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Sharing the load: Contagion and Tolerance of Mood in Social Networks

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The study was approved by the University of Birmingham Science, Technology, Engineering and Mathematics Ethical Review Committee (ERN 18-0548). The datasets generated and analysed during the current study are not publicly available to protect the privacy of participants but are available from the corresponding author on reasonable request. The authors declare that they have no competing interests. The study was conducted using intramural funding from the University of Birmingham and ETH Zürich. Part of the research was conducted while PB was employed at ETH Zurich. Both authors contributed equally. Both authors designed the study. SBH collected and PB analysed the data. Both authors wrote the paper. The authors gratefully acknowledge the contribution of the youth musical ensembles.

Abstract

The relations between self and others are fluid and constantly changing but exert a profound influence on our identity and emotional experiences. Indeed, human emotions are frequently and intensely social, and the people with whom we interact can alter our momentary mood. But does emotional 'contagion' extend over prolonged periods of hours to days, and if so, how does it propagate through interconnected groups? Answering this question is empirically challenging, since mood similarity in connected individuals can arise through multiple mechanisms (social influence, social selection, and shared external causation), making causal inferences hard to draw. We address this challenge using temporally high-resolution, longitudinal data from two independent, bounded social networks during periods of high communal activity and low external contact. Adolescent study participants (N=79) completed daily mood (n=4724) and social interaction (n=1775) ratings during residential performance tours of classical music lasting five to seven days. Analyses using statistical network models show that in both networks, adolescent musicians became reciprocally more similar in mood to their interaction partners. The observed contagion effect was greater for negative than for positive mood. That is, while one may 'catch' a friend's bad mood, the friend may feel less negative in the process. These results suggest a mechanism for emotional buffering and the 'cost' of social support. We found no evidence for social selection based on mood. Indeed, participants were remarkably tolerant of their peers' mood fluctuations, and showed no evidence of altering their patterns of social interaction accordingly.

Keywords: Social networks; emotion; social influence; mood contagion; stochastic actor-oriented models

Sharing the load: Contagion and Tolerance of Mood in Social Networks

Pop psychology blogs advise us to stay away from people with a foul disposition, but to seek the company of those in good spirits; because moods and mind-sets are believed to be contagious. But is it true that we can catch acute states of emotional well-being through our social networks, in a manner analogous to an infectious disease? Will finding a cheerful partner give us a more positive life outlook? Will spending time with a depressed sibling in adolescence increase our depression risk? The answer to these questions has implications not only for how we should lead our lives (if we want to be happy), but also for public health, with pathological mood disorders being a global health concern (World Health Organization, 2017). Understanding how emotional experiences are transmitted in interconnected groups could enhance understanding of the costs, benefits and dynamics of social support (Kawachi & Berkman, 2001; Strazdins & Broom, 2007). Such understanding could promote better group therapy (Kanstrup et al., 2019) and community interventions, for example for individuals vulnerable to low mood, stress and loneliness (Castillo et al., 2019; Valente, 2012).

Affective experiences vary widely in duration and intensity. Emotions are defined as short-lived behavioural, physiological, and subjective responses elicited by an immediate goal or trigger (Gross, 2009). Moods are typically longer-lasting (hours to days), more diffuse, and potentially less intense; they may arise without a clear trigger, and outlast their presumed cause (Gross, 2009). Emotional experiences also vary in valence, being either positive or negative (Gross, 2009). A diverse body of evidence indicates that moods and emotions may be transmitted between individuals. At the psychological level, mechanisms underlying this contagion include automatic, unconscious mimicry of emotionally expressive behaviours and the subjective perception thereof (Dimberg et al., 2000; Hatfield et al., 1993), and more conscious, deliberative processes such as those based on cognitive inference and verbal communication (Rimé, 1998, 2009; van Kleef et al. 2009). In the current study, we define

(mood) contagion at the network level, as the tendency for connected individuals to become more (emotionally) similar over time. In the long run, such mechanisms could underlie observations that connected people, such as friends, married couples and sports teams, show higher mood similarity than expected if they were not connected (Feldman, 2007; Friedkin & Johnsen, 2011; Levenson & Gottman, 1983; Totterdell, 2000; Totterdell et al., 2004). However, conclusively showing social influence on mood in naturalistic settings is notoriously difficult, as this tends to be confounded by three factors.

First, the causal relationship between mood and social interactions may also run in the opposite direction, with mood shaping our social interactions. Social network research on homophily suggests that people have a preference to interact with others who share similar characteristics (McPherson et al., 2001), and there is some evidence this may apply to emotional similarity (Elmer et al., 2017; Van Zalk et al., 2010). If we choose our partners on the basis that they are as cheerful as ourselves, this social selection could explain why connected individuals show more mood congruency than the population at large. In addition to homophily, other forms of social selection exist, such as popularity (I choose to interact with you based on your positive attribute, e.g. happy mood) and sociability (e.g. my happiness level increases my tendency to interact). In the case of mood, all such mechanisms are plausible (Schaefer et al., 2011). Consequently, observational studies of mood contagion need longitudinal research designs and appropriate methodology that can disentangle social influence from social selection, including homophily.

Second, environmental influences on mood tend to affect connected people to a greater extent compared to random, unconnected pairs in the population: The adolescent siblings that experience depressive symptoms might not have influenced each other, but instead grew up together in the same distressing home environment, or share a genetic disposition that contributed to their symptoms. Recent literature has shown that, to obtain credible evidence for

social influence in observational data, we must take into account all environmental factors that substantially influence the mood of connected people (Shalizi & Thomas, 2011). In observational studies, this is often not practically possible and as such, apparent contagion could instead (or additionally) reflect shared unmeasured external causation. Study designs are needed in which participants are exposed to highly similar variation in environment, limiting unmeasured external sources of heterogeneity.

Third, longitudinal social influence studies must take into account measurement timescales. In order to show plausible evidence for social influence on a measured variable (e.g. mood), studies should align the temporal resolution between measurement time-points (i.e. how often mood is measured) with the temporal resolution of functionally relevant changes in the measured variable (i.e. how quickly mood fluctuates). While mood changes in the realm of hours to days (Gross, 2009), longitudinal network studies often rely on large-scale panel data that take measurements months or years apart (Fowler & Christakis, 2008; Hill et al., 2010). In the period between observation points, mood has potentially changed hundreds of times. In such cases, observed emotional convergence is likely to indicate a disposition of connected people to show similar moods, rather than mood contagion.

These three confounding factors and threats to internal validity – social selection, external causation, and temporal alignment – present difficult challenges to the study of mood contagion in real-world social networks. As such, we have surprisingly little empirical evidence on the prevalence of mood contagion in the real world, despite its intuitive appeal.[1]

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[1] Studies using online social media data have studied emotional contagion, too, sometimes using randomised control trials to establish causality. However, we pay less attention to this literature for theoretical, methodological, and ethical reasons. Theoretically, the mechanisms underlying contagion in depersonalised, text-based online interaction and face-to-face interaction in real-world contexts differ. Timing between action and reaction, availability of social and psychological cues, or the motivation for positive navigation of interaction situations are only a few examples of differences between these interaction forms. Methodologically, the meaning and content of online network connections are highly variable within and between individuals and media sites. Measures for mood are typically not validated, either. For example, the extent to which the use of positively and

The Current Study

In the current study, we investigate mood contagion using an observational social network paradigm. Our interdisciplinary research design addresses classic research questions in psychology and sociology by exploiting recent advances in social network concepts and methodology. This allows us to overcome many of the outlined challenges.

We investigate the relationship between social interactions and mood in two real-world social networks (N=40; N=39). The two networks comprised two non-overlapping sets of individuals, providing an internal replication opportunity. Each network consisted of mutually acquainted adolescent musicians (age range 15-19 years) on a residential music performance tour. This provides an optimised setting to investigate the interplay between social interactions and mood, since collective music playing enhances social bonding (Dunbar et al., 2012; Weinstein et al., 2016). Furthermore, during adolescence, mood is normatively variable (Maciejewski et al., 2015) and social interactions highly salient (Foulkes & Blakemore, 2016), making this a pertinent population within which to investigate social interactions and emotion.

The study was conducted during residential tours (5 days and 7 days) in which each group was relatively isolated from external contact and spent the majority of their time together. The constraints imposed by the tour schedules resulted in a high degree of control over common external factors, as participants were exposed to the same external events, such as travel, rehearsals, and performances. Consequently, participants experienced similar daily variation in environment, limiting the unobserved heterogeneity of environmental influences on participants. Furthermore, the setting provides enhanced sensitivity to investigate contagion of

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negatively connotated words in online media posts reflects experienced mood in everyday life and whether the mimicry of such words after online exposure reflects actual change in mood is speculative. Finally, ethical problems of scientific practise in parts of the online network literature include the privileged access to social media company data by few researchers that make research not reproducible, and, critically, lacking research ethics procedures as these are outsourced to the profit-oriented companies in question. Accordingly, we do not cite studies that circumvent established scientific practises, so as not to implicitly give them scientific legitimacy.

negative as well as positive mood, since individuals experiencing low mood had reduced opportunity to physically withdraw.

We elicited mood and social interaction data across consecutive days, providing temporally high-resolution data on both dimensions and aligning our measurement intervals with a theoretically plausible timescale for mood changes. As mood varies at the most fundamental level in valence (Dejonckheere et al., 2019), we measured six positive and six negative mood states using mood descriptor words adapted from the PANAS (Watson & Tellegen, 1985). The selected mood words represent theoretically and empirically distinct dimensions of negative mood (sad / angry / afraid) (Watson & Clark, 1994) and positive mood (excited / calm) (Gruber et al., 2011), as well as dimensions related to sociability. These allowed us to investigate whether certain types of mood might be particularly contagious or guide social selection. Finally, compared to previous studies that measure abstract relations like friendship, we measure reported daily interaction partners of adolescents. Each day, participants nominated between two and six individuals that they spent the most time with that day. After accounting for missing data in the questionnaires, we elicited a total of 1,775 interaction nominations and 4,724 mood word ratings across both groups that we use in the analysis.

The data were analysed using recently established, state-of-the-art statistical network methods, in particular Stochastic Actor-Oriented Models (SAOMs) for the analysis of the simultaneous evolution of the social interaction network and individual mood state (Snijders, 2001; Snijders et al., 2010). The SAOM assumes a continuous time process, in which social ties and mood states can change interdependently. This allows disentangling potentially simultaneously occurring selection and influence processes, while controlling for common exogenous causes. As such, our study combines temporally high-resolution data in a real-world

setting that allows for tight control over potentially heterogeneous influences on participants with sophisticated statistical modelling.

With this analytical strategy, we tested four hypotheses: 1) social selection I – mood popularity: (a) individuals interact more with peers who experience positive mood, and (b) avoid peers who experience negative mood; 2) social selection II – mood sociability: individuals who (a) experience more positive moods engage in more interactions, and (b) experience more negative mood engage in fewer interactions; 3) social selection III – mood homophily: individuals interact with peers who experience similar positive and negative moods; 4) social influence – mood contagion: individuals become more similar to their peers in terms of mood. In view of the possibility of differential contagion of positive and negative mood, we examined different dynamics across different mood states.

Methods

Participants

We recruited adolescent participants from two youth musical ensembles. All participants had registered for one of two residential tours (tour 1, tour 2) before they were given information about the current study. Of the 53 individuals from ensemble 1 who registered for tour 1, n=39 consented to take part (22 female) and of the 48 individuals from ensemble 2 who registered for tour 2, n=40 consented to take part (27 female) resulting in a total sample size of 79 individuals across two networks. Self-reported ethnicity was predominantly White British in ensemble 2 (28 White British, 7 others, 4 missing); for ensemble 1, ethnicity information was missing. All participants were aged between 15 and 19. Participants aged 16 and above gave informed consent to take part, while parent/guardian consent was obtained for participants younger than 16. We collected data during July and August 2018. The study was approved by the University of Birmingham Science, Technology, Engineering and Mathematics Ethical Review Committee.

Sample size of the population was determined by practical considerations concerning recruitment of musical ensembles. Past studies with similar or much smaller analytical sample sizes (determined by number of participants and number of waves) were able to establish selection and influence effects without problems (including the studies directly relevant for the case at hand in terms of substantive interest or methodology: Block et al., 2018; Elmer et al., 2017; Schaefer et al., 2011; Snijders et al., 2013; Stadtfeld et al. 2016; and Van Zalk et al., 2010). Systematic power studies were not conducted, since arbitrarily adding days to the tours, or musicians to the ensembles was not possible for the researchers.

Materials

Daily interactions diary. Participants reported each day on their interactions with fellow tour participants by writing down the names of between two and six persons they spent the most time with that day, in order. We defined an interaction as follows: " 'Spent time with' means you hung out with them, had a meaningful interaction with them, etc." Participants were only able to report on their interactions with peers who had consented to take part in the study, to ensure informed consent (Borgatti and Molina, 2005).

Daily mood log. Participants rated their mood each day by writing a number from 1 ('not at all or very slightly') to 5 ('very much or extremely') to indicate the intensity with which they experienced each of 12 mood states (cheerful, sad, enthusiastic, upset, calm, lonely, strong, nervous, accepted, irritable, dissatisfied with self, inspired) in the present moment.[2]

Daily social media log. Each day, participants circled one of four response options to indicate the number of hours they spent on social media that day: None, less than 1 hour, 1-2

[2] Mood words were chosen as follows: First, we reduced the full PANAS to a shorter measure to make it less tedious to complete. Second, we selected equal numbers of positive and negative mood words. Third, within each valence, we selected roughly equal numbers of words in each mood word subcategory (joviality, serenity, etc.). Fourth, we selected words that we judged were appropriate for our age range and demographic (e.g. we avoided 'jittery' which British teenagers typically are unfamiliar with, we avoided 'blue' as it is perceived as non-native).

hours, more than 2 hours. This measure was used control for a potential source of heterogeneous exogenous input.

Response rates for the daily survey are equal to, or above 80% for all waves except the fifth (final) wave of ensemble 2, when 52.5% of adolescents responded. Robustness checks show that the results reported in the paper are not sensitive to inclusion/exclusion of data from this day with unusually high non-response.

Procedure

Participants provided data during one of two residential tours. Tour 1 lasted seven days and tour 2 lasted five days. The first day of each tour was spent travelling and settling in. The last day of tour 1 was spent travelling, while the last day of tour 2 was spent travelling and doing an organised group leisure activity. Intervening days of each tour were divided between organised group leisure activities, rehearsals, and performance. Therefore, for each tour, the majority of each day was spent together as a group. Participants completed the daily diary measures at the end of each day and were instructed to complete them in private and only for the current day. Compliance was not monitored on a daily basis, to ensure confidentiality and to avoid placing participants under undue pressure to comply. Measures were printed in A5 paper booklets which each participant kept in their luggage or lockable bedside table. Booklets were labelled using a unique participant identifier for which the correspondence to their name was known only to the experimenter and the participant. Booklets were collected at the end of the tour before participants went home.

Descriptive analysis

All analyses are conducted in the statistical environment R. Some parts of the descriptive analyses and visualisations use functionality from the libraries ‘igraph’ and ‘sna’. The statistical model is implemented in the library ‘RSiena’ (Ripley et al., 2019).

Initial descriptive analysis examines mood development in different empirical communities of the collected networks. It proceeds in two steps. First, a walk-trap algorithm is used to detect the empirical communities of the combined network over the entire tour (Pons & Latany, 2005). The intuition of the walk-trap algorithm is that a random walk along network ties can be used to calculate distances between two nodes by the number of steps used to commute between them. Nodes in the same community need fewer steps compared to nodes in different communities. Hierarchical clustering defines communities based on these distances and modularity is used to select the optimal partitioning. Aggregate mood valence within the communities denotes the daily averages of individual mood valence within a group, which is calculated as follows: the difference between the average value on all positive mood words (range 1-5) and the average value on all negative mood words (range 1-5). Thus, aggregate mood valence ranges from -4 to +4, where positive numbers indicate higher responses on positive mood words than on negative mood words. Our justification for combining positive and negative mood valence in this way for the purposes of this descriptive analysis is that, as can be seen in Table S2, we find exclusive positive correlations within moods of the same valence and negative correlations between moods of different valence (see Table S2)[3]. However, this aggregation was only used for this descriptive analysis; for other descriptive and for all inferential analysis, we treat individual mood words and mood valence separately.

The second descriptive analysis analyses mood homogeneity among connected individuals, that is, the tendency of connected individuals to show similar mood. It is adopted from Block *et al*. (2018). To determine mood homogeneity, we iterate through all triplets that consists of two individuals and one mood. The minimum value that either individual assigns to this mood item is multiplied by the number of ties present between two individual. Thus, when

[3] For completeness, the standardised Cronbach's alpha for the six items of negative mood items and six positive mood items are 0.70 and 0.74, respectively.

two people have a tie, mood homogeneity is higher when both partners indicate high values on the same moods and low in when they experience different moods. For reciprocated ties, mood homogeneity counts for both ties; individuals that do not have ties do not contribute to the mood homogeneity count. Overall mood homogeneity sums the values for all triplets. As the interpretation of the raw mood homogeneity is difficult, we compare the observed homogeneity value to an expected null distribution under the assumption that mood and social ties are independent. This null distribution is created by permuting the network[4] (Krackhardt, 1988). Thus, the network structure and the mood profiles are taken as given and by comparing the observed association between them to a simulated null distribution, a statistical test in a non-parametric framework can be performed.

The stochastic actor-oriented model

The strategy for the statistical analysis of social influence follows the one outlined in (Block et al., 2018). We use SAOMs, a well-established statistical model for the longitudinal analysis of the interdependent co-evolution of networks and individual traits (Snijders, 2001; Snijders et al., 2010).

In their common implementation, SAOMs apply to panel data of networks and individual attributes, in our case daily snapshots of interaction networks and individual mood indications. In the SAOM framework, it is assumed that changes in network ties and changes in experienced mood happen continuously in between two observations. These changes can be decomposed into a series of so-called mini-steps; they denote the smallest possible changes in mood experience and network ties, i.e. one person experiences a change in one mood item, or one person changes one interaction network tie. As the exact sequence of mini-steps between

[4] Network permutation is a procedure in which a given network structure is kept intact, but individuals are randomly redistributed to network positions, while keeping their observed mood profiles.

observations is unknown, they are imputed using MCMC (Markov Chain Monte Carlo) simulation procedures. The mini-step lies at the heart of the SAOM, as it determines how the network and the mood indications change.

A schematic representation of the SAOM with a focus on the mini-step is depicted in the flow-chart in Figure 1. The first part of a mini-step determines which actor is the next to enact change, as well as whether this is a network mini-step or a mood mini-step. This is modelled in the *rate-function*, which technically models exponentially distributed waiting times for the actors, based on individual characteristics and network position (see Snijders 2001). In practise, the *rate-function* is often assumed to be period-wise constant, meaning that all actors have the same propensity to be considered for a change their outgoing ties. While in the original model formulation all steps in the blue box in Figure 1 are modelled simultaneously, it is mathematically identical to the presented step-wise choice in which, first an actor *i* from any of the present actors is chosen to make the next change, and, second, it is decided whether that actor changes an outgoing interaction tie or mood nomination[5].

In case the actor is chosen to make a network mini-step, the focal actor *i* can choose three types of options. It can (i) delete an existing outgoing tie, (ii) create an absent interaction tie, or (iii) keep the interaction network in its current state. Which option is chosen is determined using the *network objective function*. The objective function assigns a value to the current personal network state of the actor, as well as each potential network state that an actor can reach by adding or deleting one tie. The higher the value of the objective function, the more likely it is that the actor chooses to change this tie. The exact probabilities are determined using a multinomial logit model.

[5] Update of the simulation time *T* is presented in the Figure for completeness only; it determines the stopping criterion in simulations using the model.

The value of the objective function is determined by a linear predictor analogous to standard logit models. It is constructed of ‘statistics’ that have the function of independent variables and statistical parameters that indicate whether actors choose network states that are higher or lower on this statistic. One example of such a statistic is mood homophily that indicates how similar actors are to their network partners in terms of mood. In case the associated parameter is positive, actors tend to create interaction ties to other that are similar to themselves in terms of mood and stop interactions with others that are dissimilar. Parameter sizes can be interpreted as in other multinomial logit models (with the caveats that apply to interpreting logit parameters).

The step-wise process in the yellow box of Figure 1 is executed as one step in the original model formulation, but the two ways of formulating the model are mathematically equivalent. Thus, we can interpret the model as the focal actor *i* first comparing how ‘happy’ it is with the current network state compared to any network state it can reach by changing one tie, and, if it decides to change one tie, it can choose which one.

The process for changing mood indications is governed by the *mood objective function*, which is in its mathematical principle identical to the network objective function; the difference is that actors change whether they experience a certain mood or not compared to changing interaction partners. As above, which mood indication an individual changes is determined by a multinomial choice model. Technically, the mood indications are modelled as a bipartite network, in which ties constitute the experience of particular moods by the participants (for further details, see Snijders et al., 2013; Stadtfeld et al. 2016; and Block et al., 2018).

In model 1 of our analysis we analyse the co-evolution of the interaction network and a bipartite network representing all mood indications. In model 2 we analyse the co-evolution of the interaction network and two bipartite networks that represent positive and negative moods. As the statistical model is defined for binary tie values (present vs. absent), we must

dichotomise the mood experiences of the participants. We code a value higher than the median value of all ratings for that particular mood as a mood being experienced by a person at any specific time-point. This naturally controls for the differential intensity to which different moods are experienced (i.e. controlling for the greater frequency of e.g. very/extremely cheerful than very/extremely lonely).

The two ensembles are analysed in a joint model that assumes the parameters of the objective functions for both groups are identical, while allowing variation in the rate-function (a so-called multi-group analysis (Snijders & Baerveldt, 2003)). This is standard practise for the joint analysis of a small number of groups (ensembles) and unproblematic when the groups are of similar sizes.

Missing data arising from non-participation or participants not responding to the questionnaire on specific days is treated as non-informative in the analysis framework in the default way of the SAOM implementation software RSiena. Past research (summarised in Section 4.3.2 of Ripley et al. 2019) found that a large proportion of missing data can, first, result in estimation problems for the software and, second, lead to a loss of statistical power. In our analysis we did not experience estimation problems and have sufficient changes in network ties and mood indications to ensure statistical power. Since we cannot collect data on participants that did not consent to participate in the study, we cannot assess whether missing individuals have different characteristics than participating individuals. Thus, our results are obtained on the measured part of the ensembles and extrapolation to the non-measure individuals requires the assumption that non-participation is unrelated to our research questions.

Since for SAOMs there is no equivalent of an R^2 or other, simple measures of model fit, model adequacy is tested using simulation procedure, outlined in Lospinoso and Snijders (2019). These Goodness of Fit (GoF) tests determine whether the model can adequately recover

unmodelled network characteristics as an indicator of whether the model is likely to represent the empirical network process. In line with standard procedure, we check the GoF for the indegree distribution and the triad census for the interaction network, the outdegree distribution for the interaction and mood networks, and the mixed triad census for the combined mood and interaction networks (see Lospinoso and Snijders 2019).

Representation of hypotheses in model parameters

In the model specification of the SAOM, the four hypotheses we test are formalised as follows: 1) mood popularity is tested in model 2 with two parameters that represent whether individuals that experience (i) more positive and (ii) more negative moods are more likely to be chosen as interaction partners in the interaction network (RSiena effect name `outPopIntn`). 2) Mood sociability is represented in model 2 with two parameters indicating whether participants that experience (i) more positive and (ii) more negative moods have a tendency to send more ties in the interaction network (effect name `outActIntn`). 3) Mood homophily is formalised by one parameter in model 1 that represents whether individuals send ties to those that experience more of the same mood items as themselves. Formally this is modelled by one type of triadic closure spanning two different networks (effect name `from`). In model 2 this is represented by two parameters for the positive and negative network. 4) Mood contagion is represented in model 1 by a parameter that indicates whether individuals tend to experience the mood of their interaction partners in the network. Formally this is modelled by a different type of triadic closure (effect name `to`). In model 2 this is represented with two parameters[6].

[6] Non-focal ('control') parameters for the network models are based on standard parametrisations from introductory articles and closely related research (Snijders et al. 2010; Block et al. 2018). In particular, the interaction and mood models include basic rate parameters and an outdegree parameter that govern the rate of change and the basic tendency to form ties, respectively. In the interaction model, the reciprocity parameter models perceptions of interaction to be reciprocal, while transitive closure (modelled as geometrically weighted edge-wise shared partners) represents the clustering of interaction in groups. The interaction of the previous two parameters models differential prevalence of reciprocity within compared to outside of groups. The spread of indegree, outdegree, and indegree-outdegree correlation is modelled using the parameters indegree-popularity,

Results

In the presentation of the results of our study we move from descriptive analysis to inferential modelling. First, we present the interaction networks, followed by describing the differences in mood evolution in different regions of the interaction network. Next, we perform a non-parametric test to evaluate whether interacting adolescents are more similar in mood than expected by chance and, finally, we present the results of the full statistical network model.

Descriptive analysis

Figure 2 displays the interaction network and individual mood states over four consecutive days for the ensemble on the longer tour. At each observation, visual inspection shows that connected individuals in the same region of the network show similar mood, as indicated by node color. In contrast, the number of ties sent and received seems unrelated to individual mood; red nodes (adolescents experiencing negative moods) are at first inspection not more isolated than blue nodes (adolescents experiencing positive moods). Thus, our first indication is that either homophily or contagion might lead to connected individuals experiencing similar moods, but we have less descriptive evidence that mood is related to sociability or popularity. Visual inspection of the other group yields similar results (see SI, Fig S1). Descriptive statistics for the mood words are found in the SI (Table S1 and S2). Basic descriptive statistics that include the change between networks over consecutive waves are presented in Table S3 and S4 in the SI.

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outdegree-activity, and indegree-activity, respectively. However, interpretation of these parameters is not trivial. Finally, the differential tendency of girls and boys to attract and send ties, as well as homophily regarding sex and musical section is included in the model. A full discussion of all these model parameters is given in the SI. In the mood model, the additional non-focal parameters include the differential tendencies of boys and girls to report moods, the tendency of mood of the same and different valence to be reported at the same time, and dummy variables for each mood type and day. Their interpretation is discussed in the Results section.

In Figure 3 we further explore mood congruency in different regions of the network for both ensembles. We inductively define social groups using community detection algorithms for social networks as outlined in the Methods section. The right-hand side of Figure 3 shows the detected communities for both ensembles, superimposed with network ties that were present for at least five days (ensemble 1) or three days (ensemble 2). The communities can be interpreted as adolescent cliques in the colloquial meaning of the word. For the purposes of this descriptive analysis, we create a single aggregated mood variable composed of the sum of positive minus the sum of negative moods. On the left-hand side of Figure 3, we see the development of aggregated mood valence for each group over, respectively, seven and five measurement days for the two groups. On the example of ensemble 1, the general trends of mood shown across most cliques (e.g. lower mood on days 4 and 6) most likely reflect shared environmental factors, such as travel and collective leisure or music activity. However, despite these general trends, aggregated mood valence within the cliques varies considerably. Further, mood changes between days differ by clique, with consecutive days showing mood improvement in some groups, but mood deterioration in others. This strongly suggests that mood development has an important social dimension in both ensembles.

Next, we move to the level of interaction pairs of adolescents, as we suspect social influence to be most prevalent here. We use a statistical test for network data that indicates whether connected individuals show more mood homogeneity than expected by chance. Mood homogeneity concerns the experience of similar mood types and, as such, goes beyond similarity in mood valence as analysed in the previous paragraph. The grey area in Figure 4 shows the 90% confidence band of expected mood homogeneity within connected pairs, if mood and social interaction were independent. The left-hand graph shows this for ensemble 1

and the right-hand graph for ensemble 2.[7] The red line displays observed homogeneity. This shows that connected individuals are significantly more similar to each other in terms of mood than expected by chance ($p<0.01$ for each day). Additional analyses show that this mood congruency between connected individuals further holds when looking at positive and negative moods separately. While these findings indicate that there is either mood homophily and/or contagion, further descriptive analyses find that the relation between experiencing positive or negative mood and popularity or sociability is not consistent (see SI, Fig S2)[8].

SAOM results

Finally, we analyse the changes of interaction patterns and mood states with SAOMs. Mood states are analysed as individual mood items (i.e. the 12 mood words) that individuals can experience (or not) in relation to the group median score for each mood word, and these dichotomised mood states coevolve with the interaction network. This analysis uses the pooled data of both ensembles.[9] The results for the parameters related to our hypotheses are shown in Table 1. For estimates of further model parameters and their interpretation, please refer to the SI (in particular table S5). In model 1 of the statistical analysis (left column), homophily and influence on each of the twelve mood states are analysed with one joint parameter for overall homophily and one parameter for overall influence. The homophily estimate indicates whether

[7] The variation in expected homogeneity results from changes in network structure and prevalence of mood in different days.

[8] Part B in Fig S2 suggests a possible correlational relationship between outgoing nominations and experiencing positive mood. However, this descriptive plot does not take into account the nesting of observations within individuals, i.e. that mood and nominations on consecutive days are correlated within individuals. Indeed, the statistical analysis does not support these suggestive findings.

[9] Analyses of either dataset on its own supports the drawn conclusions. All parameters of the individual models show the same tendencies, even though statistical certainty is often lower and some confidence intervals include zero, due to a lack of statistical power in these models with less data. Full results for these individual analyses are presented in appendix table S6 and S7.

Table 1

Results of the SAOM analysis for the co-evolution of social interactions and mood.

	Model 1			**Model 2**		
	est.	*s.e.*	*95% CI*	*est.*	*s.e.*	*95% CI*
Mood homophily	0.039	(0.063)	[-0.09, 0.17]			
Positive mood popularity				-0.244	(0.148)	[-0.54, 0.05]
Positive mood sociability				-0.114	(0.176)	[-0.47, 0.24]
Positive mood homophily				0.173	(0.139)	[-0.10, 0.45]
Negative mood popularity				0.067	(0.156)	[-0.25, 0.38]
Negative mood sociability				-0.103	(0.187)	[-0.48, 0.27]
Negative mood homophily				0.027	(0.141)	[-0.26, 0.31]
Mood influence	0.230	(0.031)	[0.17, 0.29]			
Positive mood influence				0.125	(0.053)	[0.02, 0.23]
Negative mood influence				0.251	(0.057)	[0.14, 0.36]

Notes: Further model parameters omitted from presentation in the table: Network: Rate parameters for group 1 period 1-6 & group 2 period 1-4; outdegree; reciprocity; transitivity (GWESP); reciprocity x transitivity (GWESP); indegree-popularity; outdegree-activity; indegree-activity; sex popularity; sex sociability; sex homophily; musical section homophily. Behaviour parameters for mood networks: Rate parameters for group 1 period 1-6 & group 2 period 1-4; outdegree; outdegree-activity; sex activity; influence of negative mood on positive mood (and vice versa); dummy variables for all mood categories; dummy variables for each day (see SI for definitions). Full model results are presented in Table S3.

individuals choose interaction partners who experience the same types of moods as themselves. The estimated parameter is very small, and the associated confidence interval includes zero; thus, there is no indication of mood homophily. The influence parameter indicates whether individuals adjust their mood so that they experience the same mood items as their interaction partners. The estimated parameter is large, positive, and different from zero with high confidence (99.9% confidence interval does not include zero). While keeping difficulties of translating parameters from loglinear models to probabilities in mind, if these parameters were used to simulate data, an actor would be exp(0.23) = 1.26 times more likely to experience a

mood for each interaction partner that indicates this mood experience. This is strong evidence for mood contagion suggesting that adolescents experience mood changes such that their emotional experiences align with those of their interaction partners.

We use model 2 to gain a better understanding of potentially distinct patterns of contagion for positive and negative moods, and to investigate the dynamics of hypothesised mood popularity and sociability, in addition to homophily. In this model, positive and negative mood are analysed in different sub-models, accounting for their dynamics separately. First, we find no homophily on either positive or negative mood. Thus, even when considering mood of different valence separately, participants do not adjust their interaction partners to match their own mood. Second, we find no indication of mood popularity or mood sociability for negative or positive moods. Thus, adolescents in our study do not avoid contact with others that indicate more negative mood items or seek out others that experience more positive mood items. At the same time, experiencing positive (or negative) mood does not lead to seeking more (or avoiding) contact with others. Summarising the first two points, interaction dynamics are not influenced by the mood of the study participants. Third, we find that positive mood as well as negative mood is contagious. This means that interacting with others who experience positive moods leads to a mood improvement in the sense that the same positive mood is more likely to be experienced, while interacting with others that experience negative mood probabilistically leads to experiencing the same negative mood item. Fourth, the social influence of negative mood is stronger than social influence on positive mood, both in terms of parameter size, statistical certainty (indicated by the ratio of parameter estimate to standard error) and relative

influence (see below). A score-type test (Schweinberger, 2012) indicates that the difference is statistically significant ($p = 0.016$)[10]. Thus, it is easier to 'catch' a bad mood than a good mood.

To gain better understanding of the determinants of individuals' mood states, we calculate the relative importance (RI) of model parameters (Indlekofer & Brandes, 2013). These indicate to what extent the model parameters influence mood change probabilities. Specifically, the RI assesses how much a parameter determines mood evolution relative to other parameters (i.e. it does not assess how much a parameter contributes to absolute variance explained). Figure 5 shows the RI for model 2 for negative moods (left panel) and positive moods (right panel). First, it confirms that mood contagion is more important for negative moods than for positive moods. Second, it shows how the non-focal (i.e. 'control') model parameters determine mood. The mood evolution models contain fixed effects for each excursion day for both groups to account for the changes in environmental conditions that affect positive and negative moods (daily variation). Interestingly, these fixed effects influence positive mood more strongly than negative mood. For positive mood, daily events are similarly influential compared with positive mood contagion while for negative mood, contagion is more influential. Next, a fixed effect for each of the mood items is included based on the consideration that different types of mood have different prevalence among individuals (mood type), for example that sadness is experienced more often than loneliness[11]. Finally, a significant determinant of mood experience are the feedback processes and cross-mood influences that account for the positive correlation among mood items of the same type (e.g. cheerful individuals are likely also to become enthusiastic) and the relative probability of

[10] A score-type test assesses the null hypothesis that the influence parameter for negative mood is identical to the estimated influence parameter for positive mood. The procedure simulates data using this 'fixed' parameter and tests whether the observed data could be generated by the model with the alternative parameter. Details can be found in Schweinberger (2012).

[11] This mainly technical parameter ensures that the relative frequencies of experiencing different types of mood are correctly represented in the model and can be understood as mood-specific intercepts.

reporting positive (negative) moods given that one already reports negative (positive) moods, respectively (e.g. cheerful individuals are less likely to be sad). Individual sex does not substantially influence mood experience.

All estimated models include a comprehensive battery of control parameters in the interaction network model and the mood evolution model. Control parameters for mood are outlined above. The network model includes – beside influences from mood – parameters related to individual sex and musical section, as well as all commonly included structural effects. Further models analysed whether interacting with more individuals results in experiencing less negative and more positive moods (social integration perspective), but found no positive results. For a complete discussion of the model specification, see SI. All model results are robust to self-reported daily frequency of social media use, a potential source of heterogeneous exogenous input that can influence the extent and importance of face-to-face interaction among participants.

Finally, GoF tests showed an adequate fit of model to data. In the employed statistical tests that assess whether the model corresponds to the observed data, a low p-value indicates poor model fit. Concerning the evolution of the interaction network for model 1 and model 2, the model accurately represents the outdegree distribution (p-values of 0.14 and 0.37 for model 1 and model 2, respectively), the indegree distribution ($p=0.02$ and $p=0.38$), and the triad census ($p=0.39$ and 0.37; see Lospinoso and Snijders 2019). In the modelled mood network, in model 1 we assess the fit of the outdegree distribution ($p=0.65$) and the mixed triad census ($p=0.23$; see Ripley et al. 2019). For model 2 we assess the fit of the outdegree distribution for positive mood ($p=0.46$) and negative mood ($p=0.46$), as well as the fit of the mixed triad census for positive ($p=0.05$) and negative mood ($p=0.77$). We do not assess the indegree distribution in the mood networks since this is fully captured by the model specification. While the indegree distribution in model 1 is not captured very well ($p<0.05$), such a low value is not unlikely in

one out of 12 performed GoF tests and causes little concern, especially since the indegree distribution is captured well in model 2.

Discussion

Humans are a social species: We exist, act, and feel both individually and collectively (Goldenberg et al., 2017). Indeed, the relationship between mood and social interaction is central to our happiness and health. Emotional contagion is observed in experiments with both human and non-human animal species, suggesting it may be a widespread and important mechanism to support social living (Adriaense et al., 2019). However, it is challenging to demonstrate such contagion in real world settings. Here, we used a social network paradigm and a specialised data-collection strategy to overcome challenges typically faced by observational social influence studies. We find a large mood homogeneity effect between interacting peers over consecutive days: adolescents that spend time together tend to experience similar mood. Strikingly, our statistical models show that the observed mood homogeneity results from social influence (contagion), and that homophily (a form of social selection) plays no role in structuring interaction dynamics – neither for positive nor for negative moods. This null finding extends to two other forms of social selection, mood popularity and mood sociability. The overall pattern of results is identical across the two separate networks, boosting confidence and generalisability of our findings.

We found stronger contagion for negative mood than for positive mood. This contrasts with prior research suggesting that positive mood is more contagious than negative mood, as the latter is associated with social withdrawal and reduced opportunity to influence others (Barsade, 2002). In fact, we found no evidence for social withdrawal following negative mood. Potentially, our study design conferred optimal sensitivity to detect negative mood contagion, since individuals had limited opportunity to spatially withdraw due to the large amount of time spent in communal activities. It appears that this spatial proximity suffices to keep individuals

experiencing bad mood socially engaged with others, rather than socially withdrawing while being in the same physical space. Eliminating the possibility to withdraw, we find the interpersonal dependence in experiencing negative mood appears more pronounced than influence on positive mood.

Some further points are important to note in relation to interpreting the mood contagion results. First, contagion in our model is defined as a particular temporal sequence of events: Changes in social interaction precede changes in mood, not the other way around (first I spend time with you, then our moods become more similar). While this sequence of events is highly suggestive of a causal relationship, strictly speaking it demonstrates temporal contiguity. Second, and relatedly, our study design cannot shed light on the psychological mechanisms underlying contagion observed at the network level; i.e. whether it arose due to automatic, unconscious mimicry of emotionally expressive behaviours and the subjective perception thereof (Hatfield et al., 1993) and/or more conscious, deliberative processes based on cognitive inference and verbal communication (Goldenberg et al., 2017; Rimé, 2009; Van Kleef, 2009). Further studies using different measurement variables are needed address this question.

Our study provides sound evidence for emotional contagion at a network level. We measure mood and interactions in bounded, relatively isolated networks under conditions of low environmental heterogeneity, and on a theoretically plausible timescale for functionally relevant changes in mood. Results replicate internally, across two independent networks. We suggest that mixed findings and controversies regarding interpretation across prior longitudinal network studies of mood and emotional wellbeing are attributable to failure to account for environmental effects, and issues with temporal alignment. For example, some prior studies report positive findings (Fowler & Christakis, 2008; Kiuru et al., 2012; Van Zalk et al., 2010; Workum et al., 2013), while others do not (Elmer et al., 2017; Pachucki et al., 2015). In contrast, our paradigm is tailor-made for investigating social influence on naturally occurring

mood in real-world social networks by following the evolution of mood and interaction in naturally formed, relatively isolated groups with high temporal resolution; as such it sets a new standard for future research.

We found no evidence for social selection based on mood, which extends to homophily, sociability and popularity. These null findings in interaction dynamics are unlikely to be due to insufficient statistical power. Analysis of power in SAOMs shows that social selection is generally easier to detect than social influence (Stadtfeld et al., 2018). As we find strong and consistent social influence estimates, we are confident that we could have detected effects of mood on interaction dynamics if they were of substantial sizes. Furthermore, our additional model parameters on the evolution of social interaction are fully in line with the literature on social network dynamics, strengthening our confidence in these results.[12] Nevertheless, we reiterate that the sample size of the analysed population was not determined by systematic power studies but by practical considerations that relate to the difficulty in recruitment of musical ensembles coupled with the knowledge that past studies with similar numbers of participants and observations had no difficulties in detecting selection and influence effects.

The notion that emotions influence social interactions is intuitive, and as such, our null findings in interaction dynamics may be surprising. Fundamentally, emotional displays act as signals to modify a social interaction (Parkinson, 1996). Intuitively, if you seem angry, I may curtail the interaction; if this sequence recurs, our relationship may end. However, this relationship is likely to be highly complex and contextual; perhaps in consequence there is little direct evidence in support of this intuitive idea in relation to mood specifically[13]. Indeed, to use

[12] These parameters include high levels of reciprocation in interaction, transitive clustering, and homophilous partner choice by musical section of the ensembles, which partly structure interactions during the expeditions (see SI).

[13] For evidence relating personality traits (some of which are linked to mood tendency) to interaction tendency, see (Selden & Goodie, 2018).

the previous example, if you seem angry, I may make overtures to maintain our interaction despite the momentary perturbance, for example to resolve our ongoing conflict.

We conceptualise our finding that the day-to-day dynamics of social interaction are not influenced by the mood of individuals as 'mood tolerance'. This may have implications for understanding the potential buffering capacity of social interactions on emotional well-being (Castillo et al., 2019; Cohen & Wills, 1985). Our model suggests that adolescents persist in spending time with their friends, even if they have been in a bad mood. Potentially, this 'mood tolerance' might help individuals cope with negative mood. To this end, we must consider the reciprocal nature of social influence. That is, all else being equal, interacting participants both become more similar to each other following their interactions. On the social support side, it implies that spending time with happier others reduces my negative mood. However, it also contains a flipside; spending time with others in a bad mood increases the risk that I catch it, too. Thus, providing social support is not without risk for the supporter (Strazdins & Broom, 2007), making the observed mood tolerance all the more noteworthy.

Limitations

Three limitations of our study warrant discussion. First, as is inherent in most real-life network studies in the psychological and social sciences, the participants of the study are not representative of a larger population of adolescents in particular or humans in general. However, a representative composition within groups in observational network research is often unrealistic, because real-world social networks in which individuals form subjectively meaningful relations evolve in so-called *social settings*, such as schools, organizations, sports clubs, church groups or neighborhoods; and membership in these social settings tends to be stratified by numerous individual characteristics. Even in large scale network collection projects (such as *AddHealth* or *CILS4EU*) a representative sample of schools is obtained, but composition of pupils within schools – and thus within individual networks – is still stratified

by local characteristics[14]. However, by foregoing representativeness we gain the ability to assess the importance of real-world, meaningful social relations for individual emotional well-being. This would not be possible with a research design that samples representative, but unconnected individuals. Furthermore, the use of non-representative samples is common in many related fields, with psychology students at universities being the default participants in experimental psychology studies – but even this restricted sub-population has allowed the uncovering of many fundamental psychological mechanisms (although see Henrich et al., 2010). While it is possible that self-selection into a musical ensemble is associated with particular patterns of emotional responsiveness, we believe this might influence the extent of social influence, but not the presence or absence of this fundamental psychological mechanism. Similarly, the more affluent background that classical musicians tend to come from, the large proportion of time spent together by this group (boyd, 2014; Reich et al., 2012), or their ethnicity (Soto & Levenson, 2009) should not lead to fundamentally different emotional responses than other socio-demographic groups. Relatedly, while our findings may be of particular interest to adolescence researchers, because we conducted no developmental comparisons we do not know whether the observed findings would be the same or different at older or younger ages.

A second limitation relates to the potential presence of latent homophily that can thwart findings of social influence in observational studies. As outlined by Shalizi and Thomas (2011), homophily on an unobserved (latent) characteristic that structures interactions can produce spurious findings of social influence. However, for this to be the case the latent characteristic must also have an independent effect on the individual outcome of interest, and, importantly,

[14] Potential steps towards making generalisable claims for the presented research would be to perform the analysis on a sample of multiple adolescent musical ensembles, or to sample adolescents from various voluntary association (including e.g. sport clubs) to make generalisable claims about mood contagion in adolescent voluntary organisations.

this influence must be heterogeneous over time. For example, if adolescents were to choose their interaction partners so that they are similarly extraverted (which we did not measure), if extraversion were to have an effect on mood (e.g. extraverts are happier), and if this effect were to vary by day (e.g. extraverts are happier only on sunny days), we could mistakenly detect social influence on mood. The latter condition arises since we model the change in mood over consecutive days and if extraversion had a constant effect on mood, this would be captured by the mood on the previous day which is contained in the model. In sum, despite the limited variation in external influences, our observational study might suffer from omitted variable bias under the outlined circumstances.

A third limitation stems from past research, proposing that momentary mood can influence the measurement of social ties (Shea et al., 2015). However, as we found no evidence in our descriptive analysis or statistical model that mood is related to the number of others nominated, we are confident this is not a problem in our analysis.

A final discussion point concerns the relation between our findings obtained in a relatively isolated network and other, common everyday social contexts. On the one hand, within the study setting adolescents spend more time with their peers and may have less freedom to decide their whereabouts for the duration of the trip compared to everyday life. Intuitively, this could be proposed to explain the findings on mood tolerance. If adolescents have limited discretion to withdraw physically, mood tolerance might be a consequence of these constraints rather than a genuine finding. However, this seems unlikely since there is a large between-person variation in the number of nominations adolescents receive as an interaction partner (exemplified e.g. in Figure S2). Thus, individuals are differentially integrated in the daily social interactions reflecting a possibility to withdraw from individuals if not physically, then at least socially – this degree of integration is just unrelated to mood. However, our findings that negative mood is more contagious than positive mood might be

influenced by the study design. In case the tendency to physically withdraw when in a negative mood is more pronounced in everyday social life than in the study setting, opportunities for contagion of negative mood might be more limited outside the context of this study. The observed influence effect might thus be more pronounced in our case. However, we cannot test a potential contextual variation in mood withdrawal in our study. On the other hand, the studied adolescents are within a context, doing activities, and spending time with others that is directly drawn from their everyday lives. As structure and content of interactions on the tours are likely to be strongly informed by the social relations individuals had among each other prior to the tour, the studied context can be assumed to reflect 'normal' interactions to some degree.

Future directions and conclusion

Despite these discussion points, we believe our study provides new, reliable evidence on the contagion of mood in real-world settings by tackling challenges that undermine many observational studies of social influence. We hope our study spurs further research in two directions. First, this research design with isolated networks could be extended to further analyse the short-term dynamics of interaction networks and a variety of individual outcomes. Previous research used a similar paradigm to analyse the relationship between social interactions and pain during an isolated arctic expedition (Block et al., 2018); future studies could analyse individual outcomes that are of strong interest in adolescent network research, such as substance use, delinquent behaviour, cultural consumption or changing self-image. A second direction for future research is to analyse processes of social support and social buffering from mood tolerance in more detail. In particular, the way in which mood dynamics unfold within interacting groups requires more research. Analysing non-linear dynamics, such as tipping points when collective moods turn sour, will allow insights into the 'dark side' of mood tolerance. This may be especially important to understand in adolescence, a period marked by increasing social orientedness and mental health problems (Foulkes & Blakemore,

2016; Maciejewski et al., 2015; Nelson et al., 2005; Sadler et al., 2017). Similarly, more research on dyadic processes is needed to determine under what circumstances mood shifts toward the more negative or more positive interaction partner. Previous research shows how interactions can take different dynamics that may intensify, balance, or even polarise the moods of connected people (Butler & Randall, 2013; Parkinson, 1996). Finally, an important future direction to further our understanding of mood contagion is testing whether our findings differ by stages of life, since our sample is restricted to adolescent participants.

We see ample directions for future research that will shed further light on mood dynamics, including both contagion and ‘mood tolerance’, in dyads and social groups. In our study we lay the foundation for future work by showing how adolescent social networks respond dynamically to the daily mood fluctuations of individuals.

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Figure legends

Figure 1

Flow-chart of the SAOM as described in the main text.

Figure 2

Network visualisation showing the development of mood and social ties of one of the two groups between day 3 and day 6 (of 7). Selection of days based on space concerns and to illustrate variation in networks and mood. Node color: red indicates predominantly negative mood, blue indicates predominantly positive mood. Node size: Number of outgoing nominations. Node shape: circles represent girls, squares represent boys. Tie color: black ties are reciprocated, grey ties are one-sided and light pink ties indicate connections from the previous day.

Figure 3

Top: Development of moods in interaction communities over 7 days in ensemble 1. Bottom: Development of moods in interaction communities over 5 days in ensemble 2. Left: Development of the average of aggregated mood during the tour by the different communities in either ensemble; higher value indicates more positive and less negative mood. Right: empirically observed communities as determined by a walk-trap algorithm superimposed on a network visualisation showing ties observed on 5 days or more for ensemble 1, and 3 days or more for ensemble 2.

Figure 4

Mood homogeneity between interaction partners. Left: ensemble 1; right: ensemble 2. Observed mood homogeneity is indicated by the red line. The black dotted line shows the

expected mood homogeneity between connected participants assuming independence of interaction and mood. The dark grey area and the light grey area highlight the 50% and 90% confidence bands.

Figure 5

Relative Influence (RI) of model parameters in the mood evolution models. Left hand side (a): negative mood; right-hand side (b): positive mood. Percentages indicate the extent to which different model parameters determine whether individuals experience particular moods. Percentages indicate the importance of model parameters relative to one another, not absolute explained variance. For interpretation, see main text.

Figure 1

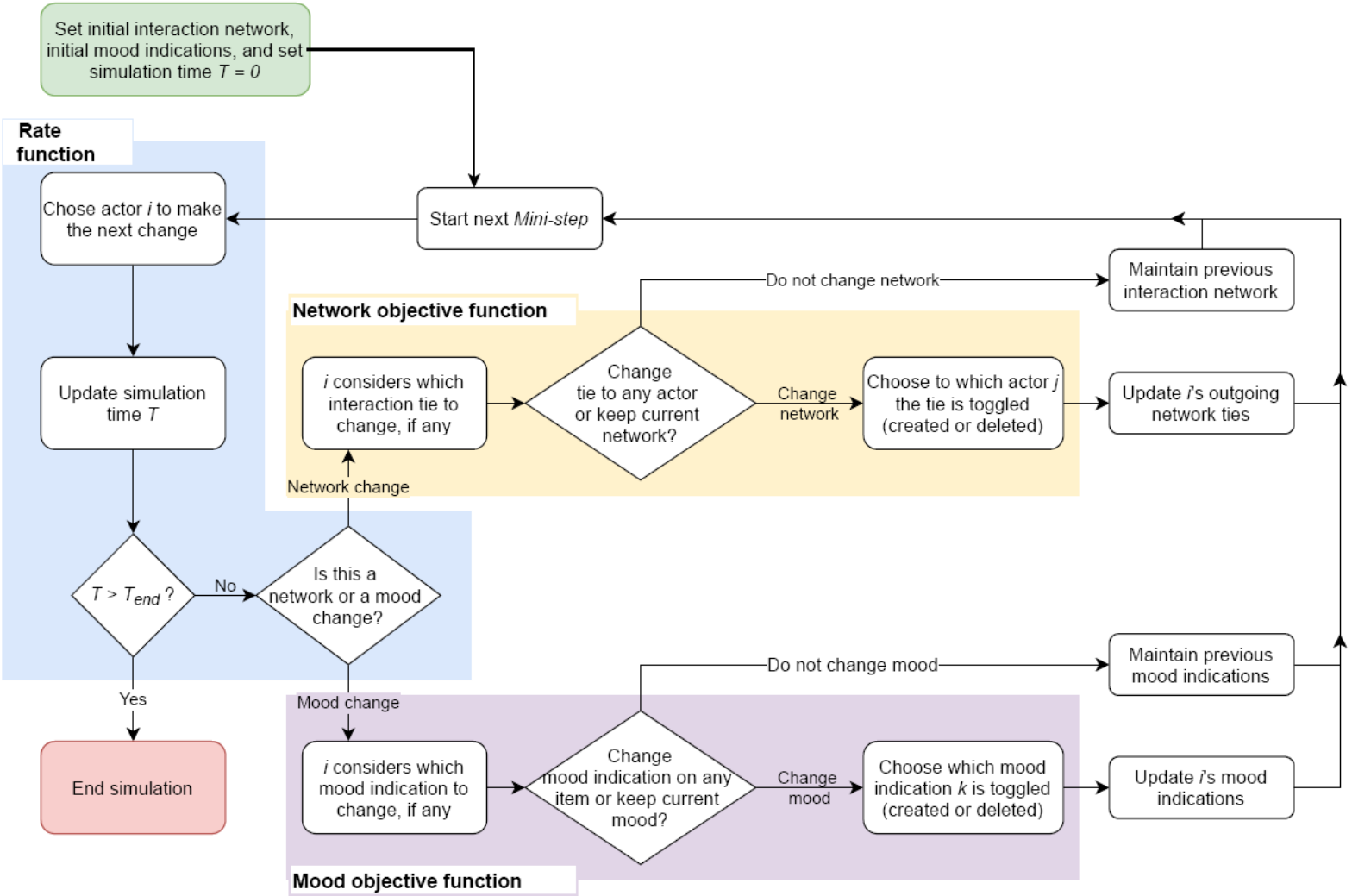

Set initial interaction network, initial mood indications, and set simulation time T = 0
Rate function
Chose actor i to make the next change
Start next Mini-step
Do not change network
Maintain previous interaction network
Network objective function
Update simulation time T
i considers which interaction tie to change, if any
Change tie to any actor or keep current network?
Change network
Choose to which actor j the tie is toggled (created or deleted)
Update i's outgoing network ties
Network change
T > T_end ?
No
Is this a network or a mood change?
Do not change mood
Maintain previous mood indications
Yes
Mood change
End simulation
i considers which mood indication to change, if any
Change mood indication on any item or keep current mood?
Change mood
Choose which mood indication k is toggled (created or deleted)
Update i's mood indications
Mood objective function

Figure 2

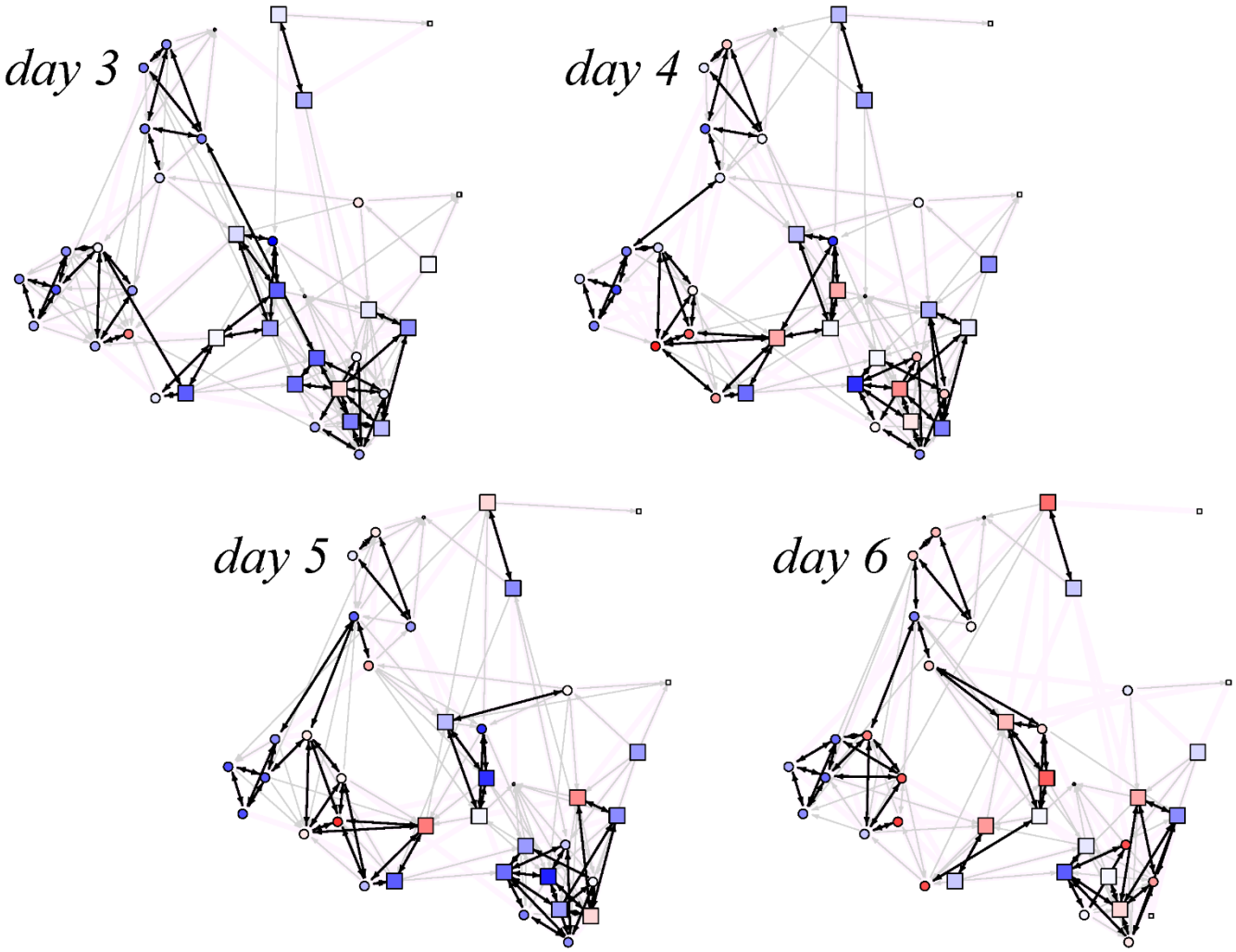


Figure 3

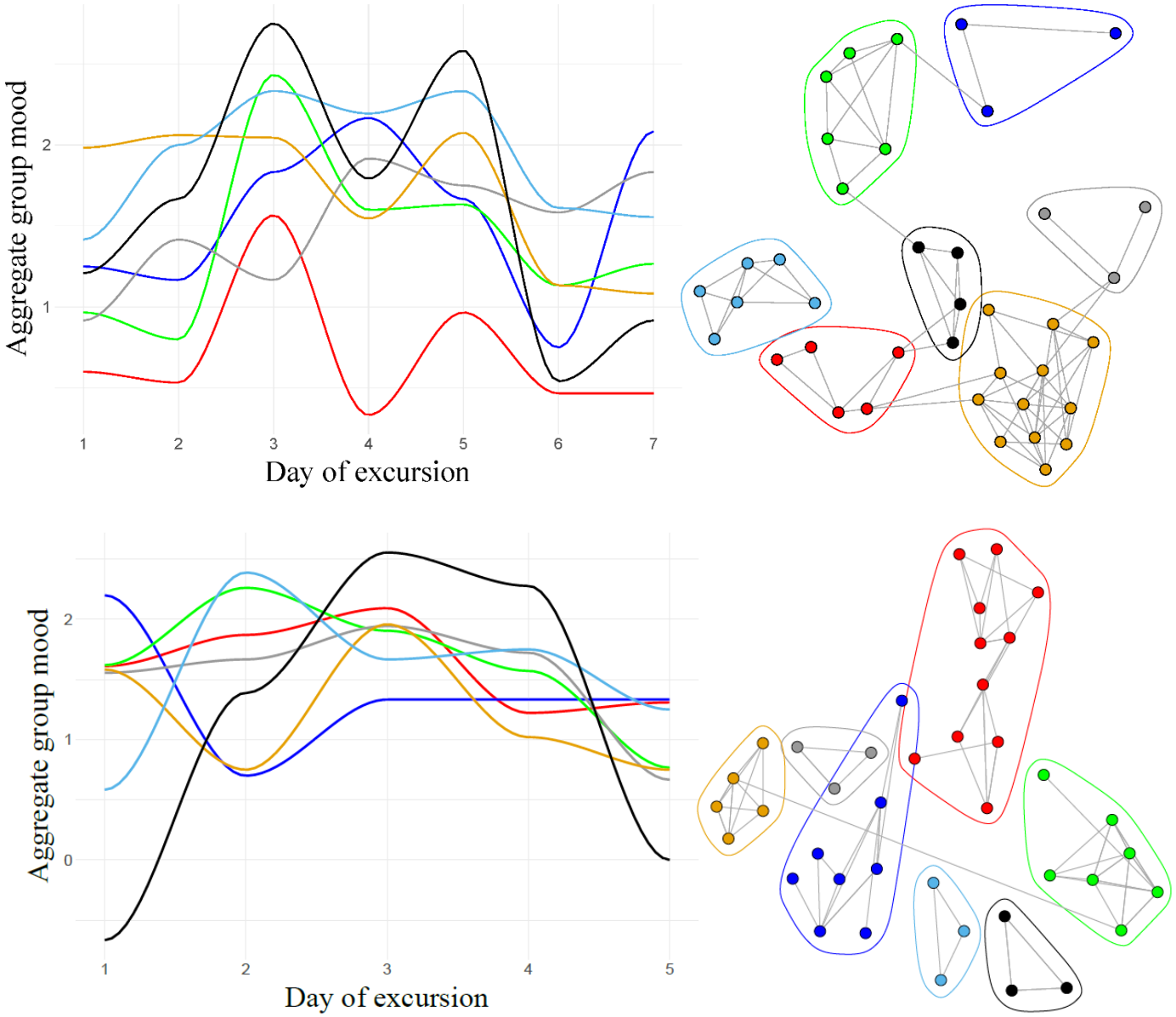

Aggregate group mood
2
1
1
2
3
4
5
6
7
Day of excursion
Aggregate group mood
2
1
0
1
2
3
4
5
Day of excursion

Figure 4

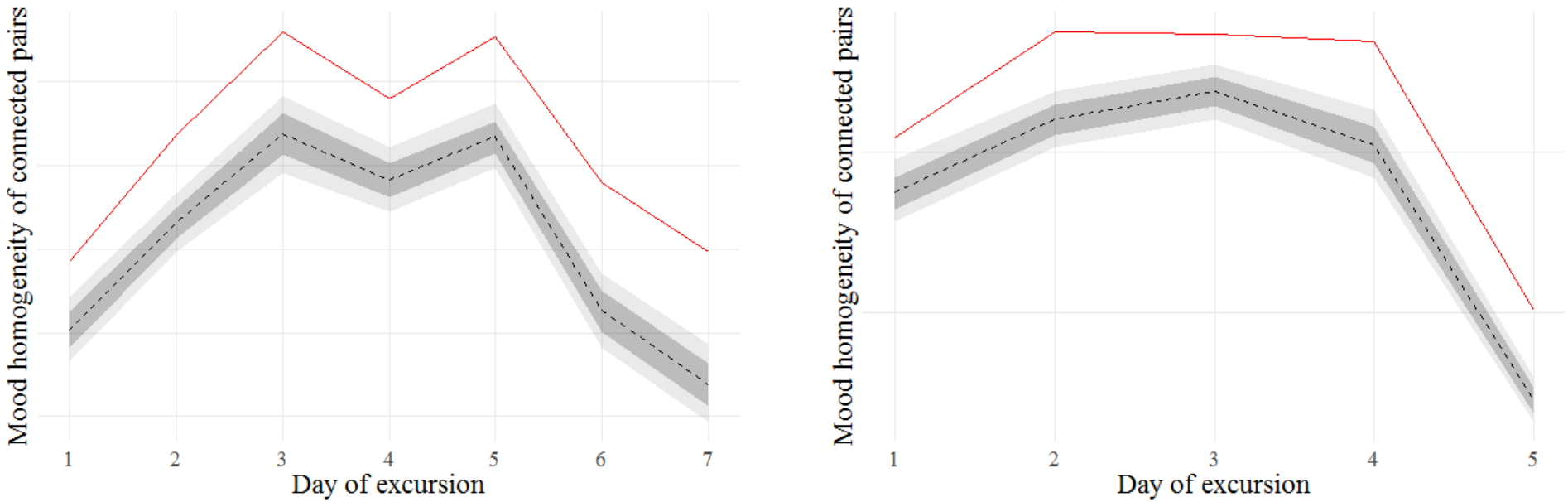
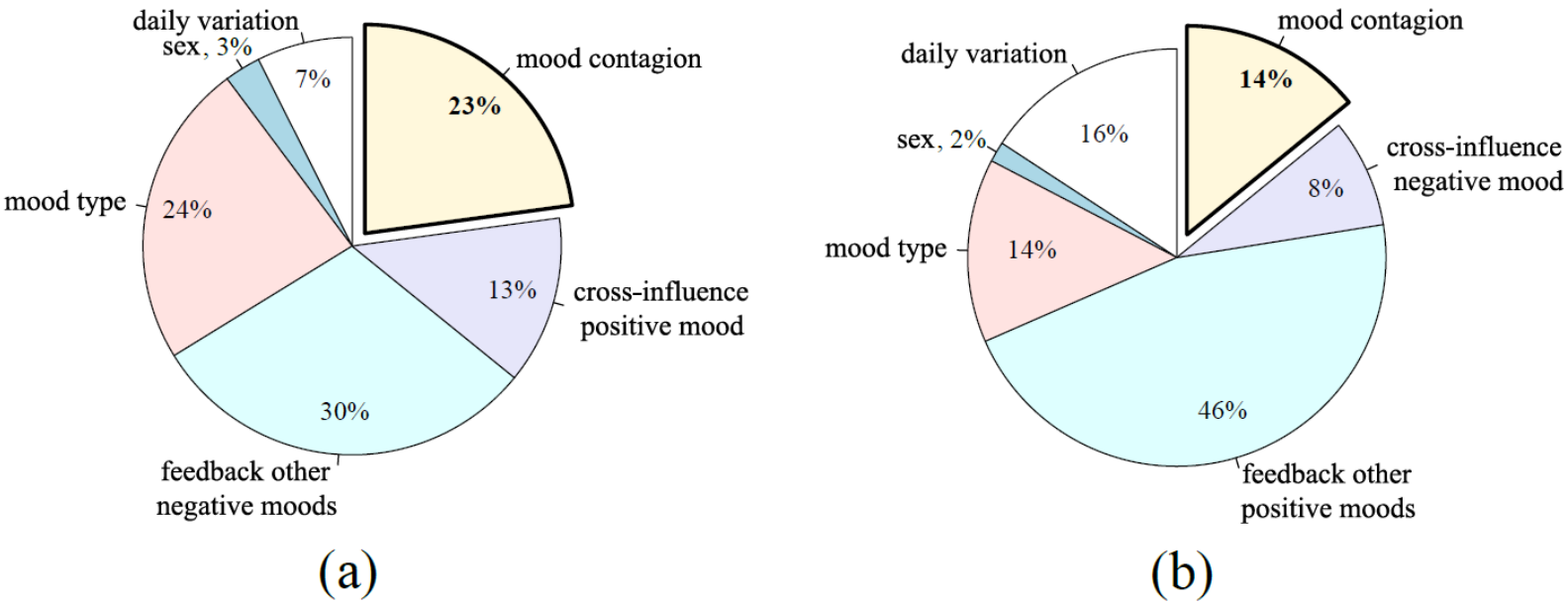

Mood homogeneity of connected pairs
1
2
3
4
5
6
7
Day of excursion
Mood homogeneity of connected pairs
1
2
3
4
5
Day of excursion

Figure 5


daily variation
sex, 3%
7%
mood contagion
23%
mood type
24%
13%
cross-influence
positive mood
30%
feedback other
negative moods
(a)
mood contagion
daily variation
14%
16%
sex, 2%
cross-influence
negative mood
8%
mood type
14%
46%
feedback other
positive moods
(b)