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Relationships between social networks and mental health. An exponential random graph model approach among Romanian adolescents

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Abstract

Social networks have an important effect on health, and social network analysis has become essential to understand human behaviours and vulnerability. Using exponential random graph model (ERGM), this study aimed to explore the associations of mental health with network structure, specifically, mental health homophily and the association of poor mental health with social isolation. Two classes of Romanian adolescents aged 12–14 years participated in the study (n=26 in each class). We assessed school network, socio-demographic covariates, and mental health using the Strengths and Difficulties Questionnaire (SDQ). ERGM was first used to test the presence of gender and mental health homophily, and then to test whether mental health was a predictor of social isolation. The results showed homophily patterns regarding gender and mental health. Moreover, participants with a higher score of SDQ had a lower probability of tie. Overall, this study showed how social networks are structured with different forms of homophily. It also highlighted that adolescents with poor mental health are more likely to be social isolates. Thus, prevention and interventions should focus on these vulnerable youths. Methodological advances like ERGM constitute a promising avenue for further research.

Keywords: adolescents, ERGM, homophily, marginalisation, mental health

Relationships between social networks and mental health. An exponential random graph model approach among Romanian adolescents

Introduction

Recent studies pointed out the important effect of social networks on health behaviours (Daw, Margolis, & Verdery, 2015), and health campaigns increasingly use network interventions (Valente, 2012). Social network analysis has thus become an essential tool to understand social relationships and their association with health and mental health (Greenblatt, Becerra, & Serafetinides, 1982; Schaefer & Simpkins, 2014). This study investigated how school-based networks of Romanian adolescents are associated with mental health and other socio-demographic characteristics, using an exponential random graph model (ERGM) approach. This was a first step in studying adolescents social network with this recent and promising analysis.

The importance of adolescents' social networks

Emancipation from the family is one of the biggest challenges of late childhood; adolescents spend less and less time with parents, while spending more time with peers such as friends and classmates (Larson & Verma, 1999). In this context, adolescents have an increasing need for affiliation and social recognition outside the family (Gonet, 1994; Macdonald, 1989). Peer social networks constitute an important source of welfare (Prinstein & Dodge, 2008). Adolescents' social networks are associated with health outcomes such as depression (Prinstein, 2007; Rubin, Bukowski, & Parker, 2007) and substance use (Daw et al., 2015; Hall & Valente, 2007; Jeon & Goodson, 2015), and also with social outcomes (e.g., academic achievement: Lavy & Sand, 2012; and aggressive behaviour: Faris & Ennett, 2012).

As schools are the primary place of adolescents' social interactions, the processes that occur in this context are likely to be generalizable to other social contexts (Haas, Schaefer, & Kornienko, 2010). More precisely, in this study we used class-based networks, in which adolescents know each other and have opportunities to interact with all classmates. Therefore, the network reveals affinities, and the absence of tie is not synonym of lack of opportunities to know each other.

Homophily in social networks

An important pattern of relationships in social networks is homophily. It can be defined as a predominance of within-category ties (McPherson, Smith-Lovin, & Cook, 2001). In other words, similar people are more likely to be friends than dissimilar people (McPherson et al., 2001). Homophily is a well-studied topic regarding socio-demographic covariates such as age, race, gender, and social status (Goodreau, Kitts, & Morris, 2009; McPherson et al., 2001). In addition, other studies reported that homophily is higher among numeric minorities, when one group had a small prevalence rate compared to the other(s) (Goodreau et al., 2009).

Some studies also mentioned mental health homophily, but they are scarce. Regarding subjective well-being (SWB), a study highlighted, for example, that high-SWB users were more likely to be connected with similar-SWB users in online social networks (Bollen, Goncalves, Ruan, & Mao, 2011). However, this study focussed only on Twitter users, and the researchers coded SWB according to the valence (positive/negative) of the tweets posted on the social network, without directly measuring SWB. Another study highlighted that depressed individuals are more likely to be friends with other marginalised individuals because of a withdrawal mechanism (Schaefer & Kornienko, 2011). To our knowledge, no study provided a more general picture of mental health using screening questionnaires dedicated to measure the

overall child and adolescent's mental health. This study overcame this gap by using a world-widely used tool with robust psychometric properties developed to measure mental health problems and risks of mental health problems/psychiatric disorders among children and adolescents: the Strengths and Difficulties Questionnaire (SDQ, Goodman & Goodman, 2009; Goodman, Meltzer, & Bailey, 1998). The SDQ is an emotional and behavioural screening questionnaire used in child psychiatric research for screening, clinical assessment, and evaluating interventions. Therefore, it should be adapted to provide a more general overview of the relationship between social network and mental health.

Social isolation and mental health

Beyond homophily patterns, mental health is associated with social isolation. For example, losing or not having friends tends to increase the probability of depression (Rubin et al., 2007), and depressed people have more marginalised network positions (Schaefer & Kornienko, 2011). However, despite the important link between mental health and social network, this topic has only been investigated recently (Schaefer & Kornienko, 2011). Moreover, most recent studies using social network analysis are US studies (Cornwell, 2009), using data from the National Longitudinal Study of Adolescent Health (Add Health, Goodreau et al., 2009; Schaefer & Kornienko, 2011). Studies outside the USA are therefore needed, and also studies using tools such as SDQ.

The exponential random graph model approach

When it comes to the modelisation of a social relationship between two people (tied, not tied), based on other variables and third-party relations, traditional logistic regression does not apply. This is mainly due to the fact that the relations in real networks are autocorrelated. These social relation structures violate the assumption of

independence of observations, and traditional analyses like logistic regression cannot be used.

Exponential random graph model (ERGM) is a recent statistical framework developed to describe and understand complex social networks' structures and features (Morris, Handcock, & Hunter, 2008). More precisely, ERGM allows statistical modelling, which can test the effect of individually measured variables on a specific social network of dichotomous ties, while also testing the effects of tie-interdependent structures that we consider important. Thus, the results are interpreted very similarly to those of logistic regression.

Different dependences related to the network's structure are taken into account in ERGM. A first one is a dyadic dependence, i.e. reciprocity: if adolescent A names B as his friend, then adolescent B is more likely to name A as his friend (I am friends with my friend). Another common network dependence is transitivity, which corresponds to the fact that friends of my friends are also my friends. Homophily is another form of dependence, where adolescents who share a common characteristic (e.g., gender, race) are more likely to name those sharing the same characteristic as friends. ERGM tests whether there is significantly less or more dependence according to these characteristics in the observed social network than expected by chance (Robins, Pattison, Kalish, & Lusher, 2007), or, in other words, whether the characteristics of the network members can predict the observed patterns of relationships (Harris, 2013).

ERGM uses a particular kind of social network. First, the network needs to be clearly delimited inside an entity, e.g., a school. Therefore, ego-centered or snowball networks cannot be used with ERGM. Second, the ties are considered as random

variables with a dichotomous outcome: the presence or absence of a tie for each possible dyad.

The ERGM approach is relatively new in public health literature. It goes beyond the descriptive methods often used to examine social networks, and thus is a very useful tool for social network analysis (Harris, 2013). Indeed, it allows one to represent social networks structures and test associations with network members' characteristics using a familiar technique (logistic regression form) to test micro-level processes. Other techniques such as multilevel modelling that take into account dependence do not allow testing such hypotheses related to the network's structure.

Thus, the aim of this study was to explore school-based networks of Romanian adolescents using the ERGM approach. It intended to replicate previous results regarding socio-demographic homophily (gender homophily), and to explore mental health homophily. Moreover, we investigated whether adolescents with poor mental health were more likely to be social isolates, by testing whether mental health was a predictor of the network structure.

Method

Participants and procedures

The study took place in two Romanian classes of the general school curriculum located near Bucarest in May–June 2011. It was part of a larger programme named MGS (Movement, Games and Sport) of the non-governmental organisation "Terre des hommes". This project provided training for teachers, and the whole study was designed to evaluate the program, including evaluation of children's welfare. A total of 52 adolescents aged 12–14 were interviewed, with n = 26 in each class (mean age: 12.9 years old, 12.9 for girls and 12.9 for boys). The participation in the study was

voluntary and the parents gave their consent for child's participation. Since it was the end of the school year, some of the adolescents were absent, respectively n = 9 (35%) and n = 7 (27%). Adolescents who were absent have been removed from the social networks. Analyses including missing adolescents have been performed, without notable difference regarding the structure of social networks. There were no missing values on other variables. Participants answered the questionnaire during class, and there was a debriefing at the end of the study. Since the study was performed in collaboration with a non-governmental organisation, no ethic committee approved the study.

Measures

Social network. Participants were asked to report the names of their friends in the class, with no maximum number. Thus, strong links (friendship) were at focus.

Mental health. The Strengths and Difficulties Questionnaire (SQD, Goodman et al., 1998) was used to assess mental health. The SDQ is a brief emotional and behavioural screening questionnaire for child and adolescent mental health problems. It includes emotional symptoms (5 items, e.g., "I am often unhappy, depressed or tearful"), conduct problems (5 items, e.g., "I get very angry and often lose my temper"), hyperactivity/inattention (5 items, e.g., "I am easily distracted, I find it difficult to concentrate"), and peer relationship problems (5 items, e.g., Other children or young people pick on me or bully me"). The 20 items added together generate a total difficulties score ranging from 0 to 40. A Romanian version is available at www.sdqinfo.com. was translated into Romanian, using back-translation and pre-test. The SDQ was used as a continuous variable since it is a dimensional measure of child and adolescent mental health (Goodman & Goodman, 2009) and was dichotomised to create two groups, with lower and higher levels of mental health, respectively, in

order to examine mental health homophily. To investigate patterns of homophily, distinct groups of participants are needed, and a continuous score did not allow for the separation of participants into subgroups. We used the mean score of the classes to define higher and lower levels of mental health. Indeed, there were too few children having a score higher than the cut-off recommended for SDQ (≥ 20).

Socio-demographic covariates. Age and gender were recorded.

Statistical analysis

As a preliminary analysis, descriptive statistics for socio-demographic variables, mental health, and network information were computed separately for each class. Regarding network information, the number of edges (i.e., the number of ties within the social network), network density (i.e., the sum of the ties divided by the number of possible ties), reciprocity (i.e., the proportion of dyads which are symmetric), and transitivity (i.e., the proportion of triads) were computed.

Next, a first set of ERGM was performed to test the presence of homophily. Two models were computed for each class, including the following predictors: 1) gender, and 2) SDQ dichotomised. These models also included reciprocity and transitivity between ties (i.e., the geometrically weighted edgewise shared partner (GWEPS) distribution parameter) which counts triangles. Two parameters were computed for each variable, e.g., one parameter for girls, and one for boys. This procedure allowed for the testing of different patterns of homophily among each subgroup, to see whether homophily was higher for one group than the others. A parameter significantly different from zero means that the corresponding configuration occurs at a greater level (for positive parameters) than expected by chance. Parameters are computed using Markov chain Monte Carlo maximum likelihood estimation (MCMCMLE, Robins et al., 2007).

Finally, a second set of ERGM tested whether mental health was a predictor of ties in the social network, to test whether participants with poor mental health were more likely to be social isolates. One model was computed for each class, including SDQ on a continuous scale as a predictor (MCMCMLE). This model also included reciprocity and transitivity. For all models, goodness-of-fit diagnostics were tested using AIC and BIC criteria, compared to the AIC and BIC of the null models including only edges.

The SDQ has a subscale dealing with peer-related problems that is related to social isolation. To take into account that there was no confounding effect, we run a sensitivity analysis excluding this subscale from all models tested with the SDQ. The results were very similar (estimates, p-values, goodness-of-fit), so we kept the entire SDQ scale in the analyses. All analyses were carried out with R version 3.2.0 using the package "statnet" version 2015.11.0.

Results

Preliminary results

Girls were the numeric majority in class B (72%), whereas in class A boys were the numeric majority (56%). Regarding mental health, the classes showed different patterns, with participants in class A having a poorer level of mental health (e.g., SDQ = 17.92) than those in class B (e.g. SDQ = 9.12). The results were significantly different (t-test for independent samples: $p < .001$).

Social network information also differed by class, with class B having a higher connectivity (number of ties = 173, density = 28.8) than class A (number of ties = 82, density = 13.7). Both classes had high levels of reciprocity (67.0% and 82.7%) and moderate levels of transitivity (39.9% and 30.9%).

Insert Table 1 about here

Patterns of homophily

The first panel of Table 2 presents the results regarding homophily patterns among the two social networks. Both classes presented gender homophily (i.e., significant positive estimates), with higher rates of homophily across the numeric minority. In class A, girls were more likely to have ties with other girls (estimate = 2.24, $p < .001$) whereas boys' homophily was significant but smaller (estimate = 1.62, $p < .001$), and in class B, boys were more likely to have ties with other boys (estimate = 0.94, $p < .001$), whereas girls were not significantly homophilic (estimate = 0.26, $p = .26$). Figure 1 displays the social network showing minority homophily in class A. Within-category preferences are clearly visible. One-sided arrows mean that a participant named the other as a friend, but not reciprocally, the other one did not mentioned the first as a friend. Two-sided arrows mean that each participants mentioned the other as a friend, and thus that the friendship was reciprocal.

Insert Table 2 and Figure 1 about here

Considering mental health, both classes seemed to present mental health homophily. Participants with higher mental health (i.e., groups with lower SDQ scores) were more likely to have ties with similar participants (lower SDQ score in class A: estimate = 1.26, $p < .001$; lower SDQ score in class B: estimate = 0.81).

Participants with lower mental health (i.e., groups with higher SDQ scores) were also more likely to have ties with similar participants (higher SDQ score in class A: estimate = 0.76, $p < .001$). Results were non-significant in class B. Figure 2 summarised the result of SDQ scores in class B, showing how participants were homophilic regarding mental health. Overall, both classes showed reciprocity and

transitivity, with a tendency for transitivity (.05 < p < .10). Fit indices showed that most models were better than the null model in each class.

Insert Figure 2 about here

Mental health and social isolation

The results of the ERGM investigation of social isolation using continuous scores of SDQ are presented in the second panel of Table 2. In both classes, participants with a higher score of SDQ had a lower probability of tie (class A: estimate = -0.03, p < .05; class B: estimate = -0.04, p < .01). Figure 3 represents the scores of SDQ in the social network of class B: the larger the circle representing a participant, the higher his or her SDQ score was. Overall, the Figure shows that participants with low SDQ scores were more central in the social network: they were more likely to have ties with others participants. Both classes showed reciprocity (p < .01), and only class A showed significant transitivity (p < .001) whereas transitivity was tendencial in class B (.05 < p < .10). Fit indices showed that the models were better than the null model in each class, excepted for BIC of model 2 in class B, which was similar to the BIC of the null model.

Insert Figure 3 about here

Discussion

This study was a first step in investigating school-based networks of Romanian adolescents using ERGM approach, focusing on friendship ties, aiming to explore homophily patterns and social isolation in relation to mental health.

Regarding patterns of homophily, the study seemed to replicate previous well-known results of socio-demographic homophily (Goodreau et al., 2009; McPherson et al., 2001), such as gender homophily. Indeed, boys were more likely to be friends

with others boys in both classes, whereas girls were more likely to be friends with other girls in class B. Therefore, gender homophily for the numeric minority in the social network seemed to be supported, as reported by Goodreau et al. (2009).

Mental health homophily was also found in the two social networks. Participants with a higher mental health were more likely to be friends with similar participants in both classes, and participants with a lower mental health were more likely to be friends with similar participants in class A. This mental health homophily was in line with the findings of previous studies which reported mental health-behaviours homophily (Bollen et al., 2011; Schaefer & Kornienko, 2011). Thus, the predominance of within-category ties also seemed to apply to mental health characteristics.

Regarding social isolation, the second set of ERGM showed that mental health was a predictor of network structure. When adolescents had poorer mental health, they were less likely to have friends within the social network. It seemed that adolescents with poor mental health were more marginalised than participants with good mental health, as reported in a previous US study (Schaefer & Simpkins, 2014).

Mental health and social network thus appeared to be interconnected (Prinstein, 2007). Because of its cross-sectional design, this study did not reveal causal relationships between the two, but the results highlighted the importance of taking social network into account for the study of health behaviours (Daw et al., 2015; Valente, 2012). Social isolation, marginalisation, and social networks are probably linked in a reciprocal relationship (Haas et al., 2010), each one influencing the other. Thus adolescents who are isolated and have low mental health may be more and more isolated and in poorer mental health. They should be a focus for prevention and early intervention because they are vulnerable youths. The relationship between social

network and health is complex and dynamic (Haas et al., 2010). However, studies using larger sample sizes and more extended social networks are needed to confirm these preliminary results.

Overall, the ERGM approach appeared to be a useful tool for the study of a social network structure and its relations with both categorical and continuous individual measures. Most previous studies focussed on categorical predictors such as socio-demographic characteristics, and this study extended social network analysis to continuous predictors. It moves beyond network description and allows for the study of micro-level processes through simple models using a logistic regression form (Goodreau et al., 2009; Harris, 2013), and taking into account the dependence between individuals. Indeed, ERGM took into account reciprocity and transitivity between adolescents, and, in most case, both were significant, except for transitivity in class B (tendency). This means that the ties in the social networks are structured with a dyadic dependence (reciprocity: I am friend with my friends) and triangles (transitivity: friends of my friends are my friends). This result illustrates the principle of "linked lives" described by Settersten (2015). Indeed, people do not exist in isolation from others, and relationships themselves are interdependent. Interdependence of lives should be at focus when studying social and psychological processes. Additionally, it confirms that analyses conducted on network structures should take into account their interdependent structure, which has long been a methodological challenge (Scott, 2012; Wasserman & Faust, 1994).

This study had some limitations. A first one was its cross-sectional design. Therefore, identifying causal paths between mental health and social network was impossible. Even if cross-sectional data had permitted us to study processes, more longitudinal network data would be needed. Second, the study involved a small

sample of Romanian adolescents, in only two classes. Thus, the results of the study should be replicated among larger sample sizes. Regarding modelling concerns, the small sample size did not appear as an issue. Indeed, sample size in ERGM model is not unambiguous as in usual statistics, because the dependent variable is the number of ties (edges), which is usually larger than the number of participants (*n*), which is the case in this study (Krivitsky & Kolaczyk, 2015). Moreover, studies in other contexts are needed, because even though school is a primary place for adolescents' social interactions (Haas et al., 2010), others environments are also meaningful. Third, school-based networks were not complete, because of the missing participants (35% and 27%) and this may have resulted in a higher number of social isolates (Valente, 2012). Even if missing participants were not frequently mentioned, the social networks within the classes were not complete, and this should have affected the density of social networks. Finally, we used an arbitrary cut-off to create subgroups of higher/lower mental health, and other cut-offs should be tested, such as clinical cut-offs to define poor mental health.

In conclusion, this preliminary study showed that social networks seemed to be structured with different forms of homophily, including mental health homophily. Adolescents with poor mental health seemed to be more likely to be marginalised and to be social isolates, and prevention and interventions should focus on these vulnerable youths. Methodological advances like ERGM permitted the exploration and understanding of such complex social processes, and they constitute a promising avenue for further research.

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Table 1. Descriptive statistics for socio-demographics, mental health, and social network

	Class	
	A	B
n	26	26
Age[1]	12.56 (0.65)	13.20 (0.50)
Gender[2]		
Boys	56 (14)	28 (7)
Girls	44 (11)	72 (18)
SDQ (0-40)		
Mean score[1]	17.92 (5.05)	9.12 (5.08)
< mean score[2]	44 (11)	52 (13)
≥ mean score[2]	56 (14)	48 (12)
Social network		
No. of edges	82	173
Density[2]	13.7	28.8
Reciprocity[2]	82.7	67.0
Transitivity[2]	30.9	39.9

SDQ: Strengths and Difficulties Questionnaire. A higher score indicated a higher number of mental health problems.

[1] Means and standard errors are given.

[2] Percentages and n are given.

Number of edges: total number of ties within the network (number of children mentioned as friends by each participant); density: sum of the ties divided par the number of possible ties; reciprocity: proportion of dyads which are symmetric; transitivity: proportion of triads.

Table 2. Model coefficients for homophily ERGM and social isolation ERGM

		Class A		Class B	
		Model 1	Model 2	Model 1	Model 2
Homophily	Edge	-3.74***	-3.29***	-2.07***	-2.04***
	Gender				
	Boys	1.62***	-	0.94**	-
	Girls	2.24***	-	0.26	-
	SDQ				
	< mean score	-	1.26***	-	0.81***
	≥ mean score	-	0.76***	-	0.04
	Reciprocity	0.76*	1.05*	0.81**	0.75**
	Transitivity	0.45	0.64**	0.51	0.49
	AIC	400.2	430.6	706.1	696.8
	BIC	422.1	452.6	728.1	718.8
Social isolation	Edge	1.84***	-3.35***	-1.14*	-2.51
	SDQ	-0.03*	-	-0.04**	-
	Reciprocity	1.31***	1.34***	0.82**	0.87***
	Transitivity	0.67***	0.72***	0.47	0.51
	AIC	450.2	454.1	704.1	712.2
	BIC	467.8	471.7	721.7	729.8

SDQ: Strengths and Difficulties Questionnaire.

$p < .05$, ** $p < .01$, *** $p < .001$.

Null models (with only edges): Class A: AIC = 480.6, BIC = 485.0; Class B: AIC = 722.8, BIC = 727.2.

Figure 1. Gender homophily in the social network of class A

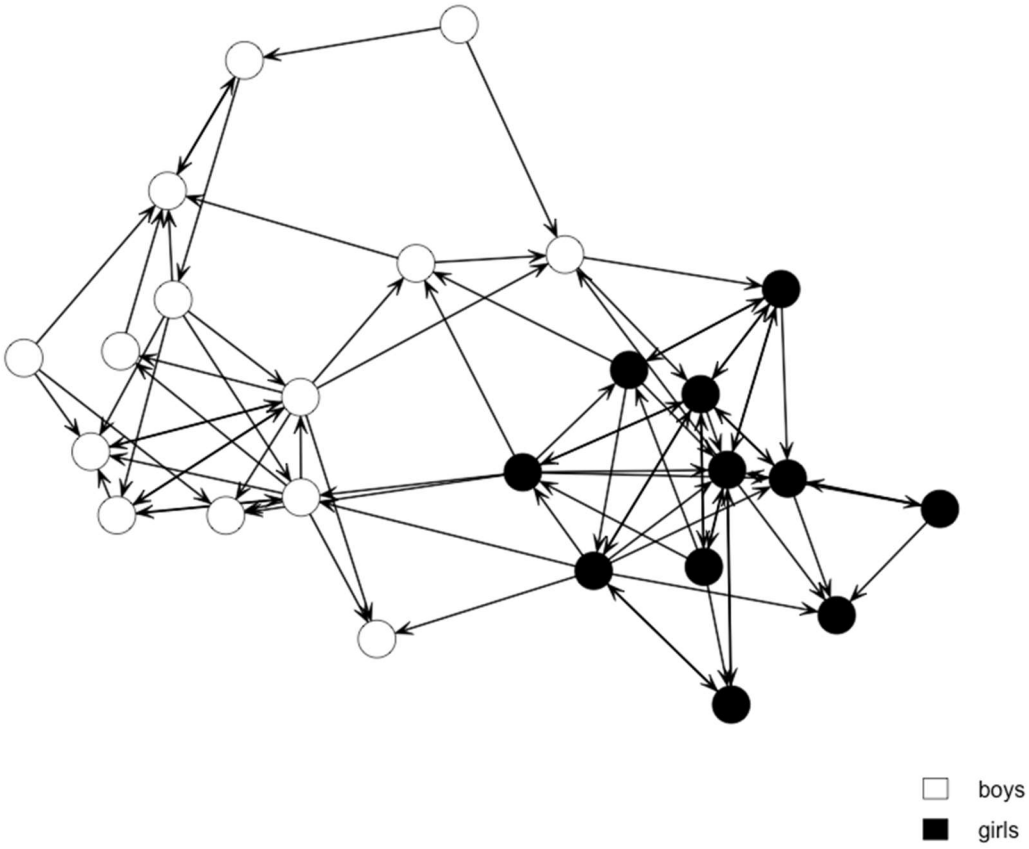
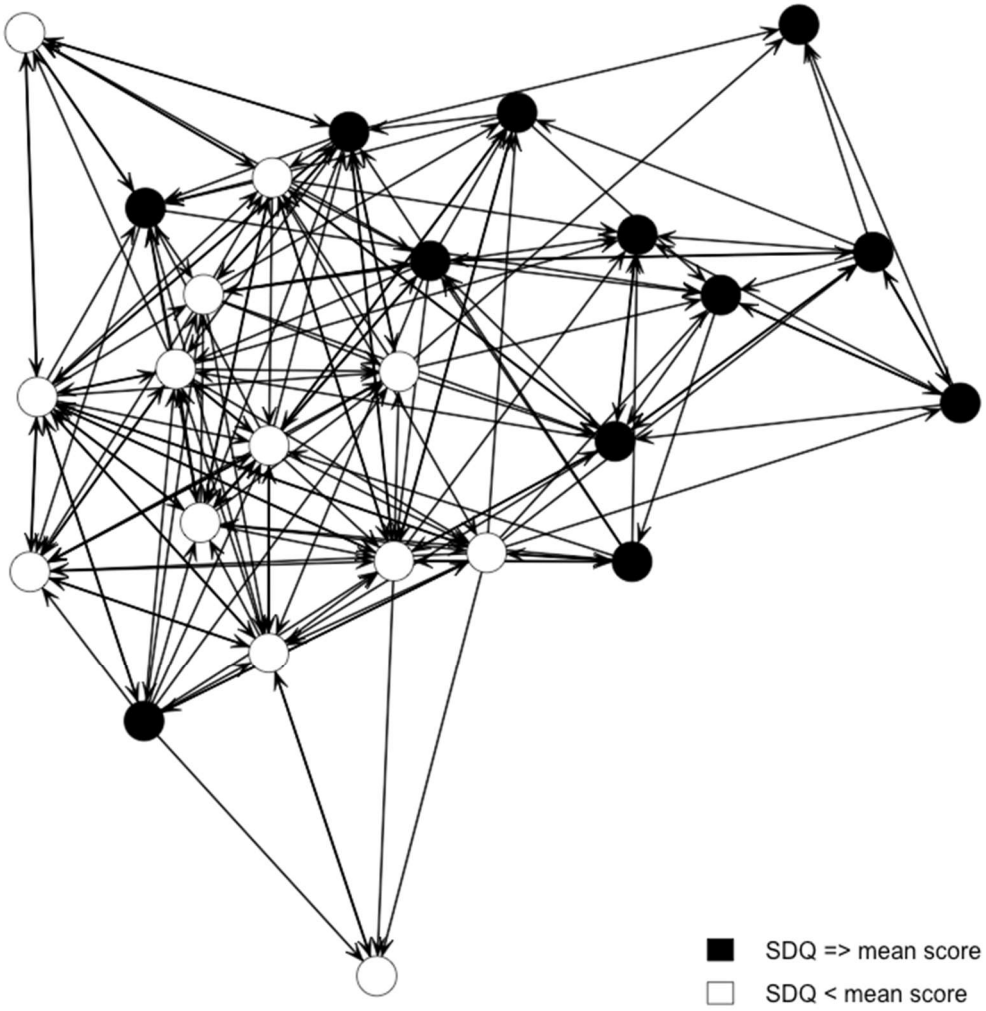
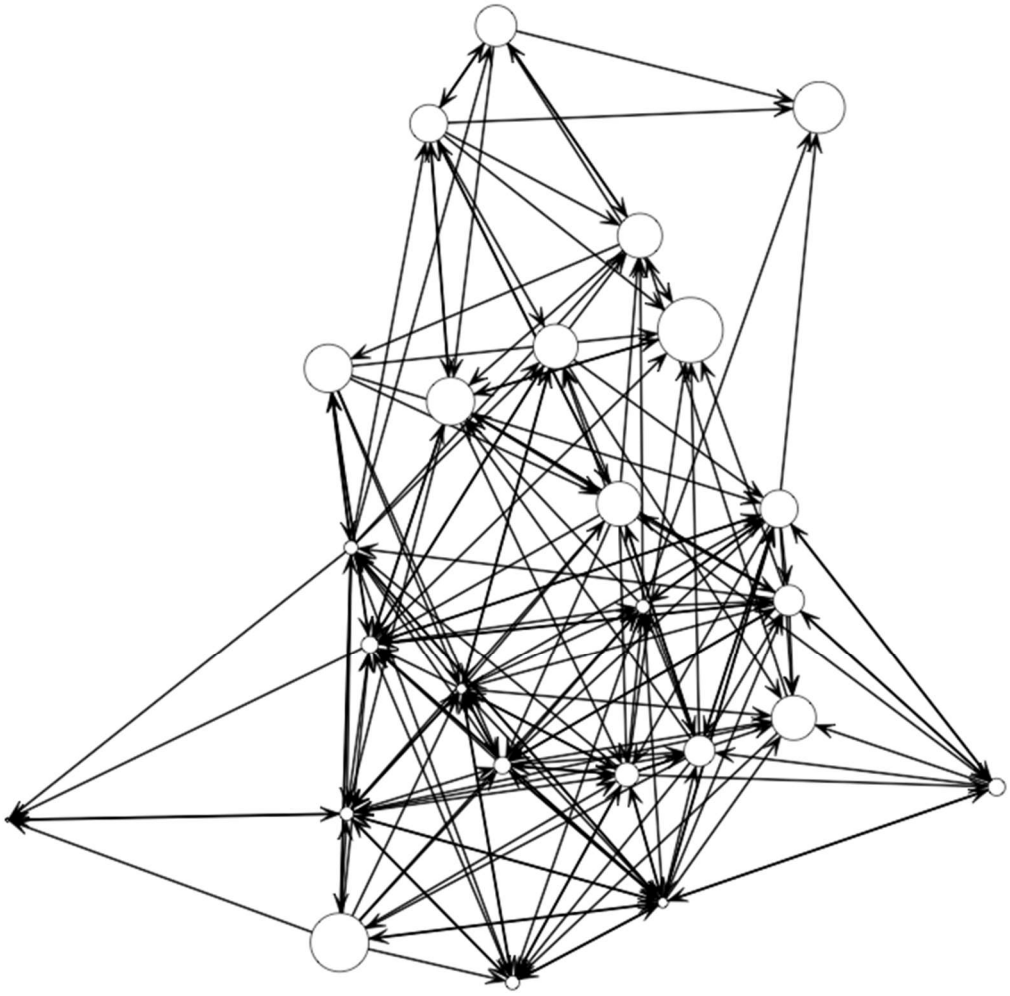


Figure 2. Mental health homophily (SDQ scale) in the social network of class B



SDQ: Strengths and Difficulties Questionnaire

Figure 3. SDQ scores in the social network of class B



Larger circles indicate higher scores of SDQ.