assessing Temporal Emotion Dynamics Using Networks

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Abstract

Multivariate psychological processes have recently been studied, visualized, and analyzed as networks. In this network approach, psychological constructs are represented as complex systems of interacting components. In addition to insightful visualization of dynamics, a network perspective leads to a new way of thinking about the nature of psychological phenomena by offering new tools for studying dynamical processes in psychology. In this article, we explain the rationale of the network approach, the associated methods and visualization, and illustrate it using an empirical example focusing on the relation between the daily fluctuations of emotions and neuroticism. The results suggest that individuals with high levels of neuroticism had a denser emotion network compared with their less neurotic peers. This effect is especially pronounced for the negative emotion network, which is in line with previous studies that found a denser network in depressed subjects than in healthy subjects. In sum, we show how the network approach may offer new tools for studying dynamical processes in psychology.

Keywords

multilevel vector autoregressive model, emotion dynamics, networks, intensive longitudinal data

Introduction

Experience sampling methods (ESM; Csikszentmihalyi & Larson, 1987; Trull & Ebner-Priemer, 2013) and ecological momentary assessment (Shiffman & Stone, 1998; Stone & Shiffman, 1994) are being increasingly used to study dynamic psychological processes such as mood (aan het Rot, Hogenelst, & Schoevers, 2012; Hamaker, Ceulemans, Grasman, & Tuerlinckx, 2015; Jahng, Wood, & Trull, 2008; Wichers, Wigman, & Myin-Germeys, 2015). A particularly relevant aspect thereof is their temporal dynamics (Nesselroade, 2004).

When studying temporal dynamics, the focus is not on detecting a gross underlying trend, as is often the case in developmental research, but rather on the intricate temporal dependence of and between variables, or how variables within an individual influence each other or themselves over time (Brandt & Williams, 2007; Molenaar, 1985; Walls & Schafer, 2006). Often the models used to study temporal dynamics are multivariate in nature, and both the influence that a variable has on itself (e.g., how self-predictive is sad mood) as well as its effects on other variables (e.g., how does sad mood augment or blunt subsequent anger emotions) are analyzed (Koval, Pe, Meers, & Kuppens, 2013; Kuppens, Allen, & Sheeber, 2010; Kuppens, Stouten, & Mesquita, 2009; Pe & Kuppens, 2012; Suls, Green, & Hillis, 1998).

One increasingly popular approach to study, visualize, and analyze multivariate dynamics is network analysis (Borsboom & Cramer, 2013; Bringmann, Vissers, et al., 2013; Bringmann, Lemmens, Huibers, Borsboom, & Tuerlinckx, 2015; Fried, Nesse, Zivin, Guille, & Sen, 2014; McNally et al., 2015; Ruzzano, Borsboom, & Geurts, 2015; Wichers, 2014). This network perspective leads to a new way of thinking about the nature of psychological constructs, phenomena or processes by offering new tools for studying dynamical processes in psychology. In the network approach, psychological constructs, processes or phenomena are represented as complex systems of interacting components (Barabási, 2011; Costantini et al., 2015; Cramer et al., 2012). For instance, emotional well-being can be considered to consist of a number of dynamically interacting components, such as behavioral, physiological, and experiential emotion components. Likewise, mental disorders can be viewed as a result of the mutual interplay of symptoms of the disorder. These components interact

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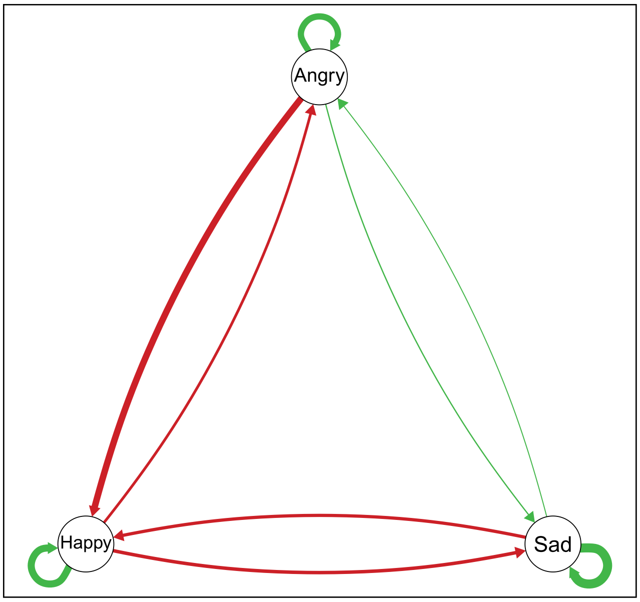

Figure 1. A hypothetical example of an emotion network. The three nodes are the three emotions: Happy, Angry, and Sad. The red arrows are the negative (i.e., inhibitory) edges and the green arrows the positive (i.e., excitatory) edges. The thickness of the arrows represents the strength of the edges. For example, the edges on the nodes (the self-loops) are the strongest links in the network.

with each other across time, making up the internal dynamics and by that, the very nature of the phenomenon under study. It is these dynamics that are studied in a network approach (Borsboom, Cramer, Schmittmann, Epskamp, & Waldorp, 2011; Cramer, Waldorp, van der Maas, & Borsboom, 2010; Schmittmann et al., 2013). In this article, we will illustrate the network approach using an empirical example focusing on the relation between the daily fluctuations of emotions and neuroticism.

The Network Approach

A network consists of nodes (i.e., the components of the phenomenon, construct, or process) and edges (or links) connecting the nodes (Barrat, Barthelemy, Pastor-Satorras, & Vespignani, 2004). In our approach, the links have a certain strength that indicates the strength of the (positive or negative) relationship between the nodes (Opsahl, Agneessens, & Skvoretz, 2010). The nodes and edges can be easily visualized graphically (see, e.g., Figure 1).

Networks can be constructed based on different kinds of data such as cross-sectional or longitudinal data and using different kinds of models for inferring the edges. Depending on the data and model used to infer the network, the edges connecting the nodes have a specific meaning. In this article, we focus on longitudinal data and on the vector autoregressive (VAR) model (Brandt & Williams, 2007). A VAR-based network allows studying the dynamics among the components that constitute a certain construct, phenomenon or process across time. For example, in the network of Figure 1, the edges on the nodes are the self-loops, or the effect the emotion has on itself from one time point to the next, and the edges between the emotions are the cross-regressive effects, or the effect a variable has on another variable from one time point to the next, controlling for the other variables.

In addition, several features of the network can be derived that can shed light on central properties of the dynamical interplay between the components or nodes. Such features can involve the overall network or specific parts of the network. One interesting characteristic of the overall network is its density, which indicates how strongly the network is interconnected. The denser a network is, the more strongly the variables interact (Newman, 2010). Another, more specific, feature of the network is node centrality. Centrality refers to the importance of a node or how focal one specific variable or node is in the network (Freeman, 1979).

Empirical Example

We will illustrate how networks can be inferred using a multilevel extension of the VAR model (Bringmann, Vissers, et al., 2013), and how they can be used to gather new insights on temporal emotion dynamics. In particular, we will focus on the relation between emotion dynamics and neuroticism in healthy subjects, using two previously collected ESM datasets. Neuroticism is one of the main dimensions reflecting individual differences in personality, and is particularly relevant for emotional experience. Specifically, it reflects a tendency to experience negative emotions, and is considered to constitute a broad risk factor for mood disorder and psychopathology (Barlow, Sauer-Zavala, Carl, Bullis, & Ellard, 2014).

In this application, we will first look at the general patterns of edges connecting the emotion variables, which are referred to as the population networks. Second, we will assess features of the network structure by studying the density of the individual emotion networks and their relation to neuroticism. In a third step, we will study whether several centrality measures of the individual networks (strength, closeness, and betweenness) and the self-loops are related to neuroticism. To our knowledge, this is the first time that both the full temporal emotion network and its parts are studied and related to neuroticism, giving a more complete picture of moment-to-moment dynamics in emotion as a function of the trait of neuroticism. The method used here will be described in detail. Moreover, *Matlab* and *R* code to replicate the main results of the first dataset will be given, so that other researchers can apply the network method to their own data (see online appendices available at http://asm.sagepub.com/supplemental).[1]

Method

Dataset 1

Parts of Dataset 1 have been published elsewhere (Bringmann, Vissers, et al., 2013; Koval, Kuppens, Allen, & Sheeber, 2012; Pe, Raes, et al., 2013; Pe, Koval, & Kuppens, 2013). A total of 95 undergraduate students from KU Leuven in Belgium (age: *M* = 19 years, *SD* = 1; 62% female) participated in an ESM study. Over the course of 7 days, participants carried a palmtop computer on which they had to fill out questions about mood and social context in their daily lives 10 times a day. Participants were beeped to fill out the ESM questionnaires at random times within 90-minute windows. They had to rate, among other things, their current feelings of negative and positive emotions on a continuous slider scale, ranging from 1 (*not at all, e.g., angry*) to 100 (*very, e.g., angry*). On average, participants responded to 91% of the beeps (*SD* = 7%). To avoid selection bias, we analyzed all six emotion variables measured in this study (positive affect: *relaxed* and *happy*; negative affect: *dysphoric, anxious, sad*, and *angry*), which were selected to capture all quadrants of the affective circumplex defined by the dimensions of valence and arousal (see e.g., Russell, 2003). Furthermore, neuroticism was assessed with the Dutch version of the Ten Item Personality Inventory (Gosling, Rentfrow, & Swann, 2003; Hofmans, Kuppens, & Allik, 2008), resulting in a score ranging from 1 to 7 (*M* = 3.4; *SD* = 1.5). Participants were selected from a large pool of participants to ensure a wide range of depression scores. Therefore, the participants in this dataset have a wider range of neuroticism scores than the participants in Dataset 2.

Dataset 2

Parts of this dataset have been published elsewhere (Kuppens, Champagne, & Tuerlinckx, 2012; Kuppens, Oravecz, & Tuerlinckx, 2010; Pe & Kuppens, 2012). In this study, the participants consisted of 79 undergraduate students from KU Leuven in Belgium (age: *M* = 24, *SD* = 8; 63 % female). A similar ESM procedure as in the first dataset was used. Participants were beeped to fill out the ESM questionnaires 10 times a day, again on a scale ranging from 0 to 100, but for a longer time period, namely 14 consecutive days. We extracted all emotion variables, which were 10 in this case (positive affect: *relaxed, happy, satisfied, excited*; negative affect: *dysphoric, anxious, irritated, sad, stressed*, and *angry*), again selected to cover all quadrants of the affective space. Participants responded on average to 82% of the programmed beeps (*SD* = 10). Neuroticism was assessed with the 12-item scale of the Dutch version of the NEO Five-Factor Inventory (Hoekstra, Ormel, & De Fruyt, 1996), which resulted in a score ranging from 1 to 5 (*M* = 3.0, *SD* = 0.7).

Estimating the Networks

To assess temporal emotion dynamics and their relation to neuroticism, an emotion network was created for each individual. The edges or links of the individual networks were obtained using a multilevel VAR model (Bringmann, Vissers, et al., 2013; 2015). The standard VAR model (Brandt & Williams, 2007) estimates the extent to which a current emotion (time point *t*) can be predicted from all other emotions at a previous moment (time point *t* - 1), corresponding to the network edges. Each emotion is regressed on its lagged values (autoregressive effect) and the lagged values of each of the other emotions (cross-lagged effects). In the present context, time *t* - 1 and time *t* refer to two consecutive beeps within the same day (overnight lags were removed). It is assumed that the data are stationary, implying that the mean and the moment-to-moment interactions of the emotion processes stay stable over time (Chatfield, 2003, Hamaker & Dolan, 2009). As we study multiple individuals, we implement the VAR model within a multilevel modeling framework, to allow for random, person-specific auto- and cross-regressive effects, and so that we can model the temporal emotion dynamics not only within an individual, but also at group level, estimating both average or population (fixed) and individual (random) effects.

Univariate multilevel VAR analyses are conducted for each emotion separately using restricted maximum likelihood estimation. This results in 6 univariate regression equations for the first dataset and 10 univariate regression equations for the second dataset. Taking the first dataset with 6 emotions as an example, we get the following equation for each emotion *j* (i.e., *relaxed, happy, dysphoric, anxious, sad*, and *angry*, or *j* = 1, . . ., 6, respectively):

$$\begin{aligned} Y_{ptj} &= \gamma_{0pj} + \gamma_{1pj} \cdot relaxed_{p,t-1} + \gamma_{2pj} \cdot happy_{p,t-1} \\ &+ \gamma_{3pj} \cdot dysphoric_{p,t-1} + \gamma_{4pj} \cdot anxious_{p,t-1} + \gamma_{5pj} \cdot sad_{p,t-1} \\ &+ \gamma_{6pj} \cdot angry_{p,t-1} + \varepsilon_{ptj} \end{aligned} \tag{1}$$

Thus, for Dataset 1, Y_{ptj} represents the value for the *j*th emotion for person *p* (*p* = 1, 2, . . ., 95) at beep *t* (*t* = 2, . . ., 10). The regression coefficients (i.e., the intercept and the regression weights) of this equation (1) are decomposed as follows:

$$\gamma_{kpj} = \beta_{kj} + b_{kpj}, \tag{2}$$

where the slopes β_{kj} ($k > 0$, since $k = 0$ codes for the intercept) represent the fixed effects (the edges in the network), or the extent to which the emotions at time *t* - 1 can predict the emotion *j* at time *t* over all individuals. The person-specific deviation (random effect) from the average effect is captured in the component b_{kpj}. The random effects are assumed to come from a multivariate normal distribution, estimating an unstructured covariance matrix of the random effects.

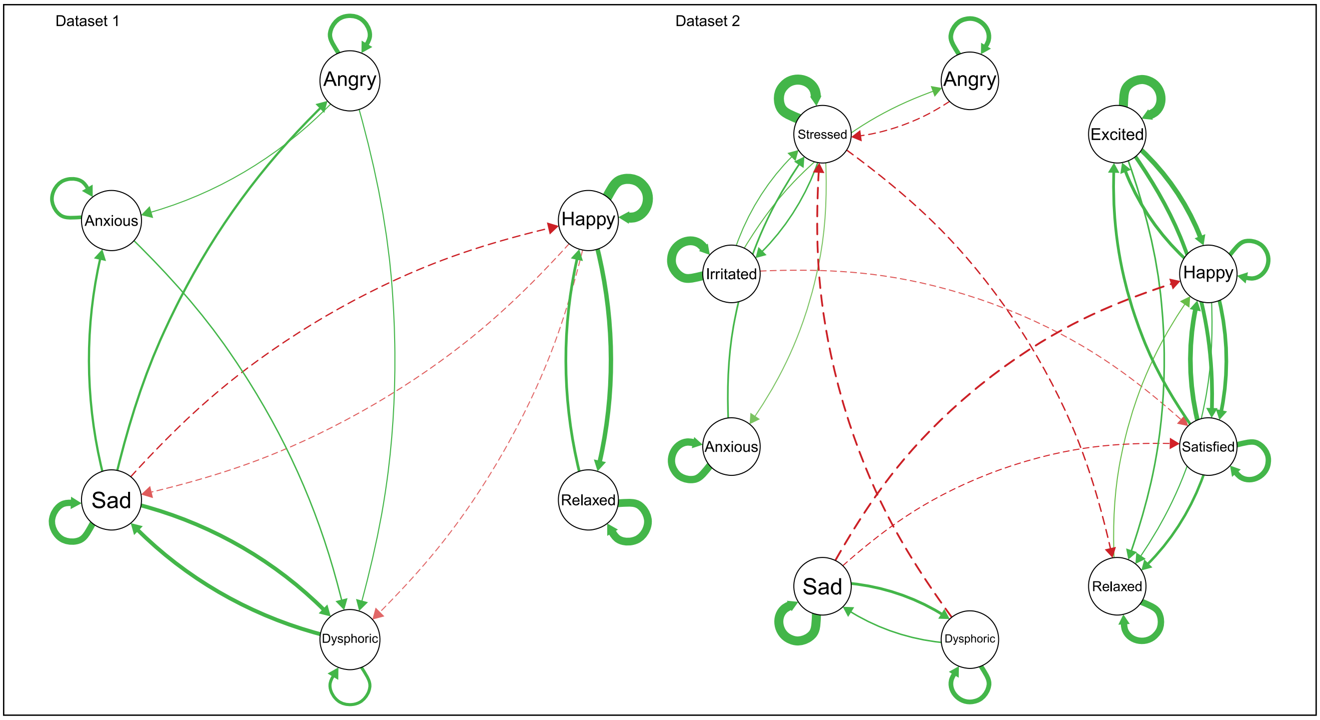

Figure 2. This figure shows the population network of the Dataset 1 (left panel) and the Dataset 2 (right panel). Solid green edges correspond to positive and dashed red edges to negative connections. Only edges that surpass the significance threshold are shown (i.e., for which the *p* value of the *t*-statistic is smaller than .05). The emotions in the networks are organized so that they align with the emotion circumplex from which they were selected.

Using the empirical Bayes estimates of the random effects, emotion networks for each individual are constructed. Specifically, for each edge in the network, the individual random effect is added to the fixed effect for each emotion variable. For instance, the edge from emotion k to emotion j has a value of $\gamma_{kpj} = \beta_{kj} + b_{kpj}$ in the individual network of person p.

To reduce the likelihood of errors in the analyses, all multilevel analyses were run in Matlab (Mathworks, Inc.) as well as in Mplus (Muthén and Muthén, 2012) and by different researchers. Visualization and computation of the measures of centrality relied on the *qgraph* R package (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012).

Regarding the analysis, there are three important additional aspects to mention here. First, as we estimate multivariate networks with both autoregressive and cross-lagged effect, all predictors were person-mean centered (centered on each individual's mean score) before the analysis (Hamaker & Grasman, 2015). Note that this might lead to a slight underestimation of the autoregressive effects. Second, to control for differences in variability between individuals, that is, to make sure that associations between neuroticism and network characteristics were not driven by differences in emotion variance, we conducted analyses involving both nonstandardized and standardized coefficients.[2] Within-person standardization of the coefficients was done as described in Schuurman, Ferrer, de Boer–Sonnenschein and Hamaker (2016).[3] Third, note that the edges only represent the unique direct effects of the variables and not the shared effects (just as in standard multiple regression; Bulteel, Tuerlinckx, Brose and Ceulemans, 2016). This means that a part of the explained variance cannot be taken into account and thus an edge might be less strong or stronger if this shared variance was taken into account.

Network Analyses

The Population Networks

Before we focus on individual networks and their relationship to neuroticism, we will first look at the average networks. These population networks show the general patterns of connections between the emotion variables. The edges in the population networks represent the slopes β_{kj} ($k > 0$; i.e., the fixed effects). The population networks are presented in Figure 2, made with the *R*-package *qgraph* (Epskamp et al. 2012).

Density

For each individual network, the density was computed of (1) the overall network (all emotions), (2) the negative emotions only, and (3) positive emotions only. This was done by averaging over the absolute values of the slopes or edges in the network of the emotions of interest. We used the absolute values so that negative and positive edge values do not cancel each other out.

Furthermore, to illustrate the relation between density and neuroticism, we created three neuroticism groups (i.e., low, medium, and high neuroticism) by ranking the neuroticism scores. In a next step, we constructed networks for the low and high neuroticism group separately (eventually resulting in two networks for overall, negative and positive emotion density for both datasets). If we focus on the overall network for simplicity of explanation, then the arrows indicate the edge strengths of the temporal connections between emotions. The average absolute value of the edge strength and the corresponding standard deviation (SD) is calculated across all participants and pairs of variables. Next, edges get classified: 1 SD below the mean (weak connection strength, dotted arrows), between 1 SD below and above the mean (moderate connection strength, dashed arrows) and 1 SD above the mean (strong connection strength, solid arrows).

Centrality

We calculated the most common centrality measures *degree* (or in case of a weighted network the term *strength* is used), *closeness*, and *betweenness*. Each centrality measure defines centrality of a node (variable) in the network in a different way (Freeman, 1979; Newman, 2004).

To explain these concepts, it is instructive to think metaphorically that the nodes transmit information across time to one another. As the network used here is a directed network, we can study both the out-strength centrality and the in-strength centrality. Out-strength indicates the (summed) strength of the outgoing edges or how much information a node sends away to the other nodes, and thus a node with a high out-strength centrality tends to excite or inhibit many other nodes in the network. In-strength indicates the strength of the incoming edges, or how much information a node receives from the other nodes, and thus its susceptibility to being excited or inhibited by other nodes in the network.[4] Both out- and in-strength take only into account the edges to which a node is directly connected.

A node high in closeness centrality is at a relatively short distance from the other nodes in the network, and is thus likely to be influenced quickly by them. Closeness thus represents how fast an emotion can be reached from the other nodes in the network. Distances between nodes are calculated based on edge strength, taking into account direct and indirect edges connecting the node to other nodes (see for more information: Borgatti, 2005; Costantini et al., 2015; Opsahl et al., 2010).

Betweenness centrality is a measure of how many times a node appears on the shortest paths between other nodes in the network. Thus, a node with a high betweenness centrality is a node through which the information in the network has to pass often and can be seen as an important node in funneling the information flow in the network. This measure also takes into account direct and indirect edges connecting the node to other nodes. Note that all the centrality measures are based on the absolute values of the edges.

The Relation Between the Network Characteristics and Neuroticism

Neuroticism scores of all individuals were correlated with density of the individual networks (calculated on the overall, negative and positive networks) and centrality measures (out-strength, in-strength, closeness, and betweenness) using Pearson's product moment correlations. Since the centrality measures are concerned with the influences between variables or nodes (cross-regressive effects) in the network, self-loops or autoregressive effects (in the emotion literature also known as emotional inertia; Suls et al. 1998) are ignored in these focal network measures. Therefore, the correlation between the self-loops and neuroticism was calculated separately for each emotion.

Results

The networks in Figure 2 represent the average patterns between the emotions. Only edges that were significant (i.e., a *p* value less than .05) are shown, which is purely for visualization purposes. The figures show that emotions can either augment or blunt each other (Pe & Kuppens, 2012). Augmenting refers to the increase of the experience of other emotions. For example, there exist clusters of negative and positive emotions. Within these clusters, emotions of the same valence tend to in general augment each other. In contrast, emotions of different valence (e.g., sad and happy) seem to blunt or decrease each other. Furthermore, the self-loops in the networks are among the strongest edges. For example, in general when a person feels sad, he or she is not only less likely to feel happy at the next moment, but also likely to still experience sadness at the next moment.[5] These results correspond with the theoretical expectations and empirical findings based on the nomothetic relations in an emotion circumplex, namely that emotions of the same valence are more likely to be correlated with each other than with emotions of different valence (Vansteelandt, Van Mechelen, & Nezlek, 2005).

The results in Table 1 show a consistent and strong positive relation between neuroticism and overall emotion density as well as negative emotion density. This pattern is not only consistent across datasets, but also when controlling for variability (i.e., after standardization), indicating that individuals high in neuroticism also have a significantly

Table 1. Density and its Relation to Neuroticism.

	Nonstandardized				Standardized			
	Dataset 1 (n = 95)		Dataset 2 (n = 79)		Dataset 1 (n = 95)		Dataset 2 (n = 79)	
Emotion Network	r	p	r	p	r	p	r	p
Overall	**.49**	**<.001**	**.42**	**<.001**	.49	<.001	.41	<.001
Negative	**.51**	**<.001**	**.44**	**<.001**	.51	<.001	.43	<.001
Positive	**.12**	**.26**	**.30**	**.008**	.11	.27	.30	.007

Note. Values in bold represent the aggregate variables that we focus on in this article, and that are illustrated in the three panels in Figure 3.

denser overall network and negative emotion network than individuals low in neuroticism. The results for the positive emotion network were less consistent. The relation between the positive emotion network and neuroticism was only significant in the second dataset and was less strong than the relationship between neuroticism and the overall and negative emotion networks. Figure 3, focusing on the high and low ends of neuroticism, also features this pattern: The difference between emotion density in individuals with a high and low score in neuroticism is more pronounced for the overall emotion density and negative emotion density than for positive emotion density.

Tables 2 and 3 show that there is a difference across the datasets in the out- and in-strength centrality. In Dataset 1, individuals with high neuroticism scores have significantly high out-strength centrality for all negative emotions and even for the positive emotion *happy*. However, none of these results replicated for Dataset 2, although the correlations are consistently positive. In contrast, the positive significant relation between neuroticism and in-strength centrality of all five emotions (*happy* was nonsignificant in both datasets) of Dataset 1 was also found in Dataset 2. Thus, there is more evidence for a positive relation between in-strength centrality of emotions and neuroticism than out-strength centrality of emotions and neuroticism.

As is apparent in Tables 2 and 3, closeness centrality is positively related to neuroticism for almost all emotions (except *stressed*) in both datasets, even after standardization. This is in contrast to the relationship between betweenness centrality (influencing the overall information flow) and neuroticism. Although in some cases the relation was significant, it was not very strong, and none of the findings replicated in both datasets.

Finally, regarding the self-loops and their relation to neuroticism, it is evident that only the self-loops of emotions *sad* and *anxious* were significantly related to neuroticism in both datasets (see Table 4).

Discussion

In this study, we found that for individuals with high levels of neuroticism, the associations found in the population level network were qualitatively the same but more pronounced (i.e., denser) than for their less neurotic peers. This effect was especially clear in the negative emotion network and was found in both datasets irrespective of standardization. Although in some cases the positive emotion network was significantly denser in individuals with a high neuroticism score, this effect was rather weak and not consistent across both datasets. These findings are noteworthy because they further reinforce the idea that neuroticism is characterized specifically by negative emotions that tend to co-occur (even across time). This is also in line with the results of Pe et al. (2015), who found that individuals with the clinical diagnosis of depression have especially a denser negative emotion network than nondepressed individuals (see also Wigman et al. 2015 for a similar result).

These results also support previous research on early warning signs reflecting vulnerability for emotional disorder. Individuals who experience a higher autocorrelation have slower dynamics, which can be seen as predictive of a transition into depression (van de Leemput et al., 2014). In the same way, people who are highly neurotic and have strong self-loops (autoregressive effects) and strong connections between their emotions (cross effects) can be seen as being prone to experience a critical slowing down and thus an episode of depression.

Regarding the relation between centrality measures of the specific emotions and neuroticism, the results were more mixed. Although in the first dataset there were strong associations between the out strength of individual emotions and neuroticism, this was not replicated in the second dataset. This could be due to the larger differences in neuroticism between individuals in the first versus the second dataset; alternatively these differences may reflect sampling error, as centrality indices are composites of many distinct parameters each of which is subject to random fluctuations due to the sampling of individuals from the population and the sampling of time points within individuals. The association between in-strength centrality and neuroticism, however, did replicate: Individuals experiencing a high degree of neuroticism were more likely to have a network in which *angry, dysphoric, sad, anxious, or relaxed* had a high in-strength centrality, that is, these emotions were more likely

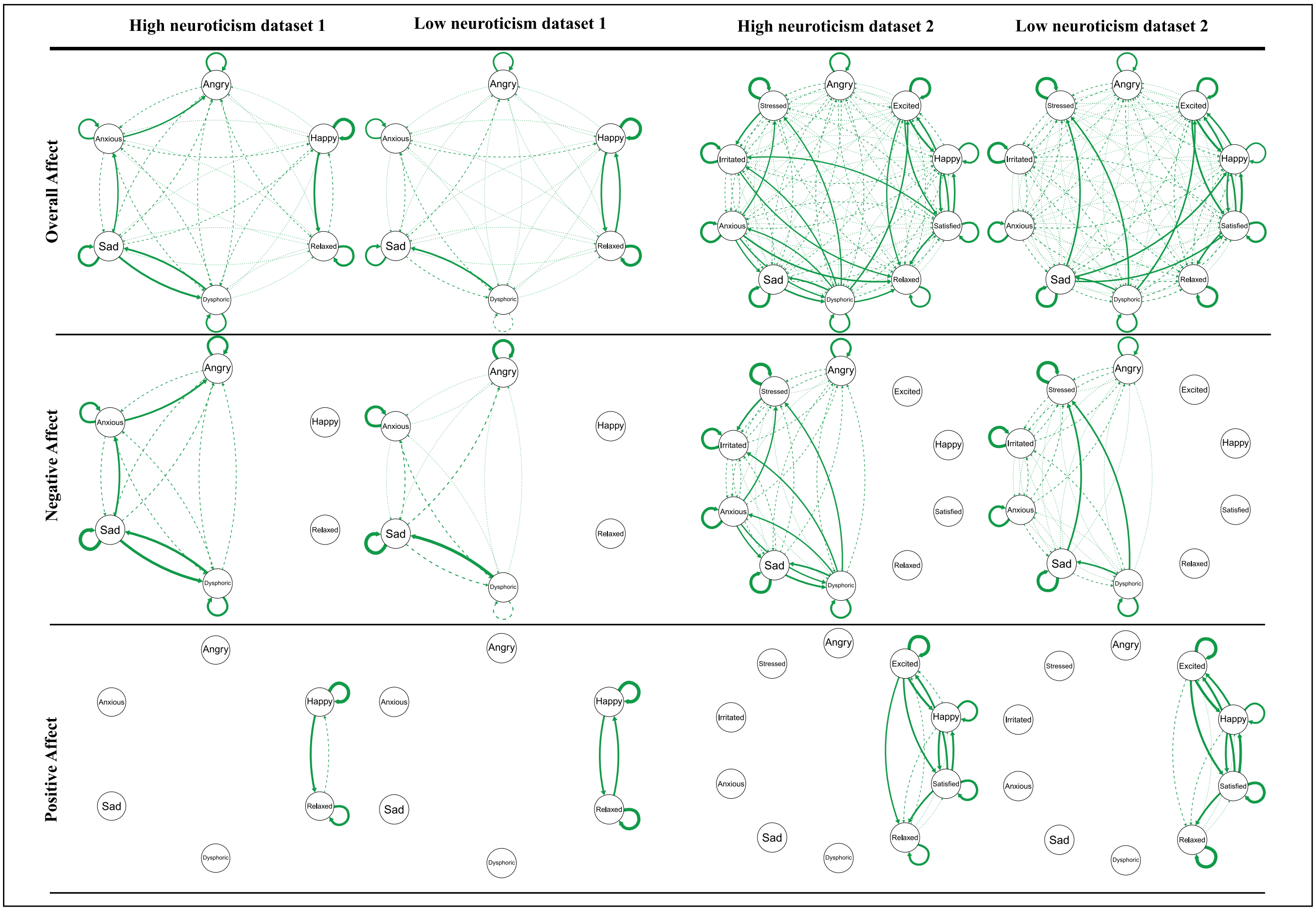

Figure 3. The emotion networks for Dataset 1 (left panels) and the Dataset 2 (right panels) for individuals with a high and low neuroticism score. In the network, the arrows indicate the absolute strengths of the temporal connections between emotions. Arrows that are dotted indicate slope values that fall 1 standard deviation (SD) below the mean of the network density (i.e., weak connection strength), arrows that are dashed indicate values around the mean of the network density (within 1 SD from the mean; moderate connection strength) and bold arrows indicate values that are 1 SD above the mean (i.e., strong connection strength). The higher the connection strength is the higher the emotion density. The emotions in the networks are organized so that they align with the emotion circumplex from which they were selected.

to be directly affected by the other emotions at the next time point.

Moreover, closeness centrality (how fast an emotion variable can be reached) was positively related with neuroticism for all emotions except for *stressed*. Betweenness centrality (the importance of a variable in funneling the emotion flow), on the other hand, did not reveal a clear association with neuroticism.

Finally, the self-loops indicated that individuals with higher emotional inertia or overspill of especially the emotions *sad* and *anxious* were more neurotic. This is in line with previous research, which found that high negative emotional inertia or the spillover of negative emotions was linked to neuroticism (Suls, Green, & Hillis, 1998; Suls & Martin, 2005).

Thus, the more strongly connected emotion networks in highly neurotic individuals seem to be driven by in-strength centrality or the fact that emotions are affected by the other emotions of the network in a negative way (negative emotions get augmented whereas *relaxed* gets mostly blunted by the other emotions). Additionally, an important feature of the networks of highly neurotic individuals seems to be that most emotions can be reached fast (closeness centrality). These results show that, to better understand the relationship between neuroticism and emotions, not only the full network density should be taken into account, but also the local structure of the network.

A limitation of this study is its generalizability. Even though the results often replicated in the two datasets, in both datasets the participants were undergraduate students living in Belgium and the studies were conducted in the same lab. To be able to generalize the results, it would be interesting to use studies from other labs with different participants (e.g., older individuals and from different

Table 2. Neuroticism and its Relation to the Different Centrality Measures (Nonstandardized).

	Out-strength				In-strength				Closeness				Betweenness			
	Dataset 1 (*n* = 95)		Dataset 2 (*n* = 79)		Dataset 1 (*n* = 95)		Dataset 2 (*n* = 79)		Dataset 1 (*n* = 95)		Dataset 2 (*n* = 79)		Dataset 1 (*n* = 95)		Dataset 2 (*n* = 79)	
Nonstandardized	*r*	*p*	*r*	*p*	*r*	*p*	*r*	*p*	*r*	*p*	*r*	*p*	*r*	*p*	*r*	*p*
Angry	.441	<.001	.219	.052	.357	<.001	.232	.040	.493	<.001	.386	<.001	.156	.131	–.033	.771
Dysphoric	.266	.009	.126	.267	.407	<.001	.406	<.001	.373	<.001	.22	.052	.151	.143	.287	.010
Sad	.407	<.001	.085	.458	.348	<.001	.338	.002	.501	<.001	.363	.001	.120	.248	.291	.009
Anxious	.289	.004	.188	.098	.374	<.001	.470	<.001	.305	.003	.312	.005	.096	.354	.324	.004
Relaxed	.157	.128	.15	.188	.391	<.001	.347	.002	.353	<.001	.351	.002	–.101	.329	–.089	.434
Happy	.42	<.001	.204	.071	–.003	.98	–.093	.416	.436	<.001	.386	<.001	–.058	.579	–.100	.382
Satisfied			.298	.008			–.068	.553			.408	<.001			–.271	.016
Excited			.361	.001			–.057	.616			.447	<.001			–.047	.679
Irritated			.315	.005			.192	.09			.456	<.001			–.016	.888
Stressed			.283	.012			.151	.184			.376	.001			–.225	.046

Table 3. Neuroticism and its Relation to the Different Centrality Measures (Standardized).

	Out-strength				In-strength				Closeness				Betweenness			
	Dataset 1 (*n* = 95)		Dataset 2 (*n* = 79)		Dataset 1 (*n* = 95)		Dataset 2 (*n* = 79)		Dataset 1 (*n* = 95)		Dataset 2 (*n* = 79)		Dataset 1 (*n* = 95)		Dataset 2 (*n* = 79)	
Standardized	*r*	***p***	*r*	***p***	*r*	***p***	*r*	***p***	*r*	***p***	*r*	***p***	*r*	***p***	*r*	***p***
Angry	.495	<.001	.238	.035	.346	.001	.212	.060	.503	<.001	.438	<.001	.133	.198	–.093	.414
Dysphoric	.249	.015	.088	.44	.394	<.001	.423	<.001	.358	<.001	.261	.020	.179	.083	.282	.012
Sad	.402	<.001	.029	.799	.376	<.001	.352	.002	.475	<.001	.381	.001	.124	.23	.160	.158
Anxious	.313	.002	.252	.025	.371	<.001	.395	<.001	.310	.002	.381	<.001	.027	.797	.299	.007
Relaxed	.18	.082	.195	.085	.341	.001	.28	.013	.394	<.001	.368	.001	–.116	.263	–.046	.687
Happy	.431	<.001	.252	.025	.024	.815	–.196	.084	.481	<.001	.435	<.001	–.094	.364	–.043	.704
Satisfied			.331	.003			–.053	.641			.437	<.001			–.163	.152
Excited			.349	.002			–.048	.672			.450	<.001			–.056	.621
Irritated			.35	.002			.163	.152			.464	<.001			–.069	.548
Stressed			.267	.017			.130	.254			.367	.001			–.150	.187

countries) to replicate the results. In addition, only a limited number of emotions were assessed, especially regarding positive emotions. Additionally, only the unique effects of the edges in the network are taken into account and thus a (possibly large) part of the explained variance is not included in the network. Solutions to take both unique and shared variance into consideration, such as the relative importance matrices, are currently only suitable for VAR models, and are not straightforward to generalize to a multilevel framework (Bulteel et al., 2016).

A further problem concerns spurious relationships in networks. As emotion processes are complicated dynamic systems it is unlikely that we have captured the full emotional process with the limited number of variables used in this article, and thus spurious relationships might have been revealed. A promising solution to see if an edge is truly direct or spurious is through the use of ancestral graphs, which have been used in functional magnetic resonance imaging research for studying connectivity. Ancestral graphs are able to explicitly model whether there are relevant variables missing from a network model (Bringmann, Scholte, & Waldorp, 2013; Waldorp, Christoffels, & van den Ven, 2011). Future research should focus on developing these kinds of techniques further so that they can also be used in multilevel analyses.

As this study was based on mere correlations between neuroticism and emotions networks, it would be fruitful to have a more experimental setup in which one studies temporal emotion dynamics within individuals having different levels of neuroticism at different points in time. It is likely that individuals do not experience the same level of neuroticism continuously (Fleeson, 2001; 2004). Therefore, it would be interesting to see if in periods when neuroticism is, for example, less severe, one indeed would find less dense emotion networks than in periods when neuroticism is more severe. Note that to study such changing dynamics, extensions of the multilevel VAR technique will be needed, such as the multilevel threshold autoregressive model (de

Table 4. Self-Loops and Their Relation to Neuroticism.

	Dataset 1 (n = 95)		Dataset 2 (n = 79)	
Self-loops	*r*	*p*	*r*	*p*
Angry	.226	.028	.219	.052
Dysphoric	.295	.004	.167	.141
Sad	.417	<.001	.265	.018
Anxious	.257	.012	.362	.001
Relaxed	−.122	.240	−.133	.243
Happy	.169	.102	.303	.007
Satisfied			.108	.341
Excited			.327	.003
Irritated			.128	.262
Stressed			.240	.033

Note. To standardize the edges of the network the standard deviations of the predictor and outcome variables are used. Since a self-loop has the same predictor as outcome variable the standardized and unstandardized edges are equal.

Haan-Rietdijk, Gottman, Bergeman, & Hamaker, 2016) or a time-varying autoregressive model (Bringmann et al., in press).

In this article we have illustrated some of the possibilities of the network approach for studying temporal dynamics of psychological phenomena. More specifically, we have applied the network approach to an empirical example: the daily fluctuations of emotions and neuroticism. Whereas most studies have focused on aggregated or summed negative emotions and found that individuals with neuroticism tend to have a longer recovery of their negative emotions (i.e., higher emotional inertia; Suls & Martin, 2005), network analyses give a deeper understanding of this process. We have shown that there are emotion-specific effects, and moreover, it seems that the inflow and the speed of flow from other emotions was especially driving the stronger connectivity in more neurotic individuals. These new ways of analyzing emotions and other psychological phenomena can provide important information for better understanding how emotions are related to psychopathology, and for example how individuals get "stuck" in their emotions.

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Notes

1. To use this code please read first the R file.
2. One exception is the analyses using self-loops. In order to standardize the edges of the network, the standard deviations of the predictor and outcome variables are used. Since a self-loop has the same predictor as outcome variable the standardized and unstandardized edges are equal.
3. Note that there are different ways to standardize that lead to slightly different results.
4. We thank an anonymous reviewer for suggesting this interpretation.
5. Note that the number of possible edges is proportional to the number of nodes and thus the network for Dataset 2 is not necessarily more strongly connected than the network for Dataset 1.

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