Intersection of Network Science and Psychological research: Applications of network science theories and methods in psychological studies

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Researcher Declaration

I, Srebrenka Letina, certify that I am the author of the work The Intersection of Network Science and Psychological Research: Applications of Network Science Tools in Psychological Studies. I certify that this is solely my own original work, other than where I have clearly indicated, in this declaration, the contributions of others. The thesis contains no materials accepted for any other degrees in any other institutions. The copyright of this work rests with its author. Quotations from it are permitted, provided that the full acknowledgement is made. This work may not be reproduced without my prior written consent.

Statement of inclusion of joint work

I confirm that Chapter 2 is based on a paper which was written in collaboration with Isidro Maya-Jariego and Elena González Tinoco (University of Sevilla, Psychology Department). I conceived of the general idea about research questions a few years before and contacted Professor Maya-Jariego to apply as my host for Marie Curie Sklodowska Action (MSCA Individual fellowship). Although we did not get the funding, Professor Maya-Jariego and his student González Tinoco were able to collect the data that was partly similar to what we had planned for the project. He kindly invited me to co-author a paper with him that was to follow some of the research questions defined for the funding application, as much as possible. Professor Maya-Jariego and I collaborated on writing the paper and the analysis plan. I developed and carried out all the newly used measures (named KR triadic measures), while we both contributed to the rest of the analyses (it was carried out simultaneously by both of us separately using different software). We worked jointly on editing, finalising, and submitting the paper to a journal.

I confirm that Chapter 3 is based on a paper which was written in collaboration with Professor Denny Borsboom and PhD candidates (at that time) Tessa Blanken and Marie Deserno. I used secondary data from "MyPersonality" project to which I got access after contacting the leading researchers (David Stillwell and Michal Kosinski). I developed the research idea and analytical strategy on my own and executed all the analyses. During my research visit at the University of Amsterdam I presented my ongoing work to Professor Borsboom and his group, He, Tessa Blanken and Marie Deserno offered to contribute to the paper. They contributed by discussing the results and editing the paper. I had submitted the paper and worked on further revisions before it was accepted for publication.

I confirm that Chapter 4 is based on a paper which is written in collaboration with researchers at MRC/CSO Social & Public Health Sciences Unit at the University of Glasgow (M. McCann, E. Long, K. Mitchell, J. Riddell, P. McCrorie, S. Simpson, C. Zucca, and L. Moore). The Unit was responsible for the project within which the data used for this paper was collected (The Peers and Levels of Stress ('PaLS') Study). I developed and presented the research idea, developed, and performed all the analyses and wrote the manuscript. Mark McCann discussed the results with me, helped with the editing and advised me regarding the statistical analyses and paper structure. Other co-authors contributed by giving me valuable comments on the analysis plan, the first draft and in editing in general.

Signature of PhD Candidate:

Abstract

One of the earliest applications of networks or graph theory as a theoretical and analytical framework for studying relationships among people originated in psychological research. Recent developments of network theory and methodology impacted the mainstream psychological research with a wider use of network concepts and tools to describe the relationships not only among individuals – social networks, but also among psychological constructs – psychological networks. In such a context, this thesis sets out to contribute by applying a more nuanced theories and analyses in three psychological subdisciplines: social psychology, personality psychology, and health psychology. The overarching aim is to advance the theoretical and methodological development in the three areas of applications by using network methodology and theory.

In the introduction, we give an overview of relevant network-related research in psychology.

In the second chapter, network theory and methods are applied to social psychology to examine the associations of Big five personality traits and Psychological sense of community with structural properties of individuals' ego-networks. In addition to typically used bivariate correlations to analyse the relationship between variables, two approaches are proposed, one that employs typologies of networks and personality, and one which introduces modified versions of triadic census in ego-networks. Results show that different personality types tend to occupy different kinds of networks, and that newly introduced triadic measures show relatively higher associations with examined psychological attributes than global network measures.

In the third chapter, network theory and methods are applied to examine relationships among well-studied psychological constructs in personality psychology. The analysis of psychological networks in previous research has been limited to the inspection of centrality measures and the quantification of specific global network features. However, a psychological network entails more potentially useful information that can be reaped by other methods widely used in network science. The chapter explores the potential value of minimum spanning trees, participation coefficients, motif analyses, and demonstrates the relevant analyses using a network of 26 psychological attributes. These three methods are used to investigate how the network of different psychological concepts is organized, which attribute is most central, and how the network can be described in terms of motifs.

The fourth chapter investigates the effects of network's meso-level properties on individuals' health-related outcomes, in the context of adolescents' peer groups in schools. Previous research has shown that some health outcomes show social clustering within adolescents' peer groups. Yet, the theories of the network meso-level effects on individual health are underdeveloped and understudied. The chapter addresses this knowledge gap, by looking at bundles of health-outcomes that tend to co-occur. Given the availability of many group detection methods that yield different results, the sensitivity of findings is checked by employing ten different methods. The results of multilevel modelling show substantive and moderate clustering on peer group level for substance use and mental well-being, respectively. Crucially, some of the community properties included in the model were significant predictors of individual health outcomes, but their effects were the opposite for the two outcomes.

Acknowledgements

PhD candidates, myself included, often find that while writing the thesis about certain social phenomena, that phenomena seems to become more salient and important in their personal and/or professional life. That is hardly surprising, especially when the topic involves social networks and psychological networks. My path (as for most candidates) in progressing with the work on this dissertation, could be well described in network terms of social support and in terms of interdependency of different internal states. To add complexity, my networks spanned three different countries and an even bigger number of institutions.

There are many people, including my supervisor Prof. Balázs Vedres, other professors, colleagues, friends, and family, whose support contributed in – small or big, direct, or indirect – ways to this work. I am especially thankful to Olga Peredi, Network and Data Science coordinator, and my PhD colleagues (alphabetically): Milan Janosov, Tamer Khraisha, Rebeka O. Szabo, and Johannes Wachs. I am very grateful to researchers that I have met while working on this thesis and that have provided a significant support (alphabetically): Isidro Maya-Jariego, Robert Krause, Rodrigo Martinez-Peña, Mark McCann, Flóra Samu, and Károly Takács. I am grateful to the Department of Network and Data Science at Central European University for the opportunity to do this work. This work opened many doors and enabled me to meet many exceptional researchers in different countries, interaction with whom not only shaped my knowledge and work but enriched my life in general. I want to express a special gratitude to my family, especially my sister Sunčica for being a constant source of support and I devote this work to her.

Srebrenka Letina
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List of Abbreviations

A – Agreeableness, one of Big Five personality traits

BIA – block-modelling with indirect approach

C – Conscientiousness, one of Big Five personality traits

CDA – community detection algorithm

CP – Clique percolation algorithm

E – Extraversion, one of Big Five personality traits

EB - Edge-betweenness algorithm

ERGM – exponential random graph models

ES – Emotional stability (neuroticism reversed), one of Big Five personality traits

FG – Fast greedy algorithm

GDA – group detection algorithms, including community detection algorithms and block-modelling techniques

I – Intensity, the geometric mean of all the weights in a motif/triad

ICC – intra-class correlation coefficient

IM – Infomap algorithm

KR measures/triads –triadic measures based on Kalish and Robins (2006)

KR variant 1 – the count of each of the seven triadic configurations in the ego-net, divided by the number of all possible unique triads

KR variant 2 – normalized counts of seven possible triads with the number of all present triads (open and closed) in the ego-net

KR variant 3 – controls for the density of the personal network and the individual tendency to assign strong or weak ties, based on z-score of occurrence of each of seven triads in the comparison with individual null-model which is a random graph with the same density and number of weak and strong ties

LASSO – least absolute shrinkage and selection operator is a statistical procedure for feature selection and regularization of data models

LE – Leiden algorithm

LO – Louvain algorithm

LP – Label propagation algorithm

MLM – multilevel model

MST – Minimal Spanning Tree

MW – mental wellbeing

N – Neuroticism, one of Big Five personality traits

N0N– an open triad with two negative weights (negative 2path)

NNN – a triad with three negative weights/ties

NNP – a triad consisting of or two negative and one positive weight

O – Openness to experience, one of Big Five personality traits

P0N/N0P– an open triad with one positive and one negative weight (mixed 2path)

P0P – an open triad with two positive weights (positive 2path)

PC – Participation Coefficient

PCA – principal component analysis, data reduction method (its components are called principal components, e.g., PC1, PC2)

PPN – a triad consisting of two positive and one negative weight

PPP – a triad with three positive weights

PR – Participation Ratio

PSC – Psychological Sense of Community Scale

Q – Coherence ratio, quantifies how internally coherent the weights in motifs are by computing the ratio between the geometric and the arithmetic mean

ROTC/RTOC – Ratio of outside community ties, a community property

RQ – research question

SBM – Stochastic block-modelling

SSN – an open triad between alters made of two strong ties

SSS – a closed triad between alters made of three strong ties

SSW – a closed triad between alters made of two strong ties and one week tie

SU – substance use

SWN– an open triad between alters made of one strong and one weak tie

TIPI10 – Ten-Item Personality Measure

WT – Walktrap algorithm

WWN – an open triad between alters made of two weak ties

WWS – a closed triad between alters made of two weak ties and one strong tie

WWW – a closed triad between alters made of three week ties

Chapter 1

Introduction

1.1 Background

One of the most prominent features of network science is its interdisciplinary nature. Brandes et al. (2013; p. 2) define network science as “the study of collection, management, analysis, interpretation, and presentation of network data”, and compare it with general statistics, since both are not tied to any particular field of science but are applied to many. Network science has roots and ties to many different scientific fields (mathematics, sociology, etc.), but it is not “owned” by any one of them.

One of the earliest applications of graph theory to interpersonal relationships came within the field of psychology almost a century ago from Jacob Moreno (1934), who was influenced by the collaborative work with Helen Hall Jennings (Freeman, 2004). Social psychology contributed further to the development of network science with Heider’s theory of balance (1946) and Travers and Milgram’s “small-world” study (1969). However, except for some applications in social, developmental, and organisational psychology, the use of relational data had been rather rare until the early 2000s. Despite the shared history between social networks research and psychology, a reciprocated tension between the two existed (Robins, 2008). On the one hand, early social network research held a structuralism’s view that psychological attributes were merely a “residue” in social networks (Burt, 2013). In the nascent discipline of network science, psychological attributes of nodes are also rarely considered relevant (what Hidalgo (2016) referred to as “agnostic” approach regarding nodes’ attributes). On the other hand, a “cognitive revolution” that has been taking place in psychology since the 1960s, preferred an individualistic approach that underplayed the relevance of more complex understandings and measurements of the social context. Therefore, psychological studies rarely included social network variables as explanatory of individual behaviour. Other social sciences, e.g., sociology, anthropology and economics showed relatively more interest in studying social networks.

In the last two decades, while not at the centre of the renaissance of networks in virtually all scientific fields that shaped the interdisciplinarity of network science, network-related theory and methods have inspired a renewed interest in psychology as well. That momentum has impacted mainstream psychological research, which has employed a wider and more sophisticated use of network concepts and tools to describe relationships not only among individuals (social networks), but also among psychological constructs (psychological networks).

In the following sections, we will briefly describe social network research in psychology and research on psychological networks. We focus on the two, because they are among the most used in psychology, but other kinds of networks that are neither social or "psychological" are also studied in psychology, e.g., psycholinguistic networks, semantic networks, brain (neuroscience) networks, meta-network analysis.

1.1.1 Social network studies in psychology

In this section, we will provide details about the methodological characteristics and challenges of social network studies in psychology. We will address the kind of data used, data collection, and data analysis.

Social psychology has a long history of interest in social cognition, processes of social influence, how people in groups interact with each other and theories of leaderships, social relationships, etc. However, until recently it rarely moved beyond dyadic-based research (Robins, 2015). Thus, social networks of study participants were often "assumed to be a source of uncorrelated random errors" (Robins & Kashima, 2008, p.2). Nevertheless, social network studies in psychology have been steadily growing over the past two decades (see figure 1 in Appendix 1). Typically, these studies are interested in how social networks shape and are shaped by individual attributes and behaviours. Social network data is usually collected via socio-centric or ego-centric procedures[1]. Attribute data on one or more psychological traits is also often collected, usually via self-report measures.

In a socio-centric study, studied individuals are assumed to be a part of a social system within which they influence each other through social relationships. Thus, they are directly or indirectly interdependent which is reflected in some dependency in the data. Moreover, social relationships may depend on one another, showing the characteristics of a self-organizing system. Due to dependency of observations, standard statistical procedures are not an optimal choice for the analysis as they assume that observations are independent. Instead, statistical models for social networks have been developed (e.g., for cross-sectional data Exponential Random Graph Models (ERGM, Lusher et al., 2013) and for longitudinal data Stochastic Actor Oriented Models (Snijders & Pickup, 2017)). The computational complexity of modelling makes them impractical for large networks (Amati et al., 2018),

[1] There are other approaches to network data collection, e.g., cognitive network structures approach that asks everyone in a defined group to report not only their ties with others, but also ties among all other people in the network.

although that is rarely a concern in social networks studies in psychology due to the relatively small size of networks that are studied.

For ego-network analysis, if they have been sampled randomly from a larger population, their measures can be attributed to *ego* and analysed with standard statistical procedures like regression. When interested in properties of alters (people that are connected to the ego) or ties between them, when data is longitudinal, and when a high overlap in alters between ego-networks exists, multilevel models can be used, where ties and alters are nested within an ego (Crossley et al., 2015).

Therefore, in addition to more complex data collection, the analysis of network data often requires knowledge of, and training in advanced statistical methods. That coupling makes a social network study demanding to carry out. For this reason, if there is a way to answer research questions that does not require a social network study, it will be preferred. However, there are questions that demand a network approach.

One of the challenges of dealing with social networks is that asking people directly about their positions in networks or about features of their ego-networks would not be a good start. The reason is that we do not expect people to be able to inform us with the same degree of accuracy about relationships that go beyond dyads in socio-centric research and beyond triads in ego-centric research. That is, we do not expect them to have the knowledge about the ties they are not involved in, or about the global network features, or how they are influenced directly or indirectly by others. Although some people may have a high awareness of the global network (or their complete ego-network) to which they belong and of their position in it (e.g., Simpson et al. 2011), this is rather an exception. Furthermore, some research suggests that people have certain biases in the way they perceive their social networks, e.g., they tend to overestimate reciprocity and transitivity in the network and more easily learn network structures that resemble social networks in their life (Burt et al, 2013).

The question is then, when is it necessary to use social networks in psychological studies? There are two situations when its necessity will be higher. First, when there is evidence or strong support from previous research that adding networks will bring better understanding of the phenomena of interest. For instance, our health-related behaviours are known to be influenced by such behaviours of people we are connected to (Smith & Christakis, 2008). Hence, if we want to study them, it makes sense to use a social network study. Second, when the research questions are inherently related to networks, that is, they are grounded in theory that is framed in network language. Both cases can happen only when some research or theoretical development has been already under way. This implies that trying to include a relational dimension in research where it has not been done before will be more challenging.

1.1.2 Studies of psychological networks in psychology

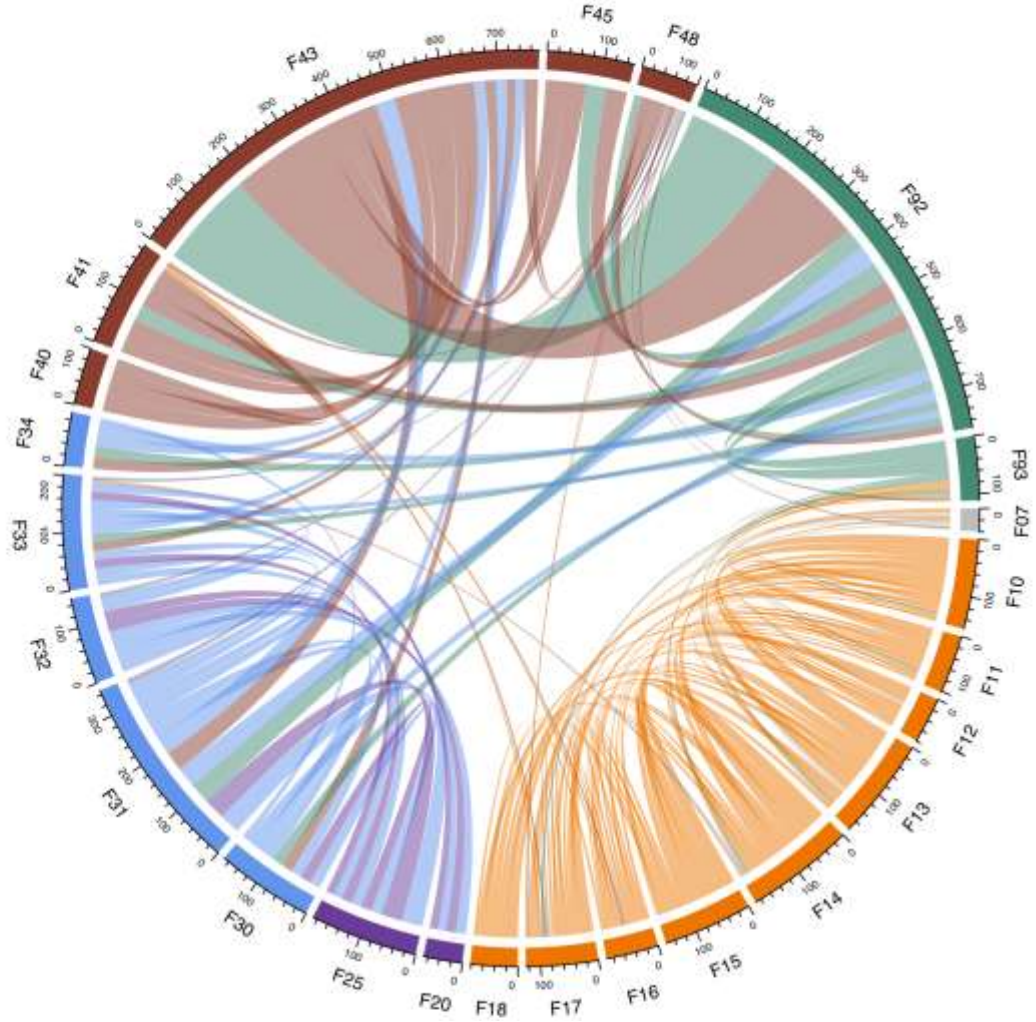
In this section, we will address how psychological networks have contributed to the advancement of the field of psychology and some of its challenges.
In psychology, besides studying social networks, network analysis was used in modelling perceptions of causality (Lunt, 1988; Kim & Ahn, 2002). But it was a small "revolution" when Borsboom et al. (2011) developed an approach that applied formal mathematical modelling for multivariate psychological data to the study of mental disorders.
The potential of the approach was demonstrated first in the field of clinical psychology (psychopathology). This network approach to mental disorders represents symptoms as nodes in a network and proposes that symptoms cluster together not because they share a cause (which is implied by the medical model of mental disorders), but because they activate or reinforce each other. This new way of thinking about mental disorders provided a long-needed alternative to research on single causes of disorders and suggested that attention should be turned to symptoms and their interaction instead. One of the strengths of the approach is that it provided a radical new explanation of comorbidity[2] of mental disorders (Cramer et al., 2010), proposing that comorbidity emerges out of direct relations between symptoms of multiple disorders. Borsboom et al. (2011) analysed the overlap of symptoms between different disorders in the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV) based on a bipartite network projection and found that distance of disorders in that network predicted empirical comorbidity rates. Similar results were found for International Classification of Diseases, ICD-10 (Tio et al., 2016). The overlap of symptoms between mental disorders (based on ICD-10) is shown as a chord diagram in figure 1.1[3]. 24 of 62 (39%) disorders that had a list of symptoms in ICD-10 had a significant overlap in symptoms with at least one other disorder. That overlap facilitates comorbidity, according to network theory of comorbidity.

A similar rationale was applied to personality traits (Schmittmann et al., 2018): some characteristic thoughts, feelings and behaviours co-occur not because they are caused by a common underlying cause (personality trait, e.g., extraversion), but because they directly influence (exacerbate or inhibit) each other. This approach was also extended to studies of beliefs, attitudes, cognitive abilities, etc.

In difference with a social network study, a research design of a psychological network study does not differ in any substantial way from typical psychological research. Psychological scales (questionnaires) are used to collect data on a sample of individuals, preferably randomly selected from a population of interest. A study can involve multiple

[2] Comorbidity means that people who have one mental disorder are more likely to have another mental disorder.
[3] More details about data and method used, see Appendix 1, section 2.

waves as network models for longitudinal data and time-series data were also developed, (see Borsboom et al., 2021).



Legend:

Grey (F0x) – Organic mental disorders; **Orange** (F1x) – Substance use disorders; **Purple** (F2x) – Schizophrenia, shizotypal and delusional disorders; **Blue** (F3x) – Mood disorders; **Brown** (F4x) – Neurotic, stress-related and somatoform disorders; **Green** (F9x) – Behavioural and emotional disorders with childhood onset; F*nn* are ICD-10 codes for mental disorders. More detailed legend is given in table 2 in Appendix 1.

Figure 1. 1 Chord diagram showing overlap of symptoms between mental disorders (ICD-10, statistically validated, only overrepresented ties are shown and disorders that have ties with at least one other disorder)

The development of free and relatively easy to use software for network analysis (qgraph R package, Epskamp et al, 2012), which also generates visually pleasing figures, made the method accessible to a wider range of researchers that do not necessarily have a high expertise in network analysis. High “popularity” also inspired criticism (Neal et al., 2022a;

for the annotated review, see Neal et al., 2022b), some of which concerns methodological aspects, while some question the validity and added value of using the network perspective. Neal's et al. (2022a) overview addresses appropriateness of study designs, possibility of important nodes missing, issues with applying network modelling to sparse binary data, robustness of network estimations, and interpretations of network metrics. For instance, since presence of a flow between nodes in psychological networks cannot be assumed, network centrality measures such as betweenness or closeness are questionable when applied to psychological networks (Bringmann et al., 2019). Some researchers questioned the added value of the network approach in comparison to methods such as multidimensional scaling, structural equation modelling, or to simply using a correlation matrix (e.g., Schimmack & Gere, 2012). Despite this criticism, the new network perspective that aims to conceptualise psychological concepts as emergent behaviours has grown substantially in the last decade (Robinaugh et al., 2020; see figure 3 in Appendix 1).

When is it necessary to use network models for psychological data? We cannot provide a straightforward answer, since the jury is still out on how useful the network perspective to different kinds of psychological constructs is. In this relatively early stage of its development many studies have an exploratory nature, and there is a danger of using network analysis on any data just because it is possible. As a very general guidance, and admittedly rather vague, we would suggest that it is justified to use it when testing a well-grounded network theory or hypotheses and when testing new network methods.
It should be noted that estimating a network based on associations measures is not a new idea within the network science field – where such networks are called similarity-based networks – and it is used for studying relations among different kinds of concepts (e.g., Hidalgo et al., 2009; Toivonen et al., 2012; Nummenmaa, et al., 2018).

1.1.3 Two fundamentally different types of networks

It is important to acknowledge the fundamental differences between social and psychological networks. The major difference is that nodes in the social network are observable, physical entities (e.g., people), while in psychological networks they represent scientific constructs operationalized via a measurement instrument (e.g., extraversion, depression). In both cases ties are not directly observable, and they must be estimated. But estimations involve very different methods. Estimation of ties in social networks is most often based on self-reported data about dyadic relationships with other people. In contrast, ties in psychological networks are estimated using statistical methods (e.g., partial correlation techniques) that assess how constructs are related. In both types of networks, ties can vary in strength and valence (positive or negative). The latter is often a characteristic of psychological networks when ties are estimated via association measures. In social networks, information about strength of ties and about negative ties is not always collected, mostly due to the fact that study participants are usually burdened by long questionnaires, so strength and valence are often not prioritised.

The differences in type of nodes and how ties are estimated limit network methods and theories that can be applied to psychological networks (Bringmann et al., 2019). Social processes do not operate within a network of constructs. For instance, if two relatively similar constructs are strongly connected in the network, we cannot use social mechanisms of "homophily" to explain it. Also, while social networks can vary in size (number of nodes in the network) considerably, psychological networks are usually small – rarely including more than 30 nodes.

The difference in the type of networks is not the only difference between the two applications of network analysis to psychological research. On the one hand, social networks studies in psychology rely on well-established theory and methodology developed in other social science disciplines. On the other hand, studies of psychological networks have become a recognised approach only in the last decade. When they use network theory and methods, they cite network science literature more than literature on social networks, while research is mostly carried out by psychologists. Maybe then it is not surprising that the study of social networks and psychological networks seems to be separated within the field of psychology. Researchers that study social networks rarely study psychological networks, and vice versa. One reason is that psychology, not unlike network science, is a very fragmented field (Zittoun et al., 2019), and the research agenda is delineated based on topics rather than on methods and general theoretical frameworks used.

It is plausible, even highly likely, that social interactions will affect individual psychological system, and vice versa. Investigating social networks and psychological networks simultaneously would enhance better understanding of both. Yet, developing a theoretical and methodological framework for studying such complex multilayer system is a challenging task, possibility of which is just starting to be mentioned (Epskamp, 2019). In such context, this thesis makes the first step by exploring the characteristics of both kinds of network research.

We aim to contribute by bridging this gap by applying more nuanced theories and analyses in three subdisciplines of psychological science: social psychology, personality psychology, and health psychology. The overarching goal is to expand their theories and knowledge by advancing their integration with and the use of network methods and theories. Two applications involve social networks (Chapters 2 and 4), and one involves a psychological network (Chapter 3).

But before we turn to studies included in this thesis, we will shortly note some specific challenges of network-related research in psychology in the following section.

1.1.3 Some specificities of network-related research in psychology

Networks-related research in psychology usually involves some considerations and challenges that are not necessarily present in applications of network science to other fields. To set the stage for the work presented in the following chapters, we will shortly mention some of those challenges. They echo the differences between network approaches in the social and natural scientists described by Hidalgo (2016).

Firstly, despite an increasing awareness and popularity of network concepts and methods in psychology in the last decade, its use still presents an interdisciplinary endeavour for researchers in the field. It is well-documented that interdisciplinary research involves many specific challenges (Cambell, 2005). Just one of many is that it requires knowledge and skills from two (or more) fields, and strong theoretical integration of these fields. Such research often addresses slightly different (than usual for the discipline) and more heterogeneous scientific audiences. Hidalgo (2016) pointed out some important differences between social scientists and natural scientists that do network research e.g., research questions asked, “incompatible style” in writing scientific papers reflected in differences in the length of a typical paper. These differences may discourage collaborations of researchers and cross-fertilization of ideas in the fields.

Secondly, psychological research has almost by default a more “microscopic” perspective than most network science research. More emphasis on and more time investment in the data collection is needed. It usually involves a collection of rich, so-called “thick” data (Wang, 2013). Data is often based on self-reports and collected on samples that are by standards of some disciplines considered too small to be relevant. Data collection is strongly guided by predefined research questions and not easily repurposed for investigating other hypotheses. Standard procedures of testing hypotheses are carried out and generalisations of findings are necessarily limited. This is very different to the “let the data speak” approach often taken in fields that deal with “big data” (data science, computer science, etc.). But some scientists caution against “big data hubris”. David Lazer (2014; cf. Robins 2015, p. 228) notes that “[…] traditional “small data” often offers information that is not contained (containable) in the big data […]”. Thus, small scale social network studies allow for a more nuanced investigation of the mechanisms operating in the network. Robins (2015) puts the discussion about “small” versus “big” data at rest by stating the obvious: we need “good” data, small or big, both kinds of studies have their unique contribution and added scientific value. Psychological network studies are also usually done on small to moderately sized samples, and the size of the estimated network (number of nodes) is usually not high, as noted before.

Finally, and closely related with the former, the data used in psychology is often personal and sensitive. There are important ethical issues to consider when collecting and using such data (anonymity, confidentiality, informed consent, right to the access, the right to erasure, duty of care for respondents and feedback), especially when it is combined with the social network data (Kotsios et al., 2019; Molina & Borgatti, 2021; McCann, 2021)[4].

With these considerations in mind, we turn to the studies in this thesis. Each chapter is an application of network theory and methods to one subfield of psychology: social psychology, personality psychology, and health psychology. These areas are chosen because they are assumed to be among psychological subfields that have been using network analysis the most in the last decade.

1.2 Structure of the dissertation: The overview of three studies

In this section, we provide a summary of general research themes in three studies; how they relate with different psychological subdisciplines and other social science fields; data and analytical strategies used.

Despite or due to a rather fragmented structure in which the academic field of psychology is organised, the same study can span across different subdisciplines and it cannot be neatly placed in just one. Furthermore, social networks studies (Chapters 2 and 4) will tend to draw from sociological literature as well. The three studies in this thesis, although presenting network research in social psychology (Chapter 2), personality psychology (Chapter 3) and health psychology (Chapter 4) also pertain to other subdisciplines.

STUDY 1 (CHAPTER 2)

In Study 1 we explore the relationship between personality characteristics, Psychological Sense of Community and the structure of personal networks. We start by reviewing the literature on the relationship between Big Five Personality traits and personal and socio-centric networks. Given the study includes a measurement of relationships with others, it falls under the umbrella of social psychology, more specifically to community psychology where network analysis has a growing use due to its focus on interplay between individuals and their social context (Neal & Neal, 2017). However, because the study includes in addition to Sense of community also five personality traits it is also relevant for personality psychology. Through its consideration of sociologist Simmel's work on triads, it relates to sociology as well.
We use data about five personality traits, Psychological Sense of Community, and some socio-demographic variables of 100 adults living in Seville, Spain. Ego-centric network data consisting of information about 45 alters and ties among them is collected via semi-

[4] Recently implemented the General Data Protection Regulation requires more legal considerations and guidance when collecting personal and sensitive data than it was the case before.

structured interviews. We used well-known network measures (e.g., transitivity) of ego-centric networks, but also new triadic measures that present a modification of Kalish's and Robins' triadic measure (2006) for ego-networks without ego and with fixed number of alters. The analytical strategy consists of the typically used bivariate correlations to analyse the relationship between psychological variables and measures of network structure. However, we also use a typological approach by employing cluster analyses to arrive at the types of personalities and types of personal networks. We proceed by using the results to address the research questions with standard statistical procedures.

STUDY 2 (CHAPTER 3)

Study 2 is methodologically oriented. We suggest three networks science methods that could enrich analysis of psychological networks but have not been previously used in that field of research. Specifically, we explore the potential value of minimum spanning trees, participation coefficients, and motif analyses, and demonstrate the analyses using a network of 26 psychological attributes. Since most of the 26 attributes are considered as personality traits, the study "belongs" mostly to the subfield of personality psychology. But since some of the constructs measured (intelligence, values, depression) come from other psychological subdisciplines, it also contains elements of cognitive, social, and clinical psychology.

We use a secondary dataset collected within the "MyPersonality" project (led by Stillwell and Kosinski, from 2007 to 2012). It included data on different kinds of psychological measures on over one million people. We used scores on 26 scales or subscales based on instruments with well-established reliability and validity in psychological research, to construct a psychological network where ties between constructs were estimated based on partial correlations for pair-wise complete observations.

STUDY 3 (CHAPTER 4)

In study 3, we address the theoretical and knowledge gap about network meso-level effects on individuals. Specifically, we investigate whether the structural and compositional properties of adolescents' peer groups in schools are associated with two individual health-related outcomes, substance use and mental wellbeing. In addition to data on students' self-reported health behaviours, we use data on friendship networks in 22 schools.

The topic relates to health psychology. It falls under a wider umbrella of health studies that are interested in psychosocial influences on health outcomes (the field is sometimes called medical sociology, medical social science, social epidemiology). Through the work of Lisa F. Berkman (e.g., Berkman et al., 2014), the field embraced network theories and concepts like social integration, social capital, and social support, recognizing their relevance for individual and population health. It was found to represent one of the largest clusters of network research in social sciences (Brandes & Pich, 2011).

Given the age of the studied population (adolescence), it is relevant for developmental psychology. Moreover, substance use and mental wellbeing – the dependent variables in the study – are typically of interest to the subfield of clinical psychology as well. Finally, the chapter draws on theories of social influence processes within peer groups and relates the meso-level theory to a framework developed in sociology, linking it with social psychology and sociological research.

We use the secondary data collected in 2006 within The Peers and Levels of Stress ('PaLS') Study on adolescents in 22 schools in Scotland. The dataset contained their self-reported health behaviours and outcomes, socio-demographic information, and data about friendship ties within schools. Based on the latter we detected peer groups with the Walktrap algorithm and then included the community membership data in multilevel models that control for several individual covariates. Furthermore, we test the sensitivity of the network meso-level effects with nine other group detection methods.

Despite notable differences, all three studies have several aspects in common:

1. They demonstrate an application of network theory and methods to psychological research.
2. An effort is made to integrate the study with the theories and/or findings in the previous research in the subfield.
3. Network methods used are innovative in the context of the field. Network methods that look specifically at the network meso-level (e.g., triads and beyond – network communities) are included.
4. The exploratory nature of the research.
5. The use of cross-sectional and self-reported data, data which is both "thick" and quantitative.
6. The target audience are not only psychologists, but other researchers that study similar topics (sociologists, health researchers, etc.) and network scientists in general.

We conclude the thesis by making a general summary of the studies and their contributions; followed by a general discussion on different aspects of doing a network related research in the field of psychology, and an overview of general directions for future research.

Chapter 2

Personal networks and psychological attributes: Exploring individual differences in personality and sense of community and their relationship to the structure of personal networks

2.1 Prelude

People utilize different interactive strategies that determine both their position in the social network and the structural properties of their personal networks (Krause et al., 2010). This notion has recently started to be investigated through the study of individual differences in social networks (Selden & Goodie, 2018). This is an innovative approach, in an area in which the emphasis on constraints that the social structure imposes on opportunities for interaction and, consequently, on individual behaviour has traditionally predominated (Wellman, 1983).

Previous research has looked into the variability of the structure of personal networks in terms of socio-demographic characteristics, such as age, gender, socioeconomic status, and educational level (Roberts et al., 2008). The changes that take place throughout the life cycle have also been examined, based on personal transitions and life events (Bidart & Lavenu, 2005; Dickens & Perlman, 1981; Ferrand, 1989; Morgan et al., 1997). The focus on individual differences in personality is recent. It is based on previous evidence of the influence of the psychological profile on the levels and styles of sociability (Digman, 1990; Furukawa et al., 1998; Roberts et al., 2008; Russell et al., 1997).

The approach that has been predominately used to explore the individual variability in the structure of personal networks is the model of the five major personality factors (Goldberg, 1993; Tupes & Christal, 1961, 1992). In this study, we rely on this background to explore the relationship between psychological attributes and the structure of personal networks. However, we aim to contribute to this body of research, first by including psychological attributes that theoretically may be more directly related with the network structure (psychological sense of community). Second, by using different analytical approaches that take advantage of typologies of both personality traits and network, and third, we additionally make an extension of previously used measures of ego-networks based on motif

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analysis (Kalish & Robins, 2006)[5]. We expand the previous use of triadic measures to the context of collecting ego-network data with fixed number of alters (45) and with information about the strength of ties between alters only. We propose that how an individual (an ego) tends to perceive their local social world – how others in their network relate to each other – will be related with their psychological traits even when ego's direct ties with those others are not considered. The relationship between network structure and psychological predispositions can result from truly different patterns of alter-alter ties that could be related with psychological traits of the ego. For instance, a less emotionally stable person may tend to be connected with alters that are less connected among each other, as previous research suggested (Kalish & Robins, 2006). That characteristic of a local social world could be partly the outcome of an intentional or unintentional strategy related with a psychological predisposition. However, it could also be a contributing and maintaining factor for the development of the psychological predisposition. That is in line with Simmel's theory of "individuality" in dyads and triads (Wolff 1950, p. 137). According to Simmel, the dyad favours a relatively greater individuality of the members, allowing for greater "individualization." Dyads "preserve the individuality" (Krackhardt, 1999 p. 185) in the sense that "no majority can outvote" one party, while an actor belonging to a triad is less free, less independent, than when they belong to a dyad. Extrapolating from those characteristics of relational settings, Simmel makes an important distinction between two types of individualities regarding the triadic setting they prefer. A "decided" (or qualitative) individuality refers to "singularity" and describes a person who will avoid groups where a majority may appear and will prefer multiple dyads instead, which will be manifested in more open triads between alters in their ego-networks. On the other hand, actors with a "strong" individuality will be more likely to look – given the choice – for a triadic than a dyadic setting, which will be manifested in having more triads among alters in their ego-networks. Furthermore, psychological traits can be related with the way the local social world is perceived by ego due to their higher sensitivity or bias to perceive certain kinds of patterns. In line with the previous example, less emotionally stable people could be more likely to perceive or even overestimate the lack of transitivity between their alters.

The results of our study suggest that psychological sense of community is associated with different aspects of the structure of personal network, while degree of association is similar or slightly higher than that of the five personality factors. Typological approach shows that individuals with different personality types have tendency to occupy different types of networks, while the introduced modifications of triadic measures give a more nuanced picture of the interplay between individual psychological differences and network structure.

[5] Given that research done by Kalish & Robins, (2006) is seminal and often referred to in this paper, sometimes the acronym KR will be used.

2.2 The influence of the Big Five personality traits on the structure of personal networks

2.2.1 Extraversion

Extraversion is characterized by sociability and seeking the company of others. Extraverted people tend to be described as sociable, talkative, friendly and predisposed to experience positive emotions (McCrae & Costa, 1987). This makes them develop better social skills (Doeven-Eggens et al., 2008; Roberts et al., 2008), which help them both to start new relationships (Asendorpf & Wilpers, 1998; Roberts et al., 2008; Wrzus et al., 2017; Zhu et al., 2013), and to maintain them over time (Zhu et al., 2013).

Extraverted people gain reinforcement in interpersonal situations, which predisposes them to make friendly relationships (Feiler & Kleinbaum, 2015; Roberts et al., 2008; Selfhout et al., 2010), to actively seek opportunities for interaction with others (Asendorpf & Wilpers, 1998; Doeven- Eggens et al., 2008; Landis, 2016; Totterdell et al., 2008; Wagner et al., 2014; Wrzus et al., 2017; Zhu et al., 2013) and to make sure that their personal contacts know each other (Kalish & Robins, 2006).

This tendency towards sociability tends to be reflected in more extensive and varied support networks (Burt et al., 1998; Cohen et al., 2000; Swickert et al., 2002; Wagner et al., 2014), with a higher frequency of interaction (Swickert et al., 2002) and a higher proportion of new contacts (Zhu et al., 2013). The studies with homogeneous samples have generally found a positive correlation between extraversion and the size of the personal network (Roberts et al., 2008; Selden & Goodie, 2018). However, extroverts' networks are not denser than those of the introverts, suggesting that they are not necessarily fostering ties among their acquaintances (Kalish & Robins, 2006).

2.2.2 Agreeableness

People who score high on this trait are characterized by a tendency to cooperate, based on empathy and altruism. Agreeableness normally corresponds to people described as trusting, sympathetic and considerate to others (McCrae & Costa, 1987). They are usually helpful, and seek the good of the community, so they inspire confidence when requesting information or other types of resources (Liu & Ipe, 2010).

Greater agreeableness is related to the development of long-term positive affective relationships (Doeven-Eggens et al., 2008; Zhu et al., 2013), reducing both the likelihood and the intensity of interpersonal conflicts (Asendorpf & Wilpers, 1998; Wrzus et al., 2017; Zhu et al., 2013), and improving the perceived quality of friendship (Demir & Weitekamp, 2007). People who excel in this personality factor attract friendships and have a greater chance of being chosen by others to start a relationship (Selfhout et al., 2010; Zhu et al., 2013).

In the studies with individuals who experience a personal transition process, a correlation has been found between agreeableness and the size of the egocentric network, mainly due to new non-kin contacts (Wagner et al., 2014). However, there is not yet much evidence in this field.

2.2.3 Conscientiousness

Conscientiousness refers to a general tendency towards self-control and discipline. People who score high on this trait are conscientious, perseverant, reliable and disciplined at work (McCrae & Costa, 1987). They are characterized by greater motivation for achievement and focus on the resolution of tasks (Fang et al., 2015; Zhu et al., 2013).

It has been suggested that conscientiousness is reflected in more stable and lasting relationships, as well as in a lower proportion of new contacts (Asendorpf & Wilpers, 1998; Baker & McNulty, 2011; Zhu et al., 2013). Indeed, several studies show that there is a significant relation between responsibility and listing more family members in the personal network and with a greater stability of these members over time (Doeven-Eggens et al., 2008; Wagner et al., 2014).

2.2.4 Emotional stability (neuroticism reversed)

At the negative extreme of emotional stability is neuroticism. Neuroticism is characterized by a tendency to experience negative emotions, along with a greater vulnerability to stress and depression. Among other aspects, it usually entails emotional insecurity, distrust, constant worry, anxiety and other forms of affective instability (McCrae & Costa, 1987). People who score high on this trait tend to evaluate their experiences negatively (Doeven-Eggens et al., 2008), express more negative emotions (Fang et al., 2015), and are less assertive in their interactions (Roberts et al., 2008).

Emotional instability is usually associated with insecure, hostile, and lower quality relationships (Wrzus et al., 2017). In fact, people with high neuroticism are commonly perceived as “high cost interaction partners” (Fang et al., 2015, p. 1245) and are less attractive as friends. As a result, they have less opportunities to develop the skills of initiating and maintaining relationships, while also experiencing more interpersonal conflicts (Demir & Weitekamp, 2007).

Although neurotic people declare themselves less predisposed to form new relationships, there is no evidence that shows a significant impact on the size and composition of personal networks (Selden & Goodie, 2018). Those who score high in neuroticism seem to be less predisposed to the connection between members of diverse groups in their personal network (Kalish, 2008), while they perceive less transitivity and greater disconnection in networks of strong ties (Kalish & Robins, 2006).

2.2.5 Openness to experience

High scores on this trait are an indicator of a personal inclination for change, creativity and imagination. Openness to experience is usually represented through adjectives such as original, imaginative, curious and preference for variety (McCrae & Costa, 1987). These are individuals who adapt to change easily and who show tolerance for novelty.

Individuals who are open to new interpersonal experiences may also be more available to establish new contacts, explore new contexts of interaction and have less consolidated relationships over time (Wagner et al., 2014). This could put them in a position to act as intermediaries, when they come into contact with new social environments where other individuals are not connected.

It has been observed that people with greater openness to experience have a higher proportion of new contacts (Zhu et al., 2013), establish ties with people from different contexts (Fang et al., 2015; Landis, 2016), maintain support relationships for less time, and tend to have a lower frequency of contacts (Wrzus et al., 2017). Although not direct effect has been noted on the size of the network, there is a positive relation between the level of openness and the establishing of new relationships at times of personal transition (Selden & Goodie, 2018; Wagner et al., 2014).

2.3 The influence of the Big Five personality traits on the centrality of individuals in socio-centric networks

To complete our examination of the Big Five model, below we review the studies that have used socio-centric designs, or complete networks. Although the focus of our research is personal networks, these other studies can also reveal the relational dynamics of interest based on personality traits. In Table 2.1, we summarized some of the most consistent evidences both in personal network surveys and in the analysis of complete networks, organized according to the five basic personality traits.

2.3.1 Extraversion

Utilizing data from socio-centric networks, various studies have documented that extroverts tend to have a greater centrality in friendship networks (Feiler & Kleinbaum, 2015), advice networks (Klein et al., 2004; Regts & Molleman, 2016), and adversarial networks (Klein et al., 2004). Extroverts are especially active in networks and generally obtain higher scores in out-degree centrality (Selden & Goodie, 2018).

2.3.2 Agreeableness

In the case of people with high scores in agreeableness, it has only been found that they are more central in friendship networks (Klein et al., 2004). Although the evidence is still scarce, in some cases, they also show a greater probability of being chosen by others as friends (Selfhout et al., 2010), or as relational leaders (Emery, 2012; Emery et al., 2013), obtaining a high in-degree. This coincides with another finding suggesting that they also act as connectors between groups that are separated from each other (Battistoni & Fronzetti Colladon, 2014).

2.3.3 Conscientiousness

Conscientiousness is often a good indicator to detect individuals who play a key role in instrumental networks (which usually involve giving timely advice, transmitting quality information, or solving tasks) (Battistoni & Fronzetti Colladon, 2014; Emery, 2012; Emery et al., 2013).

Table 2. 1 Characteristics of personal networks and position in complete networks according to the Big Five personality traits

PERSONAL NETWORKS	***SOCIO-CENTRIC NETWORKS***
Extraversion	
• They have larger friendship networks (Doeven-Eggens et al., 2008; Roberts et al., 2008). • They have a higher proportion of new contacts (Asendorpf & Wilpers, 1998; Roberts et al., 2008; Zhu et al., 2013; Wrzus et al., 2017). • Higher transitivity (Kalish & Robins, 2006)	• Occupy positions of greater centrality in friendship, advice and adversarial networks (Klein et al., 2004; Feiler & Kleinbaum, 2015; Regts & Molleman, 2016). • Have higher indicators of out-degree (activity) (Selden & Goodie, 2018).
Agreeableness	
• They have larger non-kin networks (Wagner et al., 2014). • Form long-term positive affective relationships (Doeven-Eggens et al., 2008; Zhu et al., 2013) • A smaller likelihood and the intensity of interpersonal conflicts (Asendorpf & Wilpers, 1998; Zhu et al., 2013; Wrzus et al., 2017) • Higher perceived quality of friendship (Demir & Weitekamp, 2007)	• Occupy positions of greater centrality in friendship networks (Klein et al., 2004). • Obtain higher indicators of in-degree (popularity) (Selfhout et al., 2010). • Tend to connect different groups (Battistoni & Fronzetti Colladon, 2014).
Conscientiousness	
• More family members in the personal network, more stable over time (Asendorpf & Wilpers, 1998; Doeven-Eggens et al., 2008; Baker & McNulty, 2011; Wagner et al., 2014). • Less new contacts (Zhu et al., 2013)	• Can be key actors in advice and instrumental networks (Emery, 2012; Emery et al., 2013; Battistoni & Fronzetti Colladon, 2014).
Neuroticism	
• They experience more interpersonal conflicts (Demir & Weitekamp, 2007) • Lower quality relationships (Wrzus et al., 2017) • It does not seem to affect the size or composition of the personal network, but rather the perception of it (Selden & Goodie, 2018). • Highly neurotic people perceive less connectivity in their personal network (Kalish & Robins, 2006). • Less diversity in contacts (Kalish, 2008)	• In some cases, it is related to a greater centrality in advice networks (Selden & Goodie, 2018). • Obtain higher in-degree indicators in adversarial networks (Klein et al., 2004; Xia et al., 2009).
Openness to experience	
• It is related to the incorporation of new contacts in moments of personal transition (Zhu et al., 2013; Wagner et al., 2014; Selden & Goodie, 2018). • Higher diversity of contacts (Fang et al., 2015; Landis, 2016) • A lower frequency of contacts (Wrzus et al., 2017)	• Obtain higher in-degree indicators in adversarial networks (Klein et al., 2004).

2.3.4 Emotional stability (neuroticism reversed)

People with less emotional stability (or with more neuroticism) are less likely to facilitate the development of relationships between people or groups that are disconnected from each other (Battistoni & Fronzetti Colladon, 2014). In some cases, a high score in neuroticism is related to a greater centrality in the instrumental networks and advice networks in work contexts. This has led to suggest that, under certain circumstances, it may be beneficial in organizational contexts (Selden & Goodie, 2018). People scoring high in neuroticism may also have greater in-degree centrality in adversarial networks (Klein et al., 2004; Xia et al., 2009).

2.3.5 Openness to experience

High scores in openness seem to predict a good incorporation in distributed and long-distance communication networks, in which it is important to relate disconnected individuals to each other (Xia et al., 2009). However, it has been observed that this trait has a negative relationship with centrality in friendship networks, and positive in adversarial networks (Klein et al., 2004).

2.4 Identifying the need for a different analytical approach

Research findings concur that some psychological attributes are associated with network variables. Nonetheless, the pattern of relationship found varies. This could be a result of the different methodologies employed for constructing personal networks and small homogenous samples (e.g., students, employees). The strength of correlation rarely exceeds 0.3, and recent meta-analysis of socio-centric studies (Fang et al., 2015) show that, although significant, the shared variance between psychological attribute variables and social networks variables is modest—rarely exceeding 5%. Despite being small in absolute terms, this finding demonstrates that the structure of our network is 1/20 related to our psychological attributes, which is not to be considered trivial given that our network is made of other people with their own psychological attributes. However, the research done so far is not addressing all psychological attributes and their influence on the individual's overall network structure. The findings of previous research refer only to specific dimensions of personality and their association with specific structural characteristics of an ego-network, without taking the other dimensions simultaneously into account. For example, the majority of research on extraversion and network size show that the two are positively correlated, which is highly expected given the definition of extraversion. On the other hand, an extrovert who is also emotionally unstable will have different proclivity, opportunity, and success in developing and maintaining new ties than an extrovert who is also emotionally stable. In other words, in most social interactions, we manifest several psychological attributes simultaneously (e.g., extraversion, emotional stability, and agreeableness). That is why research should look at the effect of psychological attributes on social networks in a way that considers the combination of traits. Although the Big Five personality traits are conceptualized as independent, existing research has shown that considerable correlations among the traits exist (van der Linden et al., 2010). Although the majority of studies have been based on the broad “Big Five” traits, in some studies, narrower trait-like constructs from social psychology, that capture values and beliefs of an individual, have also been used, e.g., locus of control, self-monitoring, self-efficacy (Kalish & Robins, 2006). Thus, when making assumptions about the relationship between psychological attributes and social networks, we should also be aware that previous research has not examined all the psychological attributes that may be significantly related with social networks.

2.5 This study

In this study, we explore how personality traits relate to the structural properties of personal networks. For this, we rely on the findings of previous research, reviewed in the previous sections, linking singular personality variables with the specific indicators of centrality, size, homophily and cohesion of personal networks (Roberts et al., 2008; Selden & Goodie, 2018). The novelty of our approach is summarized in three points: in addition to the Big Five personality traits, we investigate whether there is a relationship between network structure and Psychological Sense of Community, using a typological approach in analyzing the relation between personality traits and network structures, and finally, using a motif analysis of ego-networks to shed more light on the relationship between psychological attributes and personal network structure.

2.5.1 Investigating psychological sense of community and its relation to personal network structure

Psychological sense of community refers to the feeling of belonging to a collective, in which the needs of the members are expected to be met through a cooperative commitment (Sarason, 1974). Together with a sense of belonging, the members of the community develop a shared emotional connection, their needs are addressed and they are able to influence the whole group (McMillan & Chavis, 1986).

Social cohesion and the sense of belonging have been connected conceptually with the density of the social network (Maya-Jariego, 2004). However, this association has hardly been researched empirically with structural properties indicators, be it of complete networks or personal networks. The existence of a moderate correlation has been proven in some cases (Maya-Jariego & Holgado, 2015). It is expected that other indicators of structural cohesion are also related to sense of community. In this study, we carry out a systematic exploration in this respect, which allows for the comparison of the relationship between network indicators and sense of community with the relationship between network indicators and other psychological attributes that were researched previously in a greater extent (e.g., personality traits).

2.5.2 Typological approach

Structural network properties analysed in previous research are strongly associated with each other. In this respect, comparison of networks through isolated characteristics is an empirical approach with important limitations. For example, an outgoing person may tend to present their contacts to each other, which increases the density of his network. However, he is also more likely to make new contacts, which not only increases the size of the personal network, but also indirectly, the number of relationships necessary for the network to also increase in density. For this reason, analytic strategies have been proposed to address the configuration of whole networks, such as typologies based on cluster analysis (Bidart et al., 2018; Giannella & Fischer, 2016; Maya- Jariego, 2002) and triad census (Kalish & Robins, 2006). The factorial analysis of the structural properties of personal networks has differentiated the cohesion, fragmentation and integration of personal networks as significant dimensions of variability (Lozares et al., 2013; Maya-Jariego & Holgado, 2015).

2.5.3 Triadic measures

The other approach, to circumvent the problem of describing a network with many different structural measures, is to focus on the network's smallest possible units, triads. The term triad is often associated with the work of Simmel (1950) who stated that a group of three people is a basic unit of network analysis. Siltaloppi & Vargo (2017) in an overview of the triad concept state that triads cannot be defined merely as systems of three actors, but at least, by the coexistence of two ties between three associated actors. These authors suggested that triadic analysis is not limited to the specific systems of exactly three actors but applicable to any system of at least three actors. Consequently, triads can be used for analysing multiple forms of triadic relationships in systems like ego-networks.

This kind of mesoscopic network approach could be fruitful for shedding some light on the psychological attribute – social networks connection, as triads are easily adapted to measuring and theorizing (Vinacke & Arkoff, 1957). Kalish & Robins, (2006) introduced triadic measures (in the following text addressed as KR triads) derived from ego-networks that are supposed to capture differences between networks which are not captured by other measures (e.g., size, density, efficiency) and provide more accurate and informative descriptions than global network measures. The authors found that this measure could be related with individual differences in personality traits. The measure is based on proportions of several possible configuration of triads with strong and weak ties in ego-network (including ego). One of their findings was that a higher proportion of strong closed triads is positively associated with extraversion and negatively with neuroticism. The opposite holds for weak closed triads. Also, individual and group focus was positively related with proportion of open and closed triads, respectively.

In contrast to the original KR triadic measure, which looked at triads in an ego-network that included ego, in this paper we are presenting three variants of KR measure that take into account triads in ego-networks, but without the ego. It should be noted that by doing this, the implicit assumption of the original KR measures that psychological traits can predict triadic configurations that include ego is extended to triadic configurations in which ego is not included directly. Also, the original KR measures were developed and used in networks with varying numbers of alters (e.g., Staiano et al., 2012), while we have developed three versions of this measure that are also applicable to networks with a fixed size (described in Appendix 2).

When an alter *i* is connected to two other alters, *j* and *k*, the triad that describes the relationship between these three alters is denoted by a three-letter combination. As a notation system, S represents strong ties and W represents weak ties. A total of seven possible triads can occur between alters in egocentric networks, four closed triads: SSS, WWW, SSW, and SWW; and three open triads: WWN, SSN, and SWN, where N stands for an absence of tie between alters (shown in Figure 2.1). Differently from KR triads, here the ordering of letters is not informative, for example, triads SSW, WSS and SWS are equivalent as all letters indicate the strength of tie between any pair of alters. Seven distinct triads fall under one of the two groups: closed or open triads which represent a purely structural description without taking into account the strength of present ties in the triad.

We propose three different ways of calculating the triadic census for alters in ego-network with fixed size: KR variant I, KR variant II, and KR variant III. The procedure of calculating these measures is described in detail in Appendix 2 and is done with open and free software Python.

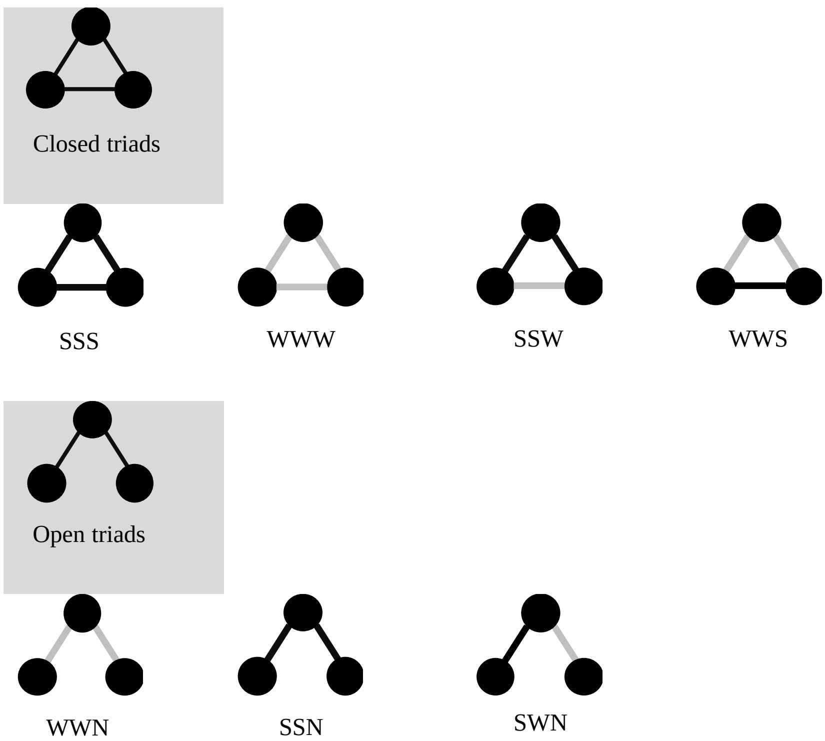

Figure 2. 1 Two groups of seven possible triads that can occur in egocentric networks among ego's alters when considering the strength of ties. Triads with a grey background represent two distinct groups of configurations, open and closed. In triads with white background, a black line represents a strong tie, a grey line represents a weak tie, while all nodes are ego's alters. The three letters are unique code for each triad (S-strong, W- weak, N- no tie is present).

2.5.4 Research questions

In this research, we combine the construction of typologies and the census of triads to describe the relationship of personality traits and psychological sense of communities with the structure of personal networks. Specifically, we aim to answer the following questions:

(1) What is the type and the strength of an association between the variability in cohesion, fragmentation and integration of personal networks and individual differences in the Big Five personality factors?

(2) How is the density and cohesion of personal networks related to Psychological Sense of Community?
(3) What is the type and the strength of an association between the presence of some triadic configurations (e.g., closed triads) in personal networks and both personality traits and Psychological Sense of Community?
(4) Do typologies and census of triads effective strategies provide new insights about individual differences in personal networks?

2.6 Method

2.6.1 Participants

We surveyed 100 adults living in the metropolitan area of Seville, of which 60 were women and 40 men, with an average age of 38.74 years (*SD* = 14.64). Socio-demographic differences were observed, both in terms of education: 46 interviewees had completed a university degree, 46 secondary school, and 8 primary school; and employment: almost two-thirds (64) were employed, 24 were students, and 14 were inactive (unemployed or retired). The data was obtained through face-to-face interviews lasting approximately 1 hour. The respondents participated on a voluntary basis and were notified that the data would be treated in an aggregated manner, guaranteeing the confidentiality of the information.

In the surveys using the five personality factors model, samples of university students predominate, although previous evidence demonstrates that the variability of personal networks can be influenced by demographic aspects (Roberts et al., 2008). For this reason, in this study, we seek to introduce some diversity in the profile of the respondents.

2.6.2 Instruments

The respondents answered two psychometric scales, a personal networks interview and a list of questions on socio-demographic aspects. Next, we describe each of these instruments.

2.6.2.1 Ten-Item Personality Measure (TIPI) (Gosling et al., 2003)

This 10-item scale measures the Big Five personality dimensions: neuroticism, extraversion, open- ness to experiences, agreeableness, and conscientiousness (N, E, O, A, and C, respectively). It is a measure with two items referring to a personality trait for each of the five dimensions (e.g., "extraverted, enthusiastic," "sympathetic, warm," "calm, emotionally stable") with two adjectives. The participants score each item on a scale ranging from 1 ("Strongly disagree") to 7 ("Strongly agree"). Each personality dimension is evaluated with two items. The overall score of the scale is the average of the response of each participant of the 10 items.

The shortness of the TIPI means no high reliability coefficients are obtained. However, the instrument obtains good indicators of convergent validity, discriminant validity and test–retest reliability. The scale allows an efficient evaluation of personality traits (Gosling et al., 2003). The Spanish version has been validated with good results (Renau et al., 2013). In general, the Big Five model shows a great consistency in different cultural contexts (Benet-Martinez & John, 1998).

2.6.2.2 Psychological Sense of Community Scale (PSC) (Jason et al., 2015)

This scale evaluates psychological sense of community through three factors: Entity, Membership, and Self. This is an inventory of nine items that respondents score on a Likert-type scale from 1 (“Strongly disagree”) to 6 (“Strongly agree”). In our case, it was applied referring to the neighbourhood where the respondent resided at the moment of the interview. The items allow to assess the characteristics of the community (Entity) (e.g., “this neighbourhood is a good neighbourhood”); the relations between the members of the collective (Membership) (e.g., “the neighbours can get help from other neighbours if they need it”); and the emotional connection with the group (Self) (e.g. “this neighbourhood is important to me”). The overall score of the scale is the average of the response for the nine items. The original validation yielded a reliability alpha coefficient of 0.923, whereas in this study we obtained a coefficient of 0.871.

2.6.2.3 Network measurement

To evaluate the personal network, the following name generator was used: Please give me a list of 45 people with whom you have a relationship throughout the week. I am interested in those people with whom you have frequent and habitual contact. They can be colleagues, neighbours, relatives, friends, or people with whom you share hobbies. They can be from your neighbourhood, from nearby neighbourhoods, or even from more distant ones. It is important that they are the 45 people with whom you have a more frequent relationship. Then, for each pair of alters, the respondents were asked to rate the type of relationship on four levels of intensity, where 0 corresponds to “they do not know each other”; 1, “they know each other”; 2, “they have a relationship”; and 3, “they are friends or have a strong relationship.” Therefore, we generated 100 symmetric and valued matrices of alter–alter relationships, with 45 actors each.

The establishment of a fixed number of alters introduces a bias in the structural properties of networks (Neal & Neal, 2017). However, it is a standardization method that facilitates the processing of data and has been shown as a reliable method of socio-metric nomination (McCarty, 2002; Molina et al., 2014). It has been used with all types of populations for more than a decade and a half, with good results of validity and reliability. In addition, it is very advantageous for the standardization and comparability of personal networks (Maya-Jariego, 2018).

2.6.2.4 Socio-demographic variables

Finally, the participants provided information on their professional situation, educational level, people with whom they live, type of housing (owned or rented), and the time they have lived in the neighbourhood of their current residence. In addition to the data about gender and age, each respondent was asked to indicate if they collaborate with a community organization, as well as, where appropriate, the time and format of participation (online or in person).

Table 2. 2 Descriptive statistics for personality and Sense of Community measures

	Minimum	Maximum	Mean	Standard deviation	Skewness	Kurtosis
Ten Item Personality Measure (TIPI-10)						
Extraversion	1	7	4.84	1.47	-.284	-.659
Agreeableness	2.5	7	5.61	1.04	-.703	.155
Conscientiousness	3	7	5.60	1.15	-.479	-.874
Emotional stability	1	7	4.93	1.43	-.626	-.421
Openness	1	7	5.06	1.34	-.661	.263
Mean TIPI-10	3.6	7	5.21	0.67	.094	.030
Psychological Sense of Community Scale (PSC)						
Entity	1	6	4.73	1.23	-.969	.247
Membership	1.33	6	4.42	1.09	-.659	.147
Self	1	6	4.70	1.24	-1.009	.355
Mean PSC	2	6	4.61	0.98	-.707	.332

Note. Emotional stability is the positive dimension of the factor "Neuroticism".

2.6.3 Procedure and data analysis

The 100 matrices of personal networks were analysed with UCINET 6.627 (Borgatti et al., 2002). To summarize the structural properties of each personal network, four specific indicators were calculated: density, degree centralization, number of components, and number of cliques. Normally the indicators of centrality, cohesion and groups are highly correlated with each other. This is why some previous studies have tried to determine which are the fundamental dimensions of variability. In two community surveys with different representative samples, it was found that density/centralization, cliques, and components report different factors (Lozares et al., 2013; Maya-Jariego & Holgado, 2015), which correspond to cohesion, integration and fragmentation of the network, respectively.

Next, we created a database in which, together with the response to the psychometric scales and the socio-demographic variables, the four summary indicators of each respondent's personal network were included.

We used quick cluster analysis to develop typologies. In our approach to cluster analysis, we used the information from the literature, our data, and combined it with the methodological considerations and other analyses done in this study. In this way, the classification "is partly constructed and partly discovered" (Maya-Jariego, 2002, p. 4). The criteria variables were selected considering previous research, descriptive analysis, while opting to choose the variables which are not highly correlated with each other (below 0.7). Using completely uncorrelated variables for cluster analysis (e.g., density and cliques), the best quality solution with the highest Silhouette score led to a high number of clusters (seven) for our sample size. Therefore, we used transitivity instead of density. Transitivity is highly related with density ($r = 0.65$) because it also captures the network connectivity, but unlike density it considers its triadic level rather than its dyadic level, which is more in line with our other analytical strategy which is focused on triads.

2.7 Results and discussion

2.7.1 Descriptive data of individual differences

Table 2.2 summarizes the descriptive statistics of personality and sense of community. The data present a slightly asymmetric distribution, although very concentrated around the average scores. In both cases, there is a positive bias in the assessment of personality traits and sense of belonging.

The five personality traits are generally independent of each other. The statistically significant correlations observed are between extraversion and openness to new experiences ($r = 0.397$, $p < 0.01$), and between agreeableness and emotional stability ($r = 0.531$, $p < 0.01$). On the other hand, three factors of PSC have a moderate correlation with each other (with $r = 0.417$, $p < 0.01$; $r = 0.499$, $p < 0.01$; and $r = 0.655$, $p < 0.01$).

Table 2. 3 Pearson correlations between psychological attributes and personal network measures in the network of acquaintances (NA) and the network of strong ties (ST)

	Density		Degree centralization		Number of components		Number of cliques	
	NA	ST	NA	ST	NA	ST	SA	ST
Personality								
Extraversion	.105	-.027	-.041	.001	-.016	.039	.065	-.020
Agreeableness	.103	-.010	-.271**	-.006	-.023	.087	-.155	.037
Conscientiousness	.072	-.092	-.004	-.125	-.034	.133	-.130	-.108
Emotional stability	.211*	.167	-.193	.019	.062	.036	-.169	-.087
Openness	.046	.084	-.043	-.066	-.064	-.121	-.006	.184
Mean TIPI-10	.209*	.058	-.201*	-.062	-.024	.056	-.137	.002
Sense of Community								
Entity	.237*	.166	-.027	.152	-.132	-.070	-.052	.010
Membership	.265**	.148	-.112	.071	-0.44	.017	-.214*	-.042
Self	.243*	.119	-0.60	.093	-.139	-.028	.100	-.053
Mean PSC	.299**	.174	-.078	.129	-.129	-.035	-.059	-.034

Note. Emotional stability is the positive dimension of the factor "neuroticism".
* *p*<.05.
** *p*<.01.

2.7.2 Relationship of network indicators with psychological attributes

Table 2.3 presents the correlations between psychological attributes (personality traits and psychological sense of community) and the structural properties of personal networks. The overall score on the personality scale has a positive association with density (r = 0.209, p < 0.05) and a negative relation with degree centralization (r = − 0.201, p < 0.05). That is, the personality profile shows a significant relationship with the indicators of cohesion, but not with the other two factors. More specifically, respondents with greater emotional stability have denser personal networks (r = 0.211, p < 0.05), while a higher score in agreeableness is significantly related to lower scores in degree centralization (r = − 0.271, p < 0.05).

On the other hand, Psychological Sense of Community has a positive relationship with the density of the personal network (r = 0.299, p < 0.01). This is the strongest correlation observed, which is confirmed by the fact that all the factors of the PSC scale maintain a significant correlation with density. Finally, the Membership factor has an inverse relationship with the number of cliques (r = − 0.214, p < 0.05).

In the context of ego-network without ego and its ties, density is equivalent to the proportion of closed triads with ego. Density is positively correlated with all four Sense of Community measures, and it has shown similar relationship with emotional stability, and the mean score of the TIPI10 scale (Mean TIPI10). The opposite pattern exists for the complementary measure of density of the missing ties. Transitivity showed a similar pattern of results as density, with correlation with the Big Five traits being slightly higher, and correlations with Sense of Community traits slightly lower than for density.

2.7.3 Relationship of triadic measures with psychological attributes

For the analysis of triads, we made three methodological variants: (1) triads as proportions of all possible triads, (2) triads as proportions of all existing triads in the ego-net, and (3) triads as z-scores in comparison to the individually tailored null model. The rationale and details of each approach are described in Appendix 2. In the results presented in this section, all correlations are Spearman's rho coefficients, and significance testing is based on 1000 permutations. If the value of coefficient had a percentile value higher than 97.5 or lower than 2.5, it was considered significant at the level of p =< 0.05. The strength of correlations is mostly low (below 0.4), as previous research suggested and due to a small sample size, we were not able to detect correlations below 0.16 that are statistically significant.

The first variant showed the greatest number of significant associations, that were the most strong as well. In Figure 2.2, KR triads of ego's alters, as proportions of all possible triads and their correlations with psychological attributes, are shown. The measures of the Sense of Community seem to be more connected with KR triadic measures than personality traits: closed triads are positively correlated with Entity, Membership, Self, and the mean of the PSC, while open triads are correlated to a similar degree only with Self. Strong closed triads (SSS) are correlated only with Entity, while weak closed triads (WWW) are related positively with both the mean score of the whole scale (Mean PSC) and Self. Additionally, weak open triads (WWN) are correlated with Self. These findings taken together suggest that, for the sense of community, alters embedded in triads with weak ties seem to be of importance.

The second variant showed more significant coefficients with personality factors than the first variant (see Figure 2 in Appendix 2). This general pattern may imply that by controlling for triads present in the network, triadic measures tend to show relatively more associations with personality traits rather than with the components of sense of community. Specifically, the SWN (a "mixed" triad) seems to be the most relevant in this regard, as it is negatively correlated with E, C, emotional stability and the mean score of TIPI scale. In fact, the latter is the highest detected correlation between network and personality in this study.

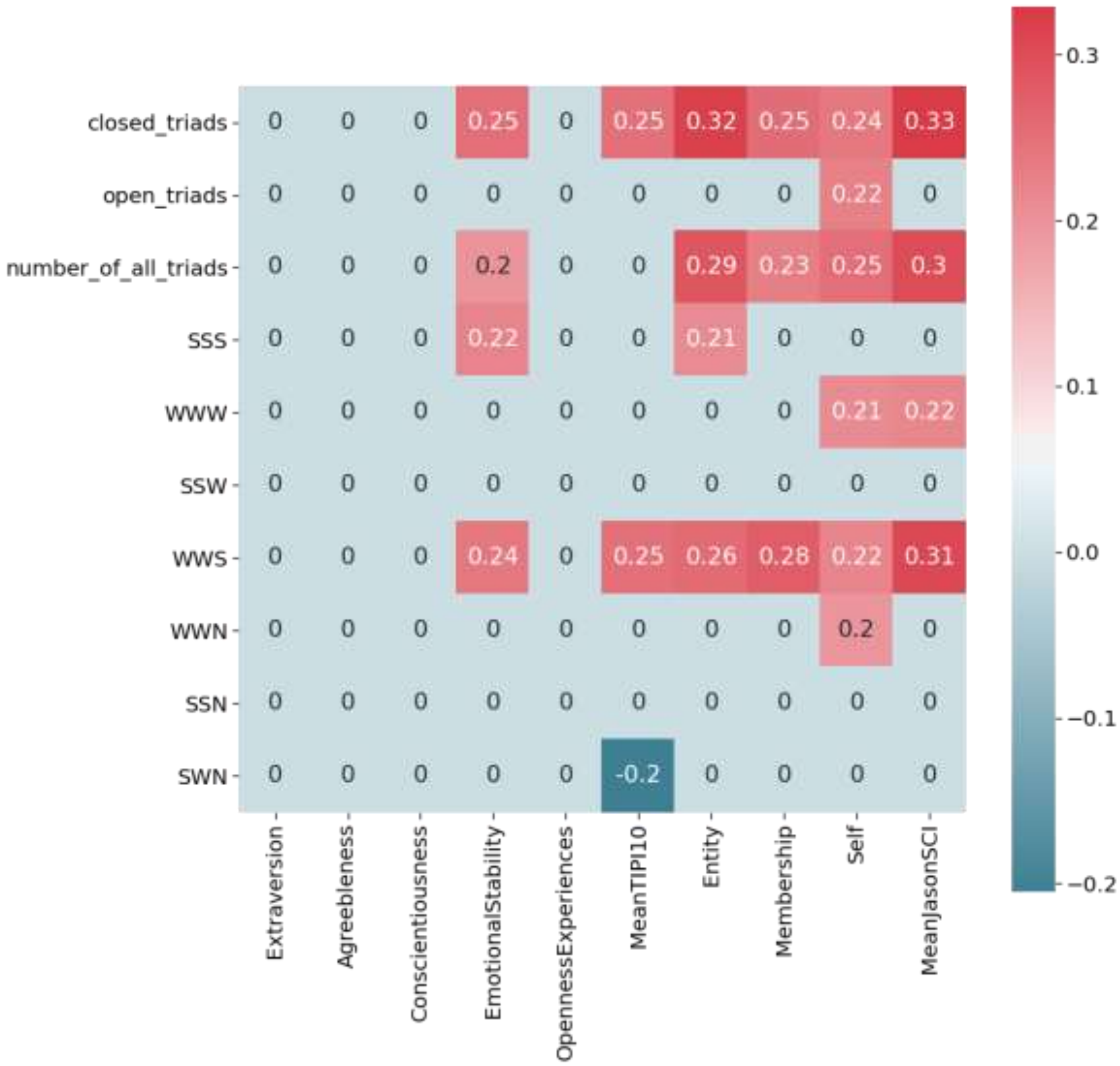

Figure 2. 2 Significant correlations between KR variant I measures and psychological attributes (based on 1000 permutations)

In the third KR variant, in which we control for the density of the personal network and the individual tendency to assign strong or weak ties, the smallest number of significant associations is observed (see Figure 3 in Appendix 2). Yet, it is interesting to note that Entity and the mean of the sense of community scale are positively correlated with WWW configurations, again suggesting that having weakly connected alters is an important aspect of psychological sense of community. This is a surprising finding due to lack of any connection of that group of psychological attributes with open or closed strong triads. This combination of results suggests that weak ties between alters are more important than strong ties between alters for some aspects of the subjective feeling of community (Entity) and the overall mean of sense of community scale.

2.7.4 Types of personal networks

We classified personal networks using transitivity and number of cliques as criteria variables. To do this, we applied k-means cluster analysis[6], with a maximum of 10 iterations. The solution of four categories showed good Silhouette score (0.426) indicating that a structure has been found and the clusters are not overlapping.

As shown in Table 2.4, the cluster 1 is the smallest and it describes networks with a high number of cliques and relatively lower transitivity. The second and third clusters are more than double in size than the first one and they describe networks with a small to average number of cliques and low transitivity, and networks with high transitivity and small number of cliques, respectively.

We found no differences between clusters regarding gender ($\chi 2$ = 0.99, p = 0.60, df = 2). With respect to age, there is a tendency for individuals having a network with low transitivity and an average number of cliques to be younger (37.4 years old), while those with high transitivity and small number of cliques are slightly older, with the smallest cluster of individuals occupying networks with low transitivity and high number of cliques is in the middle (40.3 and 38.1 years old, respectively). On a descriptive level, the participants with high transitivity and a small number of cliques expressed the highest Psychological Sense of Community, while the participants with low transitivity and a high number of cliques reported the lowest Psychological Sense of Community.

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[6] K-means cluster analysis, using updated means and a convergence criterion of 0.02

Table 2. 4 Three types of personal networks: centroids of the final conglomerates

	Cluster 1(N=16): Low transitivity, high number of cliques	*Cluster 2 (N=42):* Low transitivity, average number of cliques	*Cluster 3 (N= 42):* High transitivity, small number of cliques
Transitivity	0,69	0,67	0,84
Cliques	44,19	21,64	12,33

Table 2. 5 Three personality profiles: centroids of the final conglomerates

	Cluster 1 (*n*= 24) *High N/low A*	Cluster 2 (*n*= 38) *Reserved*	Cluster 3 (*n*= 38) *Positive profile*
Extraversion	5,52	3,43	5,83
Agreeableness	4,50	5,89	6,04
Conscientiousness	5,46	5,59	5,71
Emotional Stability	3,02	5,39	5,68
Openness to Experiences	5,02	4,29	5,86

Note. Emotional stability is the positive dimension (reverse scored) of the factor “neuroticism”.

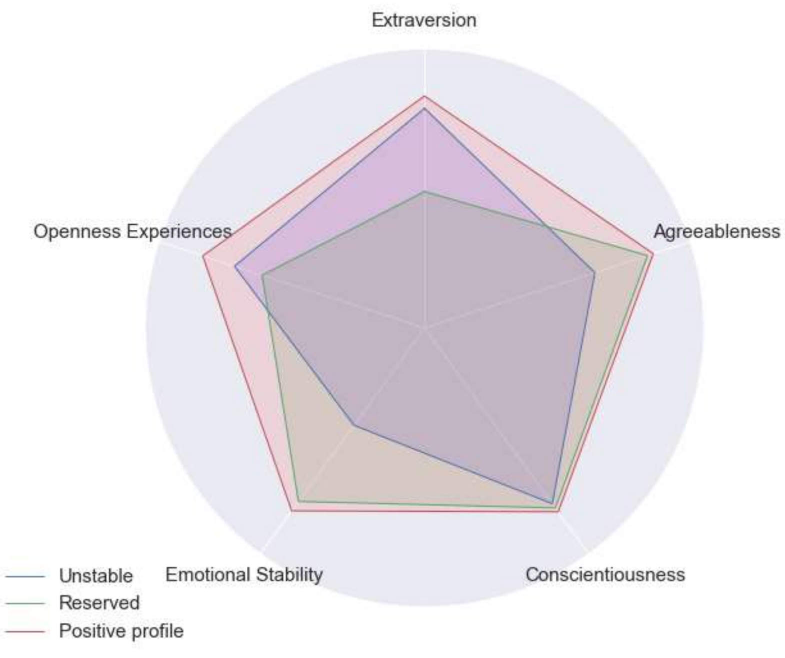

Figure 2. 3 Three personality profiles: High N/low A(Unstable, N=24), Reserved (N=38) and Positive profile (N=38)

Table 2. 6 The contingency table showing the relationship between personality types and network types with expected frequencies in the brackets

Ego-network clusters /Personality clusters	Low transitivity, high number of cliques	Low transitivity, average number of cliques	High transitivity, small number of cliques
High N/low A	7 (3.8)	12 (10.1)	5 (10.1)
Reserved	5 (6.1)	19 (16)	14 (16)
Positive Profile	4 (6.1)	11 (16)	23 (16)

2.7.5 Types of personal networks and personality profiles

With the same classification procedure as in the previous section, we obtained three personality profiles after applying a cluster analysis (Table 2.5; Figure 2.3). One cluster (Cluster 3) consisted of 38% of the respondents that have a positive profile, obtaining the comparatively highest score in each of the five personality factors. The second cluster (Cluster 2), which also included 38% of the respondents, is characterized by having comparatively lower scores in extraversion and openness to experience, forming a profile of more reserved individuals. Finally, the smallest cluster (14%) stands out for having comparatively higher scores in neuroticism and lower scores in agreeableness, that is, more emotionally "unstable"[7] individuals.

The comparison of individual variables according to the three profiles only yielded significant results in the case of degree centralization (F (2,97) = 5.195, $p < 0.01$) and the Membership factor of the PSC scale (F (2,97) = 5.777, $p < 0.01$). Specifically, from the unstable profile (cluster 1) to the positive profile (cluster 3), personal networks are successively less centralized and with higher scores in sense of belonging.

Finally, we looked at the relationship between clusters of networks and clusters of personality profiles. The results are presented in Table 2.6. The result of chi-square test suggests that occurrences are statistically different from what would be expected by chance ($\chi\ 2$ = 11.90, p = 0.01, df = 4). Individuals with unstable profile are overrepresented in the "low transitivity/high number of cliques" cluster and also in the "low transitivity/average number of cliques" cluster, albeit to a smaller degree. On the other hand, they are underrepresented in the cluster with "high transitivity/ small number of cliques." The opposite pattern holds for participants with positive profile. The individuals belonging to the reserved personality cluster show a smaller discrepancy between empirical and expected frequencies in general, although they are slightly less represented in the "high

[7] Despite its negative connotation, the term "unstable" was originally used by McCrae & Costa (1987).

transitivity/small number of cliques" cluster and slightly more in the "low transitivity/average number of cliques" cluster.

2.7.6 Triads and personality types

In this final analysis, we aim to explore at a descriptive level the relationship between different personality clusters and KR triads. The density measure is included via the information of the proportion of closed and open triads that do not contain ego. As shown in Figure 2.4, among the clearest differences between clusters exist for purely structural measures (open and closed triads and all triads), implying that measures without additional information about the weight of ties among alters are informative for differentiation between personality clusters.

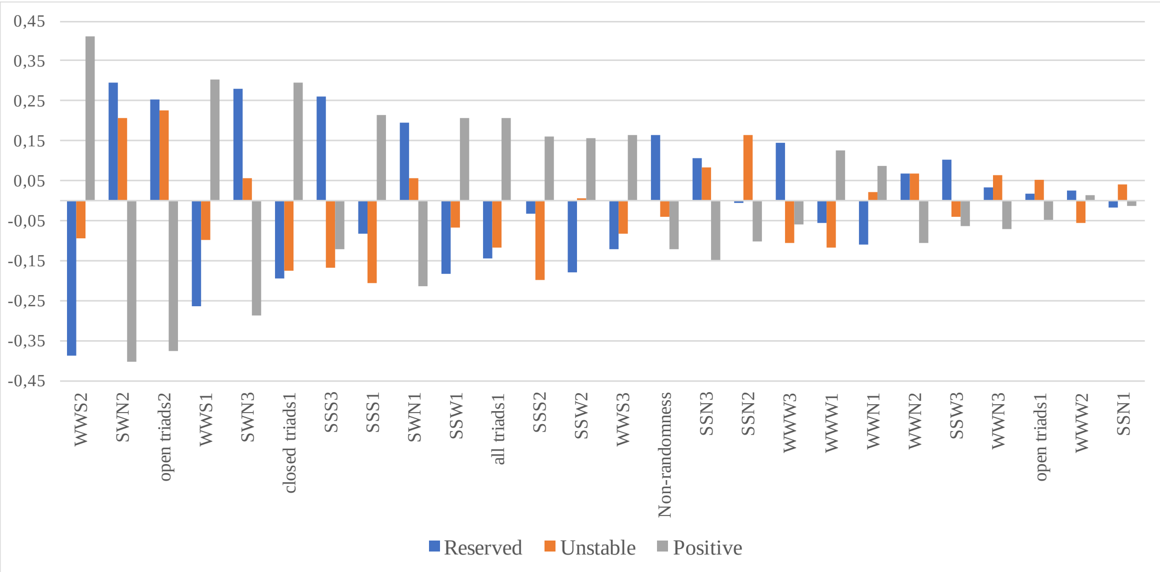

Figure 2. 4 Differences in density and KR measures among three personality types – average values for a personality type group are standardized and KR measures are ordered from the KR measure with highest diversity among clusters to the lowest.

It is fitting to try to relate the proportion of closed triads with ego (density) in different personality clusters to Simmel's theory of "individuality" in dyads and triads (Wolff 1950). Our results suggest the Simmel's theory was right, if we relate "strong" personality with positive profile and "decided" personality with other two clusters, reserved and unstable. From that we can extrapolate specific prediction regarding preference of positive personality profile for closed, and other personality types for open triads.

Our results indicate that even when ego is excluded, the proportion of all triads (meaning different closed and open triads taken together) and closed triads alone is higher in ego-networks of individuals with positive personality profile than for the other two personality clusters. Based on figure 2.4 no KR variant stands out as better in differentiating between personality types. The networks of individuals with positive profile have more weak triads with one strong tie (WWS), and less open mixed triads, than the other two personality clusters. The most likely explanation of a higher average proportion of WWS triads in this cluster is that the strong tie in a WWS triad constitutes a dyad with which ego is strongly connected. That is, a WWS triad containing three alters *i*, *j* and *k*, of which *j* and *k* are strongly connected is a proxy of a SSS triad in which ego is included (triad of ego, *j*, and k). Another general pattern visible in Figure 2.4 is that overall KR measures differentiate between the positive cluster and the other two clusters, reserved and unstable. However, the latter two seem to be almost undistinguishable by most KR measures. Figure 2.4 shows that networks of individuals belonging to the reserved cluster have more of strong closed triads, when controlling for density and strength of ties (KR measure III), than individuals in the other two clusters. This finding may be explained by a possible tendency of reserved people to form their networks around connected actors (friends of friends), or around very close individuals, such as family members.

2.8 General discussion

In this research, we have observed a significant association between individual personality differences and the structural properties of personal networks. On the one hand, the highest scores on the five aggregate personality factors are inversely related to the degree centralization of personal networks. On the other hand, emotional stability is positively associated with density. All these findings show that individual personality differences are reflected in the cohesion of personal networks. This was confirmed with the building of typologies, which showed that individuals with a personality profile with a greater presence of neurotic features were less likely to have articulated personal networks (organized in delineated clusters but with comparatively high levels of density). It is interesting to notice that of all the three personality clusters, people with reserved profile seem to be presented in each network cluster most similarly to what would be expected by chance. This pattern may be a relevant finding since it suggests the possibility that for this type of personality—less extraverted and less open to experience—psychological attributes are less associated with their networks. It could be because they are less spontaneous in the process of creation and maintenance of their networks, and/or because they simply “inherit” the networks of their alters. That, in turn, may lead to their networks being less a reflection of their psychological attributes. On a more general level, the group of people with reserved type of personality (38%) may be one of the reasons why the detection of a relationship between psychological attribute and social networks usually yields small effects and is often inconsistent. It is possible that there is no relationship between the psychological attributes and social networks for people with a reserved personality profile, while for the other two groups the association may exist and be higher than when looking at all of them together.

Regarding the introduction of other variables, besides the Big Five personality traits, in the exploration of the psychological attribute-social networks relationship, the important empirical observations of this study refer to Psychological Sense of Community. We verified that the density of the personal network is associated in a consistent way with the feeling of belonging to the neighbourhood and, more broadly, with Psychological Sense of Community.

To summarize, when looking at the psychological dimensions of an individual and dimensions of individual's social network in the manner where different aspects are analysed separately, we may "fail to see the bigger picture." This was already recognized in both, network research literature on immigrants (Lubbers et al., 2007; Maya-Jariego, 2003), and the personality research. In the latter, the typological approach has been often contrasted with the traditional dimensional approach, but recently it has undergone a renaissance and the most prominent researchers (Costa et al., 2002) acknowledge that it may prove useful for labelling trait combinations that are associated with consequential outcomes. Those two trends taken together with our findings imply that typological approach to both psychological attributes and social networks may not only be more intuitive but also could be more useful and maybe even necessary when describing and understanding the interplay between individual psychological attributes and network structure.

In the analysis of triads, we used three different modifications of KR triadic census measure applied on alter–alter ties, suitable for networks with a fixed size. The three variants showed different patterns of association regarding the two groups of the measured psychological attributes. The important take-away message is that researchers need to be aware of which exact procedure they use when measuring triads – or indeed, any network property, as they may be differently related with individual psychological attributes.

Our findings extend those found by Kalish & Robins, (2006) that strong and closed triads in which ego is embedded are positively related with ego's emotional stability to the same triadic configuration between ego's alters (when using the first KR variant). However, we did not observe the association between both Emotional stability or Extraversion with WWW, which was found by Kalish & Robins for WWW with ego included. Instead, in our study, weak closed triads (WWW) of alters were related with Sense of Community and Conscientiousness, noting that the latter may be an indication of possible methodological artefacts.

Regarding open triads, we did not expect to arrive at a similar pattern of results as Kalish & Robins, since an open triad with ego, in which ego is the "bridge," is psychologically and socially different from an open triad between three ego's alters. While Kalish & Robins reported a significant relation of open triads (where ego is a broker) with psychosocial traits (individual focus, locus of control), but not with the Big Five personality traits, we found that open triads among alters are associated with ego's emotional stability and the mean score of the TIPI scale. SWN triads in the second KR variant and the mean score of the TIPI scale had the highest correlation found and negative, implying that individuals with high scores on all Big Five traits ("positive profile") are less likely to report all three kinds of ties (absent tie, weak, and strong) appearing in the same triad of alters.

The most sophisticated measure of KR is the third variant which is based on individually tailored null model, and a generation of sample of 100 random networks in comparison to which the z-score for every triad is calculated. By using this variant, we controlled for density and the composition of ties strength and uncovered new associations between specific triads and traits Agreeableness and Conscientiousness. Additionally, we constructed the measure of non-randomness of the alter–alter ties in ego-network based on absolute z-scores of triadic motifs, and found it to be negatively associated with Agreeableness. A possible interpretation could be that people with higher Agreeableness tend to either inhabit, perceive or report more random triadic structures among theirs alters.

Although in our case we did not include ego in the analysis, the triad census showed a degree of relationship with psychological attributes similar to that originally observed by Kalish & Robins, (2006) and Staiano et al., (2012). We moved "one step" away from the ego—due to excluding ego's ties to alters from the analysis – to its immediate social environment. Nevertheless, we found that an association between psychological attributes and differently measured triads of alters still exists. Therefore, we may interpret this finding as an additional "lead" that individual psychological attributes and social networks influence each other seeing that even ties in which ego is not directly involved are related with ego's attributes.

It is important to note that these findings do not necessarily apply to other relationships in ego's network, e.g., ties among ego's alters and their friends (alters of alters) who are not directly connected to ego (two links away from ego). Thus, we are not able to generalize to all the triads in ego's social life – but only to triads among his/her alters. Given that we did not measure ego's ties in terms of strength, the direct comparison of different kinds of triads regarding their distance from ego is not possible and should be examined in future research.

2.8.1 Limitations of the study and future research

On the one hand, in our analysis, we implicitly regarded all alters as equally important. However, this is not the case, and it may be that the proportions (KR measures) would be different if we looked at alters with only high importance (with strong tie to ego). Based on KR measures, there is no information about where these triads are concentrated and among which alters exactly. Nonetheless, obtaining a fixed number of 45 alters seems an efficient strategy, which simultaneously allows for the examination of the most significant relationships for the individual, and at the same time obtaining a representation of the diversity of structures in personal networks. Another limitation of our study, typical of this kind of research, is a small sample. It can affect the range of observed correlations and introduce a bias in the statistical inference (due to multi-testing). Although small, our sample is made of adults for whom we can assume that on a group level the psychological attributes, as well as networks, are more stable than it is the case of student population on which the data has been collected for some of the most notable previous studies.

We took advantage of well-established measures of network motifs often used in the application of network science in biology (Milo et al., 2002), to measure the network's on meso level—the level which is more appropriate for interpretation and theory development for our topic than the macro level captured by most network measures. These fine-grained and individually tuned measures of configurations may be more elegant and straightforward alternative to specifying the same exponential random graph model for each personal network and looking for meaningful differences in parameters between networks. It does not mean that we exhausted all possibilities of motif analysis. For example, including additional constraints (e.g., controlling for degree distribution in the ego-net) may yield to different observations about the relationship with psychological attributes. Therefore, future studies should further extend our approach of measuring different motifs in individual ego-network.

Our results are based on self-reported measures of one's network, making the network measure inherently subjective. From a psychological perspective, this subjectivity is not necessarily problematic as individual behaviour is in large part determined by our own subjective experience. The reported networks are not, however, likely to be the exact reflection of reality, and there is always a possibility that people with certain traits have a tendency to see their social environments with a specific bias (e.g., highly emotionally unstable people may underestimate the strength of ties between their alters). To investigate this interesting research question on its own, future research should incorporate objectively collected measures of social interactions. Furthermore, longitudinal data would allow examining the co-evolution of networks and individuals. In the same vein, incorporating the intensity of the relationship of ego with each alter, as well as the information about the affective quality of ties represent some of the many possible future research avenues.

Chapter 3

Expanding network analysis tools in psychological networks:

Minimal spanning trees, participation coefficients, and motif analysis applied to a network of 26 psychological attributes

3.1 Prelude

In the last decade, network approaches have been increasingly used in psychological science for the investigation of psychological constructs and their interrelations in psychological science, as complementary or alternative to typically used and well-established methods (e.g., confirmatory factor analysis, structural equation modelling). This approach has introduced a different perspective on psychological constructs and has found its application in many subfields of psychology: intelligence (Van Der Maas et al., 2006), psychopathology (Cramer et al., 2016), personality psychology (Costantini et al., 2017), and social psychology (Dalege et al., 2017). One specific asset of the network approach is that it defines psychological constructs as constituents of a complex system of direct interactions enabling us to ask detailed questions about relationships of mutual influence among these constructs (Schmittmann et al., 2013; Cramer et al., 2012; Borsboom & Cramer, 2013; Kossakowski & Cramer, 2017). Specifically, Gaussian graphical models (GGM, Epskamp et al., 2017) for continuous variables and Ising models for binary variables (van Borkulo et al., 2015) have been used for network estimation with the aim to describe conditional independence relationships between variables, operationalized as partial correlations or conditional associations between variables (Borsboom & Cramer, 2013, Epskamp et al., 2018; . Epskamp & Fried, 2018). In this approach, a psychological network consists of nodes - psychological variables – and connections between nodes that represent the degree (and direction) of associations between each pair of variables, when the influence of every other variable in the network is controlled for.

After the construction of psychological networks, the quantitative analysis often proceeded with the computation of a centrality analysis to answer which variable is most "dominant"

Adapted from:
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or "important". Also, some global features have been of interest, such as network connectivity (Van Borkulo et al., 2014). However, besides centrality measures and global measures of network structure, which focus on microscopic and macroscopic level of network, respectively, other analytical tools have been mostly ignored and rarely used in the study of psychological networks. This limited focus results in a limited set of questions that can be answered. We argue that, in order to answer research questions using psychological networks, researchers should go beyond the measures commonly used in psychology. The field of network science offers many alternative metrics that are worth considering when translating one's research question into quantifiable network properties. The main idea of this paper is to apply such techniques, which are already widely used in network science, to provide deeper understanding of psychological networks.

The structure of the paper is as follows. Firstly, we will describe some of the challenges in the analysis of psychological networks and link them with the three methods we propose in this paper, following with the general overview of the network that will be used for the demonstration of these methods. Next, we describe an illustrative dataset and apply the methods typically used in network analysis. Subsequently, we explain three methods that can be used to shed light on the network topology: Minimum Spanning Trees (MSTs), the Participation Coefficient (PC), and motif analysis. For each method, we will explain specific procedures and modifications, and conclude with results and discussion. Finally, in the general discussion we summarize the benefits and possibilities of including the proposed methodologies in the field of network psychometrics, and highlight interesting hypotheses that we arrived at using these analytical tools.

3.1.1 Identifying challenges in the analysis of psychological networks

In this paper, we propose three methods that not only provide novel insights into the network but circumvent some prominent methodological issues in the field of psychological networks as well: finding a way to operationalize the importance of all variables included in the network in a more general way, dealing with network of variables that are not of the same kind, and how to investigate the intermediate network level.

1. Finding the hierarchical arrangement of nodes in the network: The main purpose of centrality analysis used in the analysis of psychological networks so far was to determine how entities in the network may be ordered regarding their connections with other variables (e.g. using the number and strength of connections) and regarding their overall position in the network, that is, to find out which entity is the most "dominant". The answers that arise from the application of different measures (typically strength, betweenness, and closeness) are likely to be different, as all of them capture different notions of what centrality means. However, the selection of the "right" measure is not the only challenge. Due to the small and dense nature of psychological networks, centrality measures may not meaningfully differentiate among specific nodes.

As a solution to those issues, we suggest the use of the Minimum Spanning Tree (MST), applied firstly on economics in the stocks analysis of time-series data (Mantegna et al., 1999). The MST is a reduced sub-network that connects all nodes based on the identification of the minimal set of edges needed. Besides providing a topological and hierarchically arranged skeleton of all nodes in the network, it additionally provides an insight into groupings of nodes based on their content-similarity.

2. *The implicit assumption about the homogeneity of nodes in the network:* Most used centrality measures are based on a node's relation to every other node in the network. Thereby, these techniques implicitly assume that that all nodes are a priori equally likely to be connected with any other node. This assumption is often untenable, as psychological networks may include one or more entities, or groups of entities, that differ in nature and/or measurement and therefore constitute a cluster (referred to as community or module). In psychology, such a community may arise in part because of pre-existing differences between the variables in, for example, the nature of the variables (e.g., cognitive, behavioural, emotional), kind of measurement (e.g., subjective vs objective), or some methodological aspect of data collection.

In the estimated network, variables that are more similar regarding these pre-existing differences (i.e., that belong to the same community in this sense) are more likely to be associated than variables belonging to different communities. Thus, these variables may show stronger associations among themselves and will *by construction* rank higher on common centrality measures like degree and strength. Note that this effect is especially pronounced when the size of different communities is not equal, as nodes belonging to the biggest community will by default have higher degree and strength. On the other hand, if some variables are different in some way from other variables included in the network, they may by default be expected to have less strong connections with other variables in the system. As a result, we might wrongly identify some node as central while, at the same time, a variable with a truly important role might be missed. This is important because psychological networks are increasingly starting to include psychological entities of different kinds. For example, recently some researchers (Jones et al., 2017) called for the inclusion of other variables besides symptoms when analysing psychopathological systems.

To circumvent the issue of nodes' heterogeneity, we propose the participation coefficient (PC (Guimera & Nunes Amaral, 2005)) to be used as a corrective in the procedure of estimating the most central node, because it addresses the uniformity of the edges a node has to different groups of nodes in the network.

3. The network's meso-level (or local structure): Visualization of small networks, such as psychological networks, provides immediate insights into the dyadic relationships between nodes, at the network as whole, and even can provide some notion of the grouping of nodes. Similarly, measures typically used in the analysis of networks of this kind cover analyses at the microscopic network level. Macroscopic (global) properties of a network are easily computed, although their usefulness is less clear in psychological networks due to their small size and the impossibility to claim that all relevant nodes are included in the network. The interpretation of commonly used centrality measures and global measures of network structure (e.g., average shortest path, clustering coefficient) as reflecting the importance of nodes in the system implicitly assume that the network contains all factors that are relevant to the system. However, one inherent characteristic of psychological networks is that it rarely models all factors that are relevant to the system (Jones et al., 2017). In these cases, computing centrality measures based on indirect ties (betweenness and closeness) and global network measures may not capture all relevant information. While this is a problem when analyzing the entire system, much can be learned from shifting the focus to structural patterns on a more fine-grained level (i.e., mesoscopic level, "local" network structure). Methods for investigation of small configurations in network have been first developed in social network analysis (Holland & Leinhardt, 1976), and have been redefined when applied to different types of (usually large) networks (e.g., neuronal networks, transcriptional networks, the structure of the Internet) at the beginning of the century, and have become known as 'motif analysis'. Motif analysis enables researchers to systematically investigate smaller configurations of nodes. It can help us determine, among other things, whether certain patterns, i.e., sub-graphs, represent interesting relations between constructs or methodological artefacts.

Moreover, this method addresses one of the basic questions in modeling networks: how global properties of networks can be understood from their local properties and how local topology is related to function (Milo et al., 2002). For example, in psychological networks, different measures of intelligence are known to correlate positively – they show a positive manifold. In the language of network meso-level analysis, this means that the system of different intelligence measures is characterized by smaller local structures that display positive relationships with each other. Van der Maas et al. (2006) proposed a dynamical model of intelligence in which these patterns are interpreted as indicating that reciprocal causation or mutualism plays the most important process in that system. In other words, if a network expresses certain pattern of relationships in "high" degree, it may inform us about underlying process(es) driving the system that is represented as the network.

Each of the three methods, and especially the last two (the participation coefficient and motif analysis) give a clearer picture of *all* nodes in the network. It could be argued that they provide a *more "egalitarian" approach* to nodes that constitute a network, in a sense that they allow finding that non-central (in terms of strength, betweenness, or closeness) nodes can be equally important for different parts of the network or have an interesting role in a smaller part of the network. That information can be easily overlooked when using only the most basic network analytics. Given that psychological networks are usually relatively small, it is plausible that researchers will be interested to learn more about each node in the network, whether it is central or peripheral. Moreover, sometimes nodes that are peripheral can be of special interest and/or relevance (e.g., suicidal ideation in the network of depression symptoms, intelligence in the network of psychological traits).

3.1.2 Applying three methods in the investigation of the network of different psychological attributes

Network analysis has been used mostly for looking more closely at one (or several related) psychological concepts, where nodes represent psychometric items that are part of a self-report measure (e.g., a questionnaire). In the current study, as an illustrative dataset for the proposed methods, we look at a network in which nodes are aggregated scores on self-report measures (also known as "parcels" of a questionnaire) that operationalize different psychological concepts (e.g., latent variables), most of which are not highly related, and among which direct causal relations may not be assumed. The variables in our network are supposed to measure relatively stable individual differences whose development "proceeds along mutually causal lines" (Ackerman & Heggestad, 1997:p.239). Moreover, the conditional associations between those constructs are likely to be small, as most of them are assumed to be independent. To the best of our knowledge, this is the first research that looks at the network of different psychological attributes presented as aggregated items. We use network approaches to gain new insight in how different parts of that psychological system are connected, and which attributes have the most prominent role.

In the network of psychological constructs measured by self-reports we included cognitive ability (a proxy of g-factor (Jensen, 1998)) measured with an ability test (sometimes referred in psychology as subjective and objective tests, respectively). The reason for including this substantially different variable in the network is twofold. First, we aim to demonstrate network methods that can provide more nuanced descriptions of all nodes, whatever their centrality in the network is. Including a variable – a node, which is known to be conceptually and methodologically different from others in the network, and at best only modestly associated with just some of nodes in the network, will set the stage for demonstrating the added value of proposed methods. Second, we use the opportunity to address the old question of how cognitive ability and personality are related (Griffin et al., 2015), to see how this question can be formulated and answered within the network approach.

Theoretically, intelligence is not expected to correlate with personality. For decades, researchers dealing with the personality – intelligence connection have been using correlational studies to identify if significant relationship(s) exist(s). Yet, as Eysenck (1994) in his review of the topic concludes, the research showed a striking lack of significant correlations, with few exceptions. For example, small associations have been found between intelligence and psychopathological profile (Berg et al., 1985), and introversion-extraversion related differences in style of intellectual performance (speed/accuracy ratio; Howard & McKillen, 1990). Seeing that this approach failed to find any substantial relationship, Salovey and Mayer (1994) suggest that question should be asked in a more complex way. For example, looking at the difference in the factorial structure of intelligence for groups with different personality profiles, and vice versa. Analytically, this suggestion is very much in line with a network approach, because it looks at the whole set of variables at once and is not as much focused on the size of specific effects. From a theoretical perspective, several attempts of an integrative approach to both personality and intelligence with a wider theoretical framework for understanding their interrelations can be found in the literature. For example, social intelligence theory within cognitive theory of personality (Kihlstrom & Cantor, 2011), and Motivational Systems Theory (Ford, 2019). They are closely related to Smirnov's (1994) view of intelligence as thinking, and personality as inherent component of all thought processes, while the link between the two are goals and problems in daily life.

3.2 Methods

3.2.1 Data and measures

The dataset used in the current study has been collected within the context of the *MyPersonality* project (Kosinski et al., 2015; Stillwell & Kosinski, 2019). In this project, participants self-administered one or more psychological questionnaires online, through a Facebook application (active from 2007 until 2012). Participation was voluntary, completely anonymous, and participants provided their consent. In total, more than 20 different questionnaires were offered, and participants completed a self-chosen, variable number of questionnaires at a self-chosen place and time.

Of the available questionnaires, we selected 11 questionnaires, covering 31 psychological attributes, guided by three criteria: We wanted to include psychological concepts that (i) have a clear theoretical background, and were measured with validated instruments with good psychometric properties; (ii) are considered to have high temporal reliability and stability; and (iii) had relatively high number (N>1000) of participants who also self-administered other questionnaires. To prevent including concepts that are too similar, we excluded concepts that correlated very highly to other concepts (correlations around 0.60 in absolute value) and that had a clear theoretical overlap. This resulted in the inclusion of 26 psychological concepts. To facilitate interpretation, we reversed the scores of the negatively framed variables (Neuroticism, Depression, Militaristic values, and Violent occult interests) such that all variables can be interpreted as higher scores representing more favourable outcomes, except for Schwartz's values, where such rationale was not possible since having or not having high scores on certain value should be evaluation-free, meaning not positive or negative by default. The interpretation of the variables after recoding is listed in Table

3.1. More information on data processing, sample description, descriptive of missing data, descriptive statistics of 26 psychological variables is offered in Appendix 3 (sections 1-4).

We included 1,166,923 participants with a score on at least two of the psychological attributes (hereafter: variables). Of a subsample of participants, demographic information was available on gender (44.6%, of which 64.8% female and 35.2% male) and age (20.8%; $M \pm SD$ = 26.1±6.7, range: 14-89 years). The sample consisted of participants from 220 different countries, and 35,7% of participants were from the US, UK, Canada, Australia, and India, respectively. A concise description of the included constructs and the instruments used is given in Table 3.1.

Table 3. 1 Description of 26 psychological attributes included in the network

Psychological attribute *(or Group of attributes (number of attributes in the group)), Questionnaire (author(s))* Short description of measured attribute (number of items)
Values - based on Schwartz Theory of Basic Values (6), Schwartz Value Survey – SVS (Schwartz, 1992)
Achievement - personal success through demonstrating competence according to social standards. (4 items)
Hedonism - pleasure or sensuous gratification for oneself. (3 items)
Power - social status and prestige, control or dominance over people and resources. (4 items)
Self-direction - independent thought and action—choosing, creating, exploring. (5 items)
Tradition - respect, commitment, and acceptance of the customs and ideas that one's culture or religion provides. (6 items)
Universalism - understanding, appreciation, tolerance, and protection for the welfare of all people and for nature. (8 items)
Big Five Traits (5), 20–100-item IPIP questionnaire (8 length versions), also included data on 336-item IPIP Personality Facets questionnaire (Goldberg et al., 2006). Both questionnaires are proxies for Costa and McCrae's NEO-PI-R facets (Five Factor Model)
Emotional Stability (reversed Neuroticism) **-** the tendency not to experience negative emotions, such as anger, anxiety, or depression.
Extroversion - characterized by positive emotions, surgency, and the tendency to seek out stimulation and the company of others.
Openness to experience - a general appreciation for art, emotion, adventure, unusual ideas, imagination, curiosity, and variety of experience.
Agreeableness - tendency to be compassionate and cooperative rather than suspicious and antagonistic towards others.
Conscientiousness - tendency to show self-discipline, act dutifully, and aim for achievement.
Interests (4), The Sensational Interests Questionnaire – SIQ (Egan et al., 1999)
Low militaristic interests (reversed Militaristic interests) **–** an individual with low active interest in militaristic activities (e.g., guns and shooting). (10 items)
Low violent-occult interests (reversed Violent-occult interests**)–** an individual with low active interest in violent or occult activities (e.g., black magic). (7 items)
Intellectual interests – an individual's active interest in cerebral activities (e.g., philosophy). (7 items)
Interest in wholesome activities – an individual's active interest in active recreation (e.g., camping, hill walking). (5 items)
Body Consciousness (3), Body Consciousness Questionnaire –BCQ (Miller, Murphy, & Buss, 1981)
Private body - awareness of internal sensations. (5 items)
Public body - awareness of observable aspects of body. (6 items)
Body competence – self-confidence in the body's performance. (4 items)
Integrity assessment (2), Rust's Sense of Fairness and Impression Management, Orpheus (Rust & Golombok, 1989), 36 items.
Fair-mindedness (*or Sense-of-fairness*) – measures how balanced and impartial person is in her decision making.
Self-Disclosure – measures to what extent a person conducts her life transparently. Reversed values are used as a measure of Impression Management and Social desirability (Lie scale).
"Stand-alone" traits – six psychological attributes which are not part of a group of constructs, each is measured with separate questionnaire
Awareness of physical symptoms and sensations, *Pennebaker's Inventory of Limbic Languidness - PILL (Watson & Pennebaker, 1989)*

Scale measures how often a person notice and report a broad array of physical symptoms and sensations (e.g. chest pain, heart racing, dizziness). (54 items)
Self-monitoring, *Snyder's Self-Monitoring Scale, (Snyder, 1974)* Scale measures much person monitors her self-presentations, expressive behaviour, and nonverbal affective displays. (25 items)
Low Depression, *Center for Epidemiologic Studies Depression Scale (CES-D), NIMH, (Radloff, 1977)* Reversed Depression, measures lack of symptoms of depression in nine different groups as defined by the American Psychiatric Association Diagnostic and Statistical Manual, fifth edition. (20 items)
Empathy, *Empathy Quotient - EQ, (Baron-Cohen & Wheelwright, 2004)* Scale measures self-reported ability to tune into how others are feeling, and to understanding what they may be thinking. It measures both the affective and cognitive components of empathy. (60 items)
Life satisfaction, *Satisfaction With Life Scale- SWLS (Diener, Emmons, Larsen, & Griffin, 1985)* Scale measures general wellbeing and satisfaction with one's life. (5 items)
Intelligence, *MyIQ test, myPersonality's* 20-item proxy for Raven's Standard Progressive Matrices (Raven, 2008) Ability test measures cognitive skills and clear-thinking ability, and pattern recognition abilities known to have the highest correlation with the general intelligence factor. (20 items)

3.2.2 Network estimation

We used partial correlations to estimate[8] the network. Partial correlation networks do not contain spurious correlations that are generated by common cause and chain structures within the network and can encode a basic data-generating network structure (Schmittmann et al., 2015). Partial correlations are usually *smaller* than first-order correlations. To estimate the network, we used a non-regularized method recently proposed by Williams and Rast (2020) because, given our large sample size, relatively small number of variables, and our interest to detect weak ties, it is not advised to use regularization techniques like the LASSO that are often used (Williams et al., 2019). More details about the process of determining the optimal estimation method for our data, and about the non-regularization method used can be found in Appendix 3, section 5.

To prevent the inclusion of spurious edges because of our overall large sample size, we artificially reduced the sample size by setting the *N* parameter in the estimation to *N*=4 131 (i.e., the median number of completed pairwise observations, for more details see Appendix 3, section 3) instead of the total sample size of *N*=1 166 923. The estimated network is shown in Figure 3.1. The included edges were significant at alpha-level of 0.001.

At first glance (Figure 3.1) at the network it can be seen that most of the nodes from the same group (questionnaire) cluster together in the network, except for Big Five traits that are more scattered across the network, especially Openness.

[8] For network estimation, visualization, and centrality analysis the following R packages were used: BDgraph (Mohammadi & Wit, 2015), qgraph (Epskamp et al., 2012), and networktools (Jones & Jones, 2017). MST, PC, and motif analysis id done in NetworkX Python module (Hagberg et al., 2008).

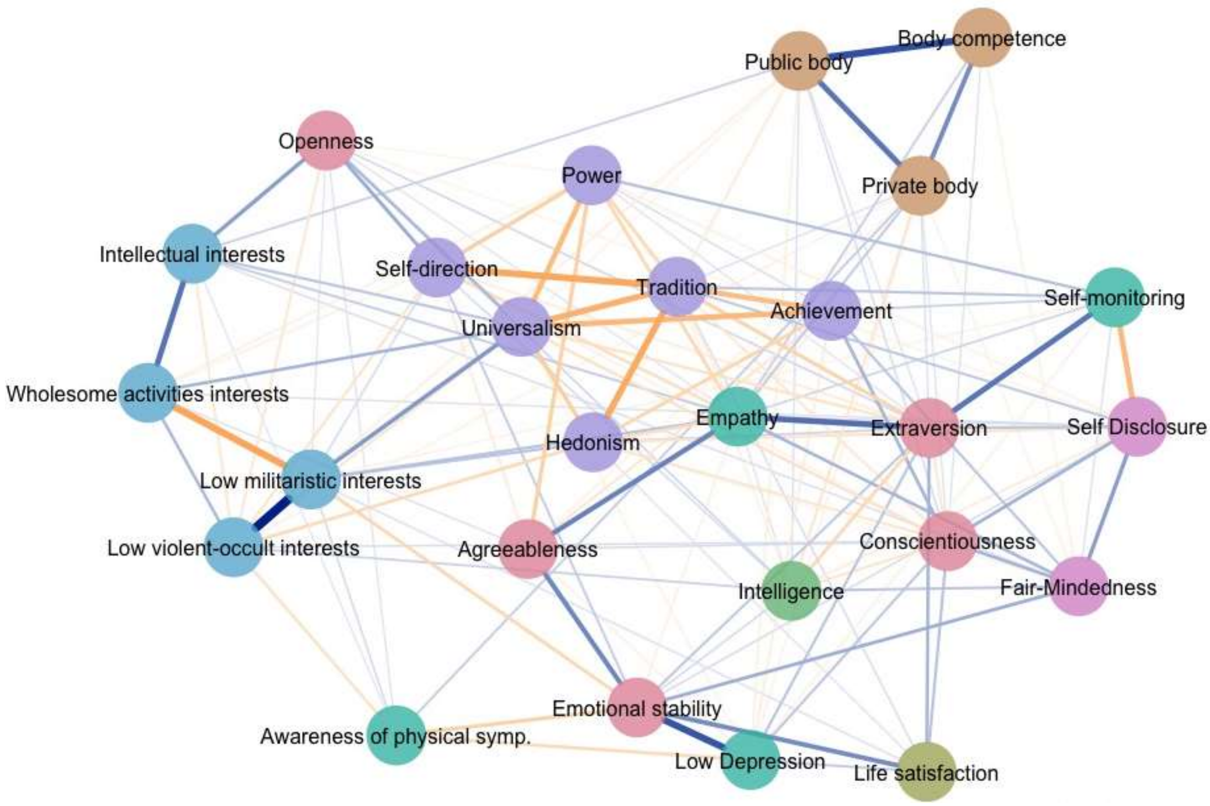

Figure 3. 1 Non-regularized partial correlation network (set N= 4131, true N=1066921, layout spring, cut = 0). Blue ties signify positive relations, orange ties signify negative relations. The thickness of a tie is proportional to its absolute weight.

3.2.3 Robustness analysis

To check robustness of our results, we tested it in two ways. First, we randomly split the sample in half 100 times, and estimate a network on each half separately. Subsequently, we compare the two estimated networks on a metric of interest. If the network estimation is reliable, then the networks should be similar for both halves of the data, and, hence, the metrics should show high correspondence. This procedure is similar to that of Forbes et al. (2017). It should be noted, however, that by using only half of the data to estimate a network, the statistical power drops considerably which will especially affect the estimation of small edges. Therefore, we conducted a second robustness analysis in which we randomly selected

100 sets containing 80% of the original sample, and compared the network estimated on this subsample to the network estimated on the complete dataset. We computed the average correlation of the pairs of matrices estimated for the split-halves (robustness analysis I) and between the whole sample and the random (80%) fractions (robustness analysis II). For the split halves, the average correlation was 0.82, indicating a high level of reliability. However, if we only evaluate the edges that are present in both estimates, on average, the reliability drops to 0.59 (similarity index). The average difference in the number of edges is 6.35, which is around 2% of all possible edges. For the random (80%) fractions, the similarity index increased to 0.85. The results are presented in more depth in Appendix 3, section 6.

3.3 Illustrative results: Network description

3.3.1 Edge weights in the network

The current estimated network has 144 edges out of 325 possible edges, showing a good balance between sparsity and density (Figure 3.2). The distribution of the edges is summarized in Table 3.2, 64 edges (44%) are negative, and 80 edges (56%) are positive. The number of negative edges is higher than usually observed in psychological networks. Note that this is dependent on the network under consideration. If a network includes variables that all come from the same questionnaire (e.g., 10 depression items), then it would be expected that many (or all) edges are positive. In the current network, variables from various psychological questionnaires are included, they are not expected to correlate highly or/and positively by definition. Figure 3.2 also shows that due to artificially decreasing statistical power and due to setting alpha to 0.001, edges around 0 are eliminated (< 0.05 in absolute value). For more details on the correlation network and estimated partial correlation network, and detailed analysis of ties, see sections 7 and 8 in Appendix 3.

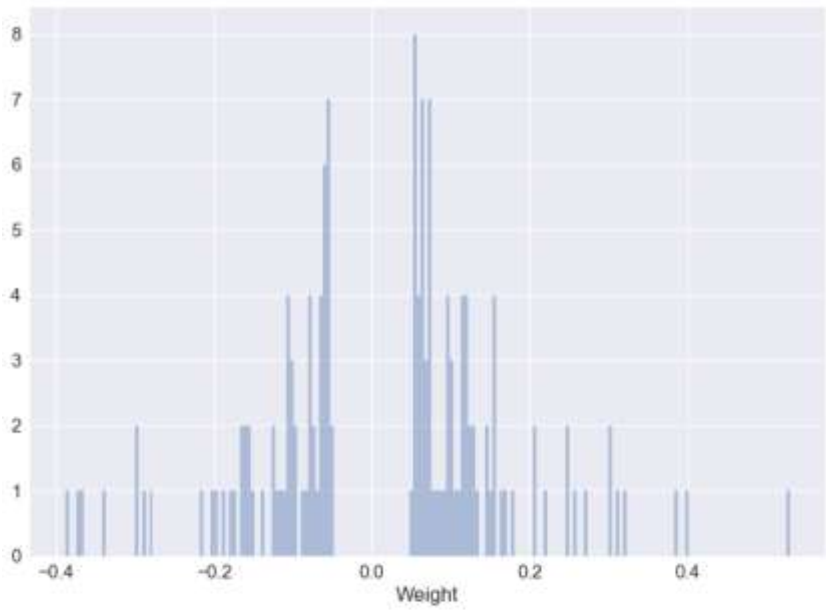

Figure 3. 2 Distribution of weights in partial correlation network (L=144)

Table 3. 2 Descriptive of ties in partial correlation network

	Signed ties	*Absolute weights*	*Positive ties*	*Negative ties*
Mean	0,01	0,13	0,13	-0,13
SD	0,158	0,090	0,092	0,088
Min.	-0,39	0,05	0,05	-0,39
25%	-0,09	0,06	0,07	-0,16
Mdn	0,06	0,10	0,10	-0,10
75%	0,11	0,16	0,15	-0,06
Max.	0,53	0,53	0,53	-0,05
N. of ties	144	144	80	64

3.3.2 Centrality of nodes

In addition to centrality measures that are typically used in psychological networks, we include more recently developed measures of node’s expected influence (Robinaugh et al., 2016, for short explanation see section 9 in Appendix 3).

Centrality measures can roughly be categorized into two groups, measures that look only at the local surroundings of a node (i.e., only the edges adjacent to the node), and measures that try to quantify the position of a node in the network by also taking into account nodes that are not directly adjacent to the node. Figure 3.3 shows centrality measures of the first category—considering only adjacent nodes. Figure 3.4 shows centrality measures of the second category—considering nodes beyond those directly adjacent to the node of interest. Comparing the different centrality measures, both within the same category or across categories, clearly shows that the measures diverge. Thus, different centrality measures indicate different nodes to be the most central. Although this follows logically from the way the different measures are computed, as each measure captures different aspects of centrality, it highlights the need to carefully consider the metrics used as it can greatly influence the answer to the question that is posed.

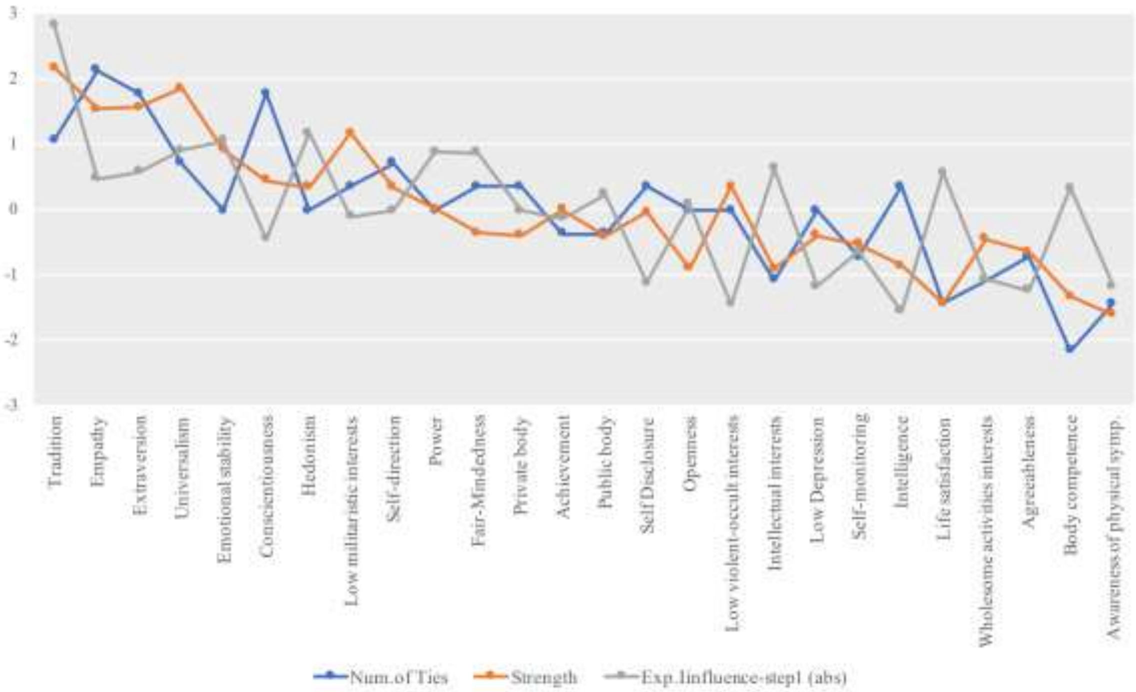

Figure 3. 3 Centrality measures 1: based on node's direct ties (standardized values)

As Figure 3.3 shows, based on a node's direct ties, the most central node varies across measures. Based on strength, the value Tradition is the most central node, followed by Empathy, Extraversion, and another value - Universalism. Among the least central nodes are Agreeableness, Body Competence and Awareness of physical symptoms.

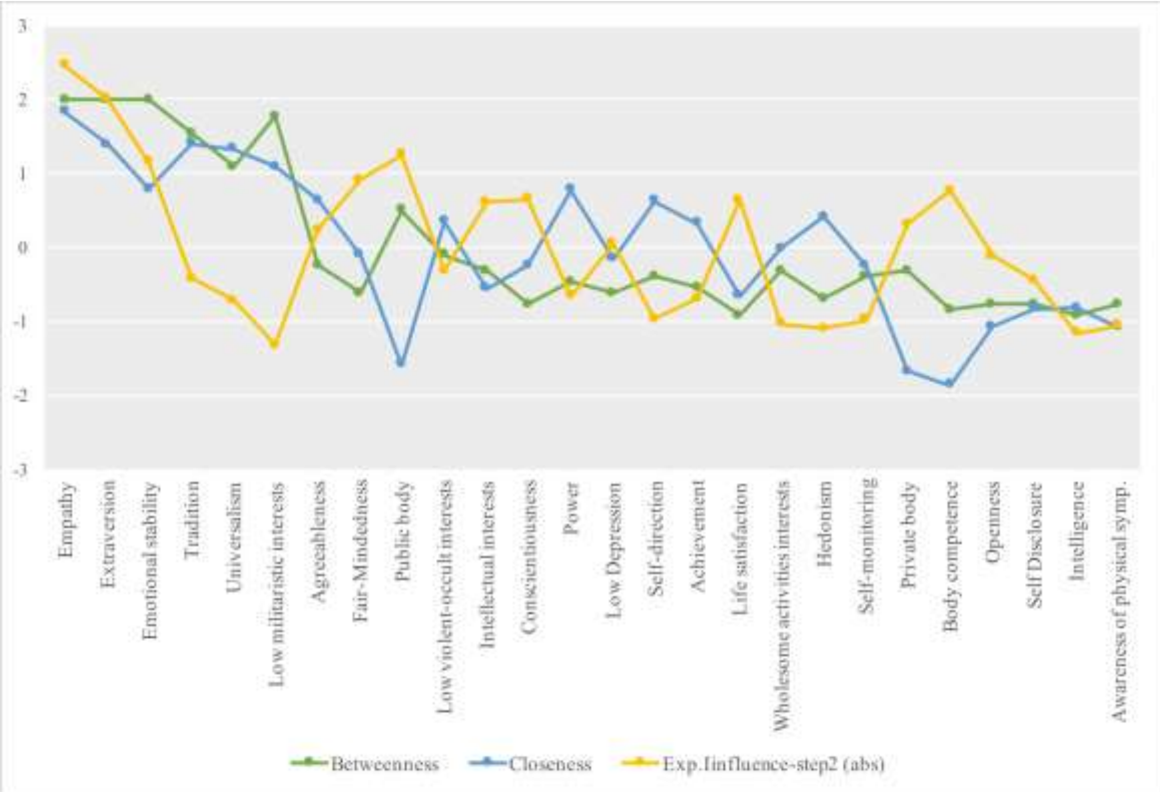

Figure 3. 4 Centrality measures 2: based on links more than one distance away from the node (standardized values)

Alternatively, when centrality measures consider more than the local environment of the node, a different arrangement of centrality emerges (Figure 3.4), with less agreement between different measures. Here, Empathy is the most central node, followed by Extraversion and Emotional stability, while Tradition drops to the fourth place. The least central nodes are Self-disclosure, Intelligence and Awareness of physical symptoms.

Robustness analysis of all centrality measures used in this study is presented in section 6 of Appendix 3.

3.4 Introducing three network methods for the analysis of psychological networks

3.4.1 The Minimum Spanning Tree

As demonstrated in the previous section, different centrality measures capture different aspects of a node's position in the network, and the centrality of a node will differ depending on the centrality measure used. For that reason, we propose a way to look at the question about centrality differently – in a more general way. To be clear, we are not stating that centrality measures used so far in the research are inadequate, but we are merely trying to assure a more general perspective to centrality. An alternative way to characterize relationship between all nodes in a network is by computing the minimum spanning tree (MST) (Mantegna, 1999). The MST detects the hierarchical organization of the nodes and reduces the number of edges to those that carry the most information on the similarity of the nodes. Specifically, the MST is based on the distance between the nodes and selects the subset of edges (*number of nodes – 1*) without cycles, and with minimal total distance possible. This "skeleton" structure of the filtered network may be used if we want to get the answer to the general question which node is the most central, by not looking at the specific centrality aspects, but instead focusing on the network's most essential and local ties.

To compute the MST of our current network, first the distances among the nodes must be computed. An appropriate function for converting correlation to distances when negative correlations are present is:

$$d(i,j) = \sqrt{2(1 - r_{ij})} \quad (1)$$

Equation 1 (Gower's distance measure (Gower, 1966; Mantegna, 1999) takes the direction of the correlation into account by assigning the largest distance to a perfect negative correlation, and the smallest distance to a perfect positive correlation. According to this equation the distances range from 0 to 2, where an intermediate distance of 1.4 is assigned to variables that are uncorrelated. The relationship between the (partial) correlation coefficient and the distance measure is shown in Figure 3.5.

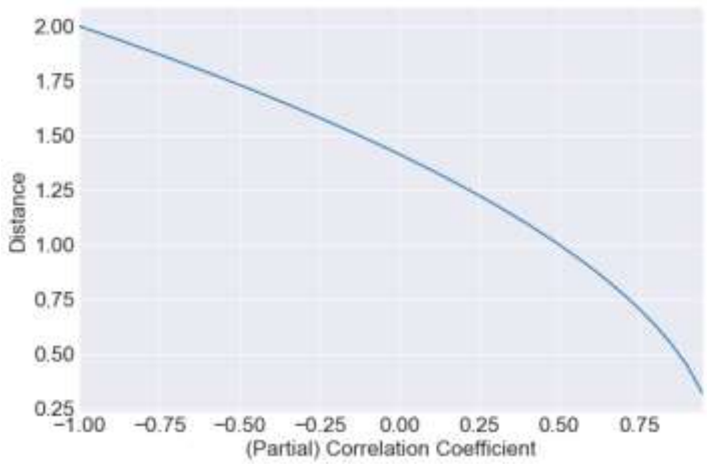

Figure 3. 5 The relationship between partial or correlation coefficients and distance measure

Equation 1 is the preferred distance measure to the distance measured as inversely proportional to shared variance ($d(i,j) = 1 - pr_{ij}^2$). From the mathematical point of view, it is more rigorous definition of the distance and it gives monotonic transformation of coefficients. Most importantly, Eq.1 gives more differentiated measure of distance than distance based on the shared variance, because in the latter the loss of information occurs since it translates partial correlations of the opposite sign and the same absolute values to the same distance. If negative ties are not present in the network, both measures will produce the same MSTs, otherwise the output will most likely differ (MST based on the shared variance is shown in Appendix 3, section 11, figure 15). Given mentioned advantages and since almost half the ties in our network are negative, we have chosen to use it for MST construction. However, as it will be discussed in section 5 and analysed in Appendix 3 – section 12, this measure is sensitive to reverse coding of variables included in the network.

Note that taking partial correlations instead of correlations when calculating distances means that for each pair of nodes it indicates how distant they are after the similarity based on covariance with other nodes in the network is excluded.

The MST of 26 psychological attributes is shown in Figure 3.6. The information about "centrality" of a node is very clear from the hierarchical structure, although centrality measures can provide a more detailed picture (see Appendix 3, section 10). The nodes with more direct edges and closer to the middle (centre) of the tree are most central.

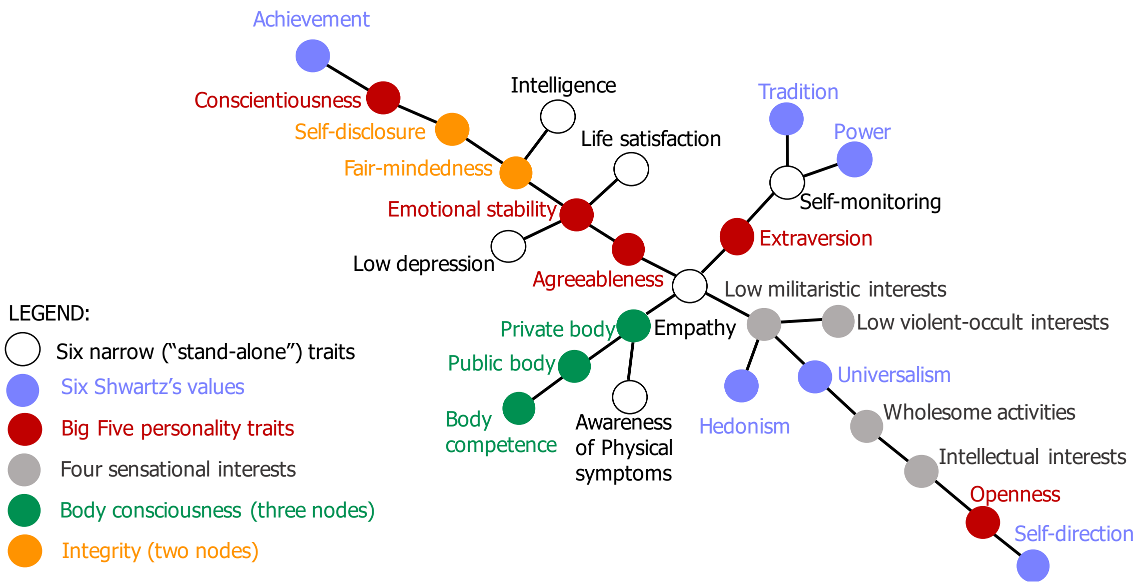

Figure 3. 6 Minimum spanning tree (MST) based partial correlation

Empathy is the most central node in the MST in the sense that it features the smallest distance to all other attributes. From Empathy, four branches emerge with only Sensational interests and Body Consciousness being on the same branch as all other attributes from the same group. All branches are heterogeneous regarding the group of attributes they consist of, but they can be interpreted as having some commonalities in meaning. The branch with three Body Consciousness constructs along with Awareness of physical symptoms captures attributes related with body perception in general. The branch starting with Low militaristic interests can be interpreted as representing interests, values and openness, which are related to what is often referred as "lifestyle". The branch that starts with Extraversion relates to the attributes that describe one's agency and control in the social world. Finally, the biggest and most heterogeneous branch starting with Agreeableness is made of attributes that are highly socially esteemed and describe one's 'relation' to others, oneself, and life in general. It is interesting to observe that Intelligence is placed on that branch and it branches out from Fair-mindedness. This visual inspection shows another useful feature of MST – it gives indirect information on the hierarchical and overlapping, data-driven, clusters in the network. For example, in Figure 3.6 we can see two pairs of branches, or clusters, that *overlap* in Empathy. Alternatively, taking Empathy as the origin, there are four branches, or clusters, that overlap in that node.

According to the MST based on the distance defined in Eq. 1, two nodes are more distant in terms of steps (ties) between them in the filtered network (tree) if they are negatively associated than if they are not associated at all. That is why, for example, Tradition and Self-direction (*pr* = - 0,37) are placed on different branches and more distant than Emotional

Stability and Conscientiousness (*pr* = 0) that lie on the same branch. From the perspective of psychological networks, the MST preserves the specific content and meaning of the variable. More importantly, since its construction was affected by signs of weights, not only their absolute value, this filtered network can be a useful tool in testing whether two networks made of the same nodes really differ. Two networks estimated on two different samples will not usually be identical. However, if their MST is the same or very similar, this may indicate that their differences are not important. Similarity indexes of MSTs converge with the similarity indexes of whole networks. Nevertheless, reliability based on MST correlations seems to be lower than based on network correlations in smaller samples (split-halves), indicating that in fact the most informative ties are differently estimated (for details see section 7 in Appendix 3).

3.4.2 The Participation Coefficient

In psychological networks, nodes (variables) may differ in their nature. Some may come from the same framework, while some may be stand-alone nodes. In network parlance, some nodes are part of a community and some nodes form a community of one or few. Note that these communities are not derived from data, but rather, they are based on pre-existing differences.

In the current dataset, for example, we had 26 psychological concepts, measured by 11 questionnaires. As such, there are groups of variables, varying in size, that belong to the same questionnaire and that are part of the same theoretical framework (e.g., three concepts on body consciousness) or measure the same kind of trait (e.g., measures of different 'values'). Moreover, the psychological concepts that are part of the same questionnaire will likely be completed at the same time, while different questionnaires may have been taken days, months, or even years apart. Therefore, it is important to take these pre-existing differences into account, if we want to explore which of the variables play an important role in the network.

One way to deal with these theoretically defined, pre-existing communities, is by employing measures that take this community structure into account and specifically evaluate connections a node has with nodes in different communities. One such method is the Participation Coefficient (PC), first introduced in the field of biological networks (Guimera & Nunes Amaral, 2015). The PC takes the community structure into account, as it specifically quantifies how the edges a node has are distributed to different communities[9]. The important departure in our application of the PC is that it is not used on an empirical community structure, but rather on "communities", that is, groups of nodes and "stand-alone" nodes that were considered to exist in the network (a kind of "ground truth"). Framed

[9] Similar in logic to Shannon entropy measure.

as a hypothesis, the null hypothesis in the use of PC would state that pre-existing groups of constructs (or data-driven communities) do not influence centrality scores of nodes. Showing that the rank order of nodes according to given centrality measure changes once the measure is corrected with PC can be interpreted as supporting the rejection of the null hypothesis.

The calculation of the PC measure follows Equation 2:

$$PC_i = 1 - \sum_{m=1}^{G} \left(\frac{k_{i,m}}{k_i}\right)^2 \quad (2)$$

where PC_i signifies the PC score for a node *i*, while G, m, $k_{i,m}$, and k_i, denote the network, each module in the network, number of ties of node *i* with nodes in that module, and number of all node's ties, respectively. The expression $\frac{k_{i,m}}{k_i}$ is simply the ratio of all node's ties that go to the specific module. In a version for weighted networks the number of links ($\frac{k_{i,m}}{k_i}$) in Equation 2 is replaced with the sum of strengths which means that the expression $\frac{s_{i,m}}{s_i}$ signifies proportion of total strength of node *i*, invested in a single module:

$$PC_i = 1 - \sum_{m=1}^{G} \left(\frac{s_{i,m}}{s_i}\right)^2 \quad (3)$$

This difference means that if a node has the same number of links to every module, but they differ in strength, it will not achieve a maximum PC value. Here, strength is defined as the sum of absolute weights of all links involving node *i*, which means we disregard the sign of ties.

If a node has an equal number of edges (in weighted networks, the sum of all tie weights) to all the communities in the network (i.e., a uniform distribution of edges or edge weights to all communities), the PC is closer to 1[10]. Alternatively, if a node has edges only to nodes within its own community, the PC is 0. It is important to note that the PC is not simply the number of links a node has to other communities in the network, but it rather quantifies the *equality of the distribution* of edges a node has to the other communities. In weighted networks, the PC is maximized if a node is connected equally to all the communities in the network: equal in both the number and strength of edges to the other communities (i.e., a uniform distribution of edges and edge-weights to all communities). More uniform distributions of nodes to all other communities correspond to higher PC values. For

[10] The highest possible value depends on the number of modules in the network, therefore average PCs of different networks can be compared only if PCs are normalized by theoretical maximum value, which is 0.50 for 2-module community, 0.80 for a network containing 5 communities; and, in our network containing 11 communities, the maximum PC value is 0.96.

example, a node with one tie to each module will have the same PC as a node with two ties to each module. Similarly, a node with just one link to *each* module will have a higher PC than a node who has many links to some, but no links to other modules. A node with a high PC can influence all parts of the network *equally*, meaning that the node is equally important to every defined community. Such a node can be seen as a common denominator in terms of its potential influence on all communities in the network, and can therefore help us understand the network as a whole. Note that PC considers only the node's direct ties, displaying the local perspective as MST. Moreover, that feature makes it a good choice for the analysis of a network where some elements of the network may not be included, and where therefore measures relying on the whole network (e.g., betweenness, closeness) may not be appropriate. However, since the PC solely quantifies the equality of the distribution of ties (or strength of those ties, in version for weighted networks) and disregards number (sum of strengths) of ties, we propose to use it in combination with a measure that considers both the number and strength of the connections a node has, and disregards the information about communities (pre-existing or otherwise). One such measure is the Participation Ratio (PR; Opsahl et al., 2010). Participation Ratio is defined with the following formula:

$$C_D^{w\alpha}(i) = k_i \times \left(\frac{s_i}{k_i}\right)^{\alpha} = k_i^{(1-\alpha)} \times s_i^{\alpha} \quad (4)$$

where $C_D^{w\alpha}(i)$ is Participation Ratio of node (i), k_i is number of ties of node (i), s_i is the strength of the node, while α is a positive tuning parameter. If its value is set between 0 and 1, having a high number of ties (degree) increases $C_D^{w\alpha}(i)$, if $\alpha = 0$, it is equal to the node's strength, whereas if α is set above 1, the number of ties decreases the value of $C_D^{w\alpha}(i)$, in such way that a node with a greater concentration of its strength on only a few nodes and low degree has higher value than a node with the same strength but more ties. In our analysis, the α is set to 0.5, so that, for example, if a node A has a higher number of links and the same total strength as node B, the node A will have higher value of $C_D^{w\alpha}$. In this way both having high total strength and having more ties is favoured.

In short, PR is a single measure that quantifies both the number of edges a node has and the strength of these edges, and weighs both equally (i.e., corresponding to an alpha of 0.5), and as other measures defined so far in this paper, focuses only on node's direct links.

We transformed both measures to the same scale (range 0-1), visualized in Figure 3.7. Subsequently, for each node we computed the geometric mean of both measures. We opted for the geometric mean as it rewards consistency in scores on the two different measures. For each node, the PC, PR, and their geometric mean are shown in Figure 3.8.

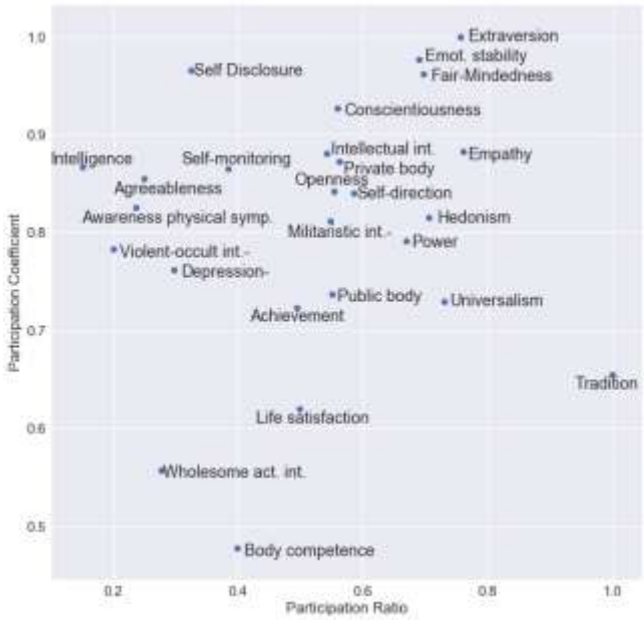

Figure 3. 7 Scatterplot of standardized values of Participation Coefficient and Participation Ratio (min-max scale from 0 to 1) for all nodes in the network

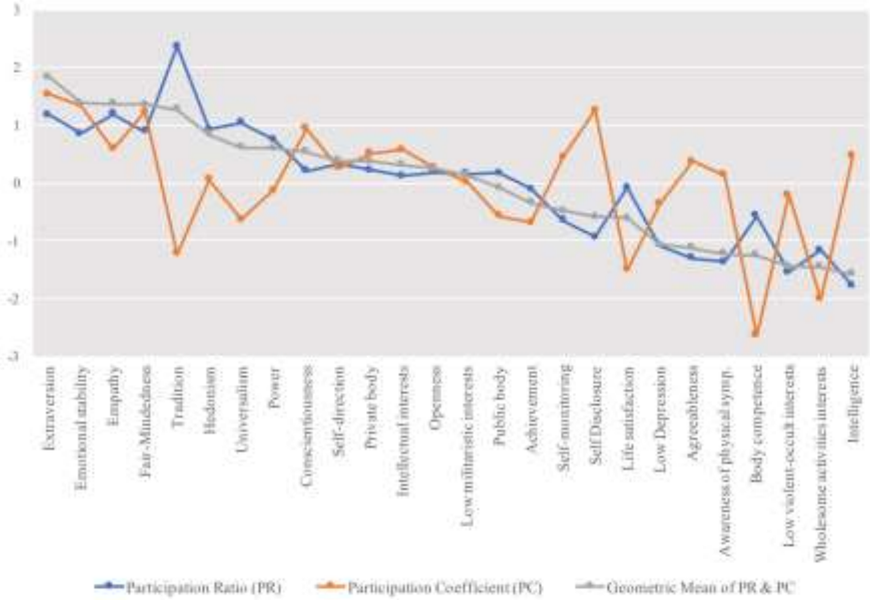

Figure 3. 8 Centrality measures 3: Participation Ratio[11] *($\alpha = 0.5$), Participation Coefficient, and their geometric mean (standardized values)*

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[11] The values of geometric means for Empathy and Extraversion are higher than both PR and PC. This is due to standardization of each measure. The plots with raw scores are shown in Appendix 3, section 9, Figure 10.

Interestingly, as can be seen from Figures 3.7 and 3.8, the PC and PR can diverge for some nodes. For example, if we only focus on the number of edges and their strength, which is summarized in the PR, Tradition is highly central. However, Tradition has a relatively low PC, indicating that while it has relatively many and strong edges, these are not equally distributed throughout the network. Inspecting the estimated network in Figure 3.1, it can be seen that, indeed, the strongest edges of Tradition are mainly within its own community. Alternatively, Intelligence is not considered central based on the number and strength of its edges, but taking the distribution of edges into account, we see that the connections of Intelligence are equally distributed to the other communities in the network (see Figure 16 in SM). This information would have been lost, if we had only focused on the number and strength of the edges (and other centrality measures related to these aspects).

In short, this example clearly illustrates that when the objective is to find out which nodes play an important role in the network as connectors, it is important to consider whether there might be pre-existing communities that should be taken into account. Not taking these pre-existing communities into account might obscure the importance of nodes belonging to small communities and “stand-alone” nodes that are not part of any community.

3.4.3 Analysis of triadic motifs

In this section, first we will explain the rationale behind the selection of motifs to be investigated, and the analysis of motif frequency, intensity, and coherence, followed by results and discussion, where the identification of specific motifs (and interpretation) is also included.

i) Selection of motifs: Motifs usually represent subgraphs of three to five nodes for which different patterns of absent and present ties are examined. Many analyses of mesoscopic structures include or focus on triads – all possible configurations of three nodes. This is a sensible choice, because a triad is the smallest and the most basic network unit that defines the clustering of a network (transitivity), and can be characterized as the “simplest nontrivial motif” (Onnela et al, 2005: p.2). For undirected, unweighted and unsigned networks, four types of triads exist: 1) triads without ties/edges (*empty triads*); 2) triads with one tie present, and two ties absent (*one edge triads*); 3) triads with one edge absent, and two edges present - referred in the literature as *two-path*, *two-star*, or *open triads* (or *forbidden triads* in weighted networks when present edges are strong); and 4) triads with all edges present (*triangles*, *closed triads*)[12]. Usually, the first two types of triads are not considered in the analysis, and some researchers define triads more strictly as systems of three nodes with at least two ties among them (e.g., Siltaloppi & Vargo, 2017). The number of possible triads increases when the sign and weights of the edges is considered (e.g., Kalish & Robins, 2006), as will be done in our analysis. Depending on the research question, some motif

[12] Triads should not be confused with triplets. Triplets are like triads, but they are defined only by the presence of the edges, and do not by the absence of edges.

configurations may be of special interest and should be investigated, while others can be excluded from the analysis.

ii) Analysis of motif occurrence, intensity, and coherence (including the identification of specific motifs): Once the motifs of interest are defined, the next step is to determine the frequency of each motif in the empirical network[13]. This yields a first insight into the network patterns at the meso-level. The most frequent motif describes the most dominant pattern of connectivity in the given network among the motifs that are examined. However, the frequency alone yields limited information, because certain motifs might occur more frequently simply because of the network structure[14] and weight distribution. For example, imagine a hypothetical network of twelve nodes (variables) in which we observe predominantly positive edges, representing partial correlations between pairs of variables, except for three negative edges (described in Figure 3.9).

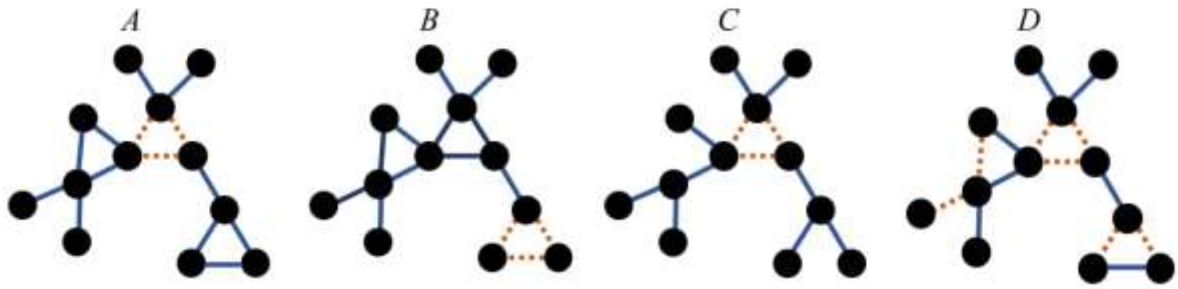


Figure 3. 9 Four networks with 12 nodes and one negative triad (NNN). Networks A, B, and C have only three negative edges, while D has the same structure and density (number of edges) as A and B, but more negative edges.

If we find one negative triad in a network, based on frequency alone we could treat that finding as somewhat interesting but not especially informative about the network as whole. However, when we consider what are the chances of observing three nodes connected with three negative edges in that system, that finding is of greater importance for understanding the whole network as a system. Figure 3.9 describes extreme (and unlikely) examples of psychological networks which are used to illustrate why is it useful to additionally look at the chance of certain motifs occurring in the system. The weight distributions of networks A and B in Figure 3.9 are the same, while network C has a different structure compared to A, B, and D, because just one closed triad (triangle) is present. Since the structure is different, the weight distribution of C is also different. The chance of a NNN occurring in a network with the same structure and weight distribution is smallest in C, followed by A and B, where it is equal. The highest chance of observing such a triad is in D, because it has more negative edges and triads than other three networks. If networks are representing

[13] Each unique combination of three nodes is counted once.
[14] In the context of describing the reference (null) model, the terms: network structure, topology, and degree sequence, are used interchangeably in this paper.

symptoms (behavioural, emotional, cognitive, or physical) of a disorder, three negatively associated symptoms in A, B, and *especially* in C are more important characteristic of the system than in network D. They are less likely to occur by chance in these three networks, and therefore more likely to describe a process which is important for understanding the network. E.g., a triad NNN in A could be interpreted as a process of negative feedback which is central for the network (it "drives" the network). In B, NNN is equally important but it describes occurrence of a negative "loop" in a peripheral part of the network – among symptoms that are less central. In C, NNN is even more essential for understanding of the network than in A, as it could be described as the sole driving force of the network – each of the negatively connected nodes in the triad relates to a different set of nodes. Note that motif analysis per se does not differentiate between A and B as the centrality of configurations is not accounted for. Finally, NNN in D is a central configuration which shows an interesting pattern of association between three symptoms, worth of attention in the interpretation of the network. However, it is not as important for describing the process underlying the network formation since other negative associations between nodes and within triads are present. The same reasoning applies if nodes are representing other non-pathological tendencies, like personality traits, values, etc. In these networks the difference will be in the average weights of edges, which is likely to be smaller than in case of networks featuring psychopathological symptoms or other more correlated variables.

Therefore, for each motif, we establish whether it occurs more or less frequently than would be expected by a null model. In weighted networks, the appropriate null model is a random network[15] with fixed topology (degree sequence) and randomized weights from the same distribution of weights as observed in the empirical network (for more details on general null models see Serrano et al., 2006). The quantification of occurrence of a specific configuration in a network is usually done by comparing it with the occurrence of the same motif in a reference model (for an introduction see Milo et al, 2002). Distribution of motif frequencies is obtained by generating a sample of random networks. The empirical frequency of a motif is compared against that distribution and if it appears significantly[16] more (less) often than it would be expected by reference model it signifies the motif is indeed "a motif"[17] – it-describes an important characteristic of the investigated network. Motifs that occur more frequently describe a common configuration of nodes, and therefore provides information about the network connectivity. Moreover, these motifs could have some important functional role in the system. For example, closed triads are usually overrepresented in social networks, because they represent a process of social (triadic)

[15] To be precise, it is not a random graph model, but a configuration model (for more details see Newman, 2018).
[16] This significance should not be confused with significance of ties in the motif.
[17] Sometimes the term "motif" is used only for these configurations for which this step of analysis shows that they are significantly over or underrepresented. In this article, we do not make such distinction, as we refer to every investigated configuration as a motif, and after the analysis is done, we describe it as significant or not.

closure, while in a network of intelligence measures they may indicate the process of mutualism (Van Der Maas et al., 2006).

However, in weighted networks the analysis of motif frequency omits the information about the weights (unless it is in some ways included in the definition of the motif). For example, if two motifs have the same occurrence in a network (let's assume for the sake of the argument that both have an equal distribution of frequencies based on appropriate random models), but the first is (on average) made of stronger ties than the second, we cannot treat them as equally describing the local structure of the network – that is, to be equally likely to describe some important process in the network. Although they are equally present in the network, the first is expressed more strongly, and is therefore more likely to describe some important process.

To address this issue, Onnela et al. (2005) introduced the Intensity measure (the geometric mean of all the weights[18] in a motif (Eq. 5, where $l_g$stands for number of ties in the motif)), that looks at the motifs not as discrete objects who are either present or not (expressed or not expressed) in the network, but rather as objects existing on a continuum, where zero or low Intensity values imply that motif is present in low degree. As such, the Intensity *I* can be used to identify high and low Intensity motifs in the system:

$$I_{(g)} = \left(\prod_{(i,j)\in l_g} w_{ij}\right)^{1/|l_g|} \quad (5)$$

In addition to Intensity (*I*), a Coherence ($Q_{(g)}$) ratio can be computed that quantifies how internally coherent the weights in motifs are by computing the ratio between the geometric and the arithmetic mean. It ranges from 0 to 1, with higher scores indicating less difference between the weights (in absolute terms). As was the case with the analysis of occurrence of motifs, the significance of both Intensity and Coherence is estimated in comparison with the distribution of their values for a given motif in reference model.

A motif that is underrepresented in the network, in terms of occurrence or intensity, describes a pattern of relationships which, for some reason, is unlikely to happen in a network. In other words, when we exclude the hypothesis that a given occurrence or intensity of a certain configuration does not come from a reference system, it points out that there may be an additional origin for the effect - possibly the function of the system (Milo et al., 2002). In case of psychological networks, the occurrence and significance of a motif which is not easily interpretable may also happen as an artefact (e.g., due to the sample on which the network is estimated, problems in the network estimation procedure, or measurement error). For that reason, a motif analysis can be useful in the analysis of

[18] In the case of absent ties in the motif, these are treated as zero weights.

psychological networks, forasmuch as it can help quantify and identify presence of unexpected configurations in the network as well.

In next section, the motif analysis on illustrative data is described in detail and results are presented and discussed.

3.4.3.1 Selection of motifs and analysis of motif occurrence

When the sign of an edge is considered, seven configurations of triads are possible (disregarding empty triads and triads with only one edge, see Figure 3.9). Four of them fall under "closed" triads or triangles: triads with either only positive (positive triad, PPP) or only negative weights (negative triad, NNN); and triads consisting of two positive and one negative weight (PPN) or two negative and one positive weight (NNP). NNN and PPN are also known as imbalanced triads[19], in social balance theory (Heider, 1946; Cartwright & Harary,1956; Davis, 1963) because they signify configurations of affective ties between persons which is not likely to appear in social networks (or if it appears it is not likely to persist, that is, it is likely to change). The remaining three triads are open triads (2paths) consisting of two ties: with only positive weights (2path pos., P0P where "0" stands for the absent weight), only negative weights (2path neg., N0N), or with one positive and one negative weight (2path mixed, P0N or N0P).

Networks, especially social networks, tend to show transitivity – if person A is connected to (friend of) person B, which is connected with (friend of) person C, A and C are likely to be connected (friends). Although in recent years we have witnessed a surge of research on psychological networks, we still do not know enough about their general properties. Correlations, and especially partial correlations, do not have to be transitive, but it is often the case that if a trait A positively correlates with trait B, which is also correlated positively with trait C, then we expect traits A and C to correlate positively as well. If that is the case, P0P motifs should appear less often than expected by the reference model. Likewise, according to the social balance theory closed triads with one or three negative edges (i.e., PPN and NNN) are less likely to occur in social networks (Heider, 1946; Cartwright, & Harary, 1956; Davis, 1963). We hypothesize that in psychological networks too, NNN and PPN triads represent configurations which are not expected to occur frequently because of two reasons. First, it is challenging to explain how three psychological attributes feature negatively partial correlations. One possibility is that a process of negative feedback among attributes exist. A second possibility is that the three nodes positively contribute to a common effect, which has been implicitly or explicitly conditioned on. A third possibility

[19] NNN is also sometimes considered as imbalanced triad in social networks, but some debate exists over whether is truly imbalanced or not. Not to confuse with too many similarly named triad, we will use term "imbalanced" in this article only when referring to triad with one positive and two negative ties and to triads that do not satisfy the triangle inequality principle (latter is explained in the following text).

is that the variables are measured with error, and the partial correlation picks up negative correlations between the error terms.

On the other hand, positive associations between A and B, and B and C, render a possible negative association between A and C difficult to interpret (PPN triad). The importance of detecting such configurations in psychological networks lies in the fact that they either describe unusual finding(s) or they may point to the existence of methodological artefacts. In both cases, we benefit from knowing about the presence of such configurations. It should be noted that while it is more straightforward to predict that such configurations could be less frequent in a correlation network, in the case of partial correlation network they could be more likely to occur. To the best of our knowledge no analysis of this kind has been performed on a network representing (partial) correlations. The summary of hypotheses is shown in Table 3.4, in section 5.

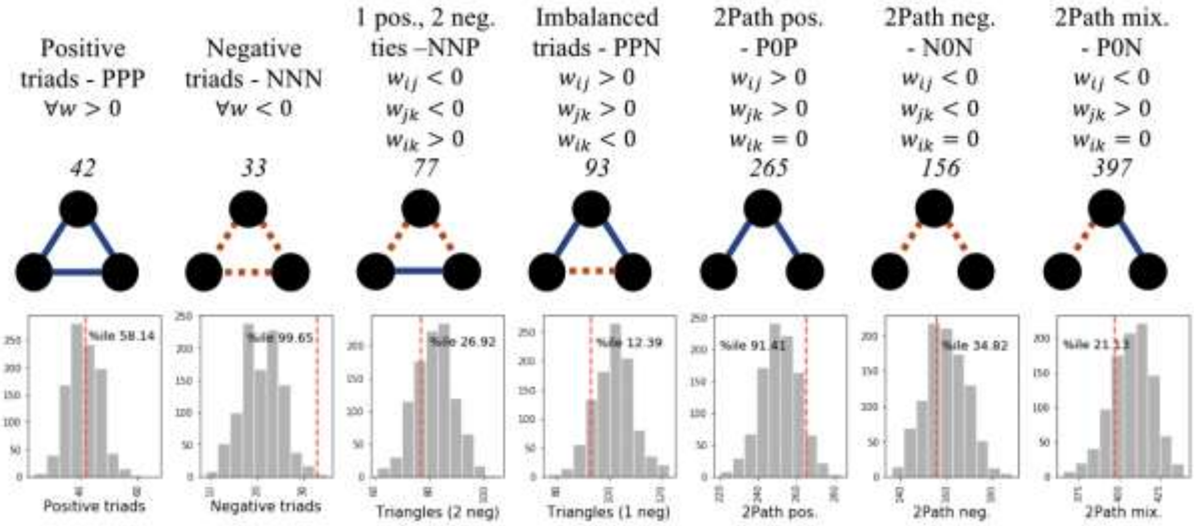


Figure 3. 10 Signed motifs, name used in this study, the definition, number of occurrences in the network, schematic figure, and the figure showing distribution of motif frequencies in 1000 random networks with the same degree sequence and weight distribution and percentile value of the frequency of empirical network in that distribution.

Among the motifs (Figure 3.10, third row), the only significant motif is the negative triad (percentile 99.7). In other words, the negative triad appears more frequently than would be expected by chance, given the same degree sequence and weight distribution. Path2 with positive ties (P0P), indicating high presence of nodes which are bridges, is overrepresented, and the imbalanced triad (PPN) is underrepresented, but neither reaches the level of significance.

To identify only the strongest motifs, we looked at signed motifs with an added threshold (see Figure 3.11). To end up with a similar number of examples for each motif, we selected a threshold of 0.15 (around 75 percentile of edge weights, see Table 3.1) for closed triads and a threshold of 0.20 for 2path motifs. Among the motifs that meet this threshold, one specific motif may be of relevance for psychological networks. This is the last motif in Figure 3.11, which we called imbalanced triplets II T., based on the work of Toivonen et al. (2012) (hence the T. in the name, for definition see Figure 3.11). Toivonen and colleagues investigated a correlation network of emotion concepts and argued that this motif describes patterns that cannot be depicted in any dimensional space without being distorted. This "imbalanced triplet" describes a pattern which is contra-intuitive, although not necessary unreal, and it is similar in logic to PPN triad. If A, B, C represent three psychological dimensions (e.g. emotions, traits), and positive correlations between A and B, and B and C exist, depending on the strength of r_{AB} and r_{BC}, A and C ought to correlate at least as the half of either of the two (r_{AB} or r_{BC}) that has the weaker correlation. Otherwise, the ABC triad does not satisfy the triangle inequality principle, that is, it cannot be described by dimensional techniques (in Euclidean space), while a network representation can be used for detecting their presence.

As mentioned for the NNN and PPN motifs, while we can expect low occurrence of imbalanced triplets II T. in a correlation network, in a partial correlation network this is quite different. An imbalanced triad in a partial correlation network implies that the partial correlation between A and B is small given C, which means that A and B approach conditional independence given C. This in turn is consistent with a chain (A→B→C or A←B←C) or a fork (A←B→C). Both may yield indirect, but important clues to the causal structure within the triad. Those triads are good candidates for more focused analytical approaches that allow for causal inference (e.g., mediation or path analysis). Thus, regardless of frequency, the imbalanced triplets II T. represents a configuration that describes possibly interesting phenomena which would go unnoticed with dimensional methods (Toivonen et al., 2012).

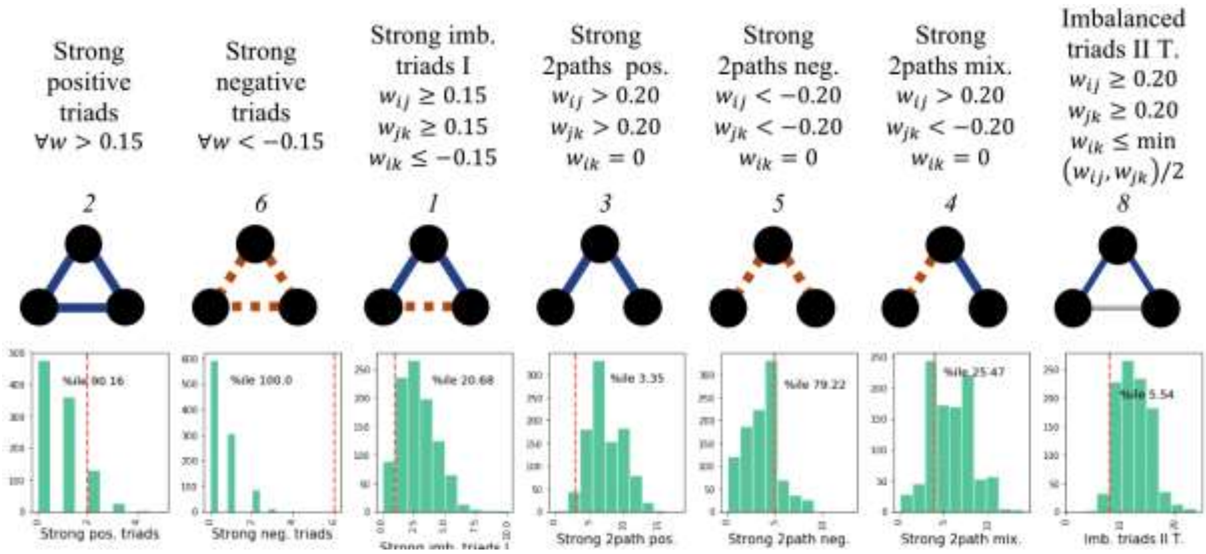
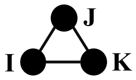
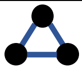
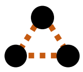
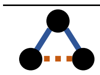
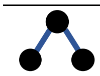
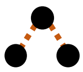
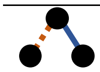
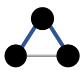


Figure 3. 11 Weighted and signed motifs, name used in this study, the definition, number of occurrences in the network, schematic figure, and the figure showing distribution of motif frequencies in 1000 random networks with the same degree sequence and weight distribution and percentile value of the frequency of empirical network in that distribution.

Results show that even when we "focus" just on motifs of relatively strong ties, (Figure 3.11 (third row), all of them identified in Table 3.3), again only the NNN triad occurs significantly and more than expected by chance. The cardinality (a term used in network analysis to address the significance of a motif) of the motifs in this network is thus not dependent on the strength of the weights. However, the strong imbalanced triads, 2paths with positive weights, and imbalanced triplets II T. have the tendency to be underrepresented. This pattern is expected in social networks, where Imbalanced triads and "forbidden triads" (2paths) are generally less expressed, and this network shows similar tendencies.

All motifs defined in Figure 11 are identified and described in more detail in Table 3.3.

Table 3. 3 Weighted and signed motifs identified

Motif 	i, j, k; (**pr_{ij}, pr_{jk}, pr_{ik}**), [r_{ij}, r_{jk}, r_{ik}]
	Private body, Public body, Body competence; **(.30, .40, .25)**, *[.52, .58, .49]* Conscientiousness, Fair-Mindedness, Self-Disclosure; **(.16, .21, .16)**, *[.34, .37, .37]*
	Tradition, Universalism, Power; **(-.34, -.29, -.16)**, *[-.20, -.46, -.11]* Tradition, Universalism, Hedonism; **(-.34, -.21, -.36)**, *[-.20, -.12, -.38]* Tradition, Universalism, Achievement; **(-.34, -.30, -.28)**, *[-.20, -.34, -.24]* Tradition, Self-direction, Power; **(-.37, -.20, -.16)**, *[-.47, -.12, -.11]* Tradition, Hedonism, Achievement; **(-.36, -.17, -.28)**, *[-.38, .01, -.24]* Universalism, Hedonism, Achievement; **(-.21, -.17, -.30)**, *[-.38, -.01, -.24]*
	Militaristic int.-, Universalism, Wholesome act. int.; **(.22, .16, -.39)**, *[.20, .19, -.37]*
	Agreeableness, Empathy, Extraversion; **(.27, .32, .0)**, *[.45, .39, .16]* Life satisfaction, Emotional stability, Agreeableness; **(.25, .26, .0)**, *[.48, .35, .25]* Wholesome act. int., Intellectual int., Openness; **(31, .21, .0)**, *[.41, .44, .17]*
	Self-direction, Tradition, Universalism; **(-.37, -.34, .0)**, *[-.47, -.20, .21]* Hedonism, Tradition, Self-direction; **(-.36, -.37, .0)**, *[-.38, -.47, .16]* Achievement, Tradition, Self-direction; **(-.28, -.37, .0)**, *[-.24, -47, .09]* Self-direction, Power, Universalism; **(-.20, -.29, .0)**, *[-.12, -.46, .21]* Hedonism, Universalism, Power; **(-.21, -.29, .0)**, *[-.12, -.46, .21]*
	Militaristic int.-, Universalism, Tradition; **(.22, -.34, .0)**, *[.20, -.20, -.10]* Intellectual int., Wholesome act. int., Militaristic int.-; **(.31, -.39, .0)**, *[.41, -.37, -.11]* Militaristic int.-, Universalism, Power; **(.22, -.29, .0)**, *[.20, -.46, -.10]* Militaristic int.-, Universalism, Achievement; **(.22, -.30, .0)**, *[.20, -.34, -.10]*
	Self-monitoring, Extraversion, Empathy; **(.30, .32, .09)**, *[.31, .39, .12]* Depression-, Emot. stability, Agreeableness; **(.38, .26, -.06)**, *[.55, .35, .17]* Emot. stability, Agreeableness, Empathy; **(.26, .27, -.06)**, *[.35, .45, .15]* Violent-occult int.-, Militaristic int.-, Universalism; **(.53, .22, -.11)**, *[.45, .20, -.07]* Life satisfaction, Emot. stability, Depression-; **(.25, .38, .11)**, *[.48, .55, .40]* *Wholesome act. int., Intellectual int., Openness; (.31, .21, .0), [.41, .44, .17]** *Agreeableness, Empathy, Extraversion; (.27, .32, .0), [.45, .39, .16]** *Life satisfaction, Emot. stability, Agreeableness; (.25, .26, .0), [.48, .35, .25]**

*Identified also as a 2path pos. motif due to overlap in the motif definition with Imb. triad II T.
(-) after the name of a psychological attribute means that it has been reversed

Strong PPP triads may indicate the presence of a common cause, for instance because the three variables measure the same underlying psychological construct, which then acts as a latent variable. Unsurprisingly, the relationships among the three constructs measured by the Body Consciousness questionnaire represent one such case. Another such motif is made of Conscientiousness and two integrity measures, Fair-mindedness and Self-disclosure, pointing out that they are likely capturing similar psychological dimension. A second possibility that may underlay PPP triads is a positive feedback between the variables, as found in the mutualism model for intelligence.

All six NNN triads involve Schwartz's values, with Tradition being present in five of them. This configuration cannot emerge from a common cause and may suggest a negative feedback loop between the attributes. Still, such an interpretation is formed on conclusions about intra-individual differences that are based on inter-individual data, which may not necessarily hold. A second possible reason for observing NNN triads is that the variables have been conditioned on a common effect to which each of them positively contributes. The logic here is the following. Suppose that three variables A, B, and C increase the probability of common effect D. If we condition on D, we only consider the values of A, B, and C for a given value of D. Suppose we observe that the effect is present (or D has a high value), but A is not present (or has a low value). Then that information makes it more likely that B or C are present (or have a high value). Thus, conditioning on D, we expect A, B, and C to be negatively related so that they form an NNN triangle in the partial correlation network.

One NNP triad consists of a negative association between Low Militaristic values and Interests in wholesome activities, while both variables are positively correlated with Universalism. This triad identifies a puzzling relationship that might suggest multidimensionality of the Universalism value. Positive 2paths show that Empathy, Emotional Stability, and Intellectual interests may play role of mediators. Negative and mixed 2paths similarly show the variable in central position (position "*J"* in Table 3.3) as bridging the remaining two attributes in the subgraph. Finally, eight configurations present the strongest imbalanced triplets II T. in the network, that are not possible to describe in the metric space. Three of them also fall under 2paths, due to the overlap in the motif definition. The variable in position "*J*" (see Table 3.3, first row) in this motif is likely to be a broad concept with multiple meanings.

3.4.3.2 Analysis of motif intensity

In previous research, the Intensity measure has been applied for triadic motifs consisting of positive weights only. Therefore, we modified the approach described by Onnela et al (2005) by calculating *I* and *Q* separately for triads with a different configuration of positive and negative ties to allow comparing the Intensities across different motifs. The average Intensity and Coherence for all investigated motifs are shown in Figure 3.12.

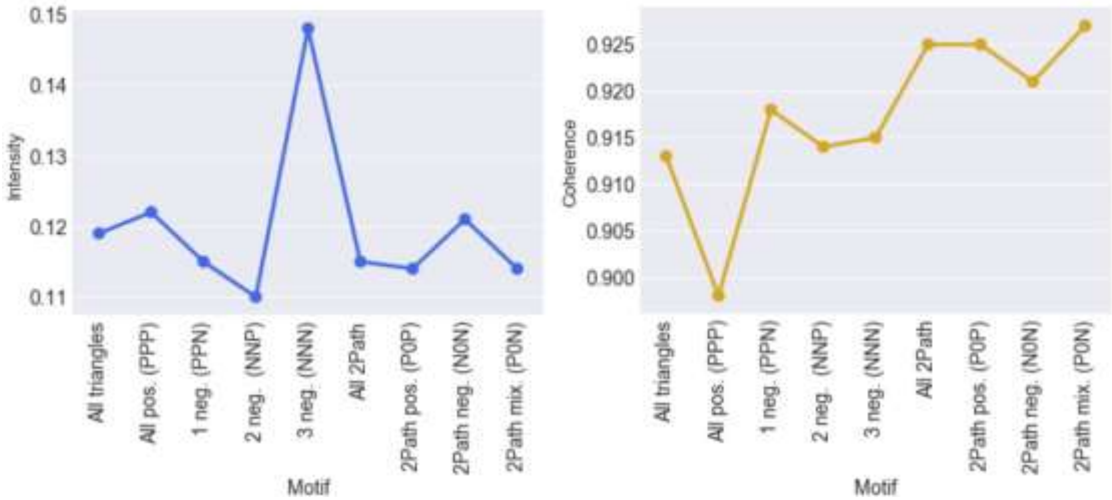


Figure 3. 12 Means of Intensity and Coherence of all triads and signed motifs in the network

Visual inspection of Figure 3.12 reveals that the differences in Intensity and Coherence between the motifs are very small (y axes show range of 0.05 for *I*, and 0.025 for *Q*). When looking at the structural motifs concerned only about presence and absence of ties, and not their weights, all triads have a higher Intensity than 2paths, but the difference is very small. In psychological networks, it would be expected that triangles have a higher Intensity than 2paths, as triangles represent mutual connections between all three nodes, making it more likely that the nodes will reinforce each other. Because of this reinforcement, it would be expected that the weights are of higher absolute value than in 2paths, where one edge is missing, making such effect less plausible.

The most intensive motif, i.e., the motif with the highest average geometric mean of weights, is a triad made of three negative ties NNN, followed by positive triad (PPP) and 2path with two negative ties (N0N). The finding that a NNN motif is the most intensive is somewhat surprising for networks of this kind, but before attempting interpretation, we will proceed first with analysis of Coherence, followed by significance testing. Internal Coherence of 2paths (open triads) is somewhat higher than for closed triads (Figure 3.12, right panel), which is to be expected as 2paths consist of one weight less than triads. PPN seems to have relatively higher, while PPP relatively lower *Q*.

Having a high (low) average Intensity of a motif does not imply that the motif is highly (lowly) expressed in the network. Therefore, the next step is to check how significant the Intensities are. The same applies to the *Q*, where a high *Q* of a motif does not imply it is significantly more coherent. To answer those questions, the Intensities and Coherences of each motif are compared with the mean of *I* and *Q* of each motif in an ensemble of 1000 random networks. The results of the analysis are shown in Figure 3.13.

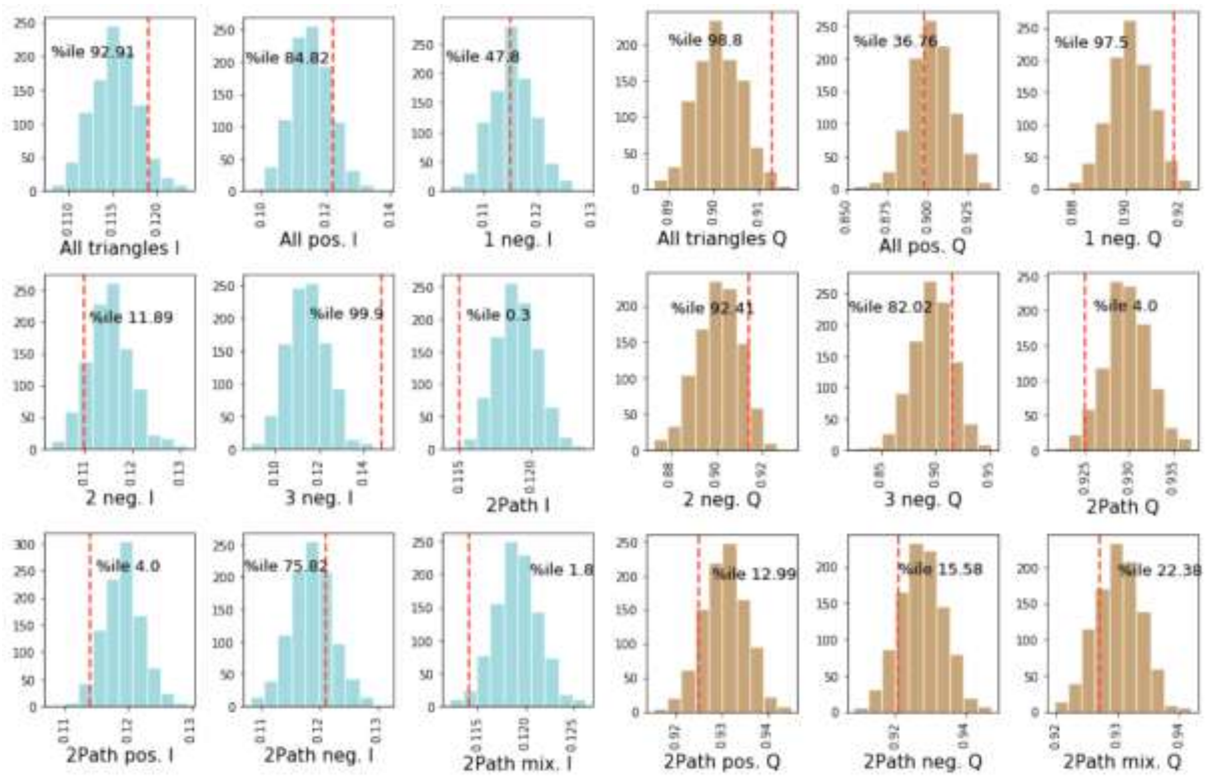


Figure 3. 13 Significance of motifs' Intensity and Coherence: Distributions of Intensity (first three columns, coloured blue) and Coherence (last three columns, coloured light brown) of all closed and open triads, 2paths, and signed motifs in 1000 random networks with same structure and weight distribution as empirical network, with its percentile values.

The only motif whose Intensity (percentile value > 97.5) is significantly high, is a triad with three negative ties (NNN), which is in line with the results on the frequency and the descriptive analysis presented in Figure 3.12. Although the average Intensity is not high in absolute terms (slightly above 0.14), the frequency and Intensity analysis both suggest that the NNN motif is an important characteristic of the network. In Table 3.3, we saw that all NNNs involve only Schwartz' values. NNN motifs show a tendency to be "nested" around few nodes – only the nodes that represent Schwartz's values are "responsible" for the high frequency (and Intensity) of that motif on a network level. Furthermore, from Figure 3.1 (and the centrality analyses) we observed that not all Schwartz's values are central. From that we may generate a hypothesis that the most prominent characteristic of the psychological system of 26 attributes is described by a negative feedback between values, although the cluster which such pattern is not central in the system. A second possibility is that some of the values are involved in a common effect with respect to one of them, which might for instance arise when, say, Tradition is caused by all other variables. Due to the conditioning on the common effect, the NNN pattern may arise for the causal variables in the partial correlation network. A final possibility would be that the high occurrence of NNN may be the result of estimating network on a sample which is self-selected (i.e. implicitly conditioned) on a variable that is a common effect of Schwartz's values.

Two motifs with significantly small Intensity (percentile value < 2.5) are all 2paths motif (structural, disregarding the signs of ties), and 2paths with one negative and one positive tie (with mixed ties - P0N). The later finding is an example of the importance of comparison with the reference system. When we analysed only the average Intensity, we have found that 2paths have a higher Intensity than other motifs. Comparing this to what may be expected given the network structure and weight distribution, we can see that, in fact, the Intensity of 2paths, although somewhat higher in absolute value than Intensity of other motifs, is significantly smaller than it would be expected by the null model. The "intuitive" expectation about smaller Intensity of 2paths due to the lack of third link is supported.

Closed triads (all triangles) display significantly high internal Coherence. From the tie's perspective, this may suggest that weights of similar strengths show the tendency to form triads. Or, from a node perspective, that psychological attributes that form a triad tend to be connected with ties of similar strengths (in absolute values). Imbalanced triad (PPN, called "1 neg." in Figure 3.13) is also significantly more coherent, meaning that the weights within this triangle tend to be equally distributed (they do not show big variations). Interestingly, so-called imbalanced triads in this network consist of "balanced" edge weights. The overall pattern of results show that a significant I does not imply significance in Q, which highlights that they measure two different aspects of this system.

More details about procedures and results of the analyses are organized in 13 sections of the Appendix 3: data processing, sample description, descriptive of missing data, descriptive statistics of 26 psychological attributes, the choice of the estimation method, robustness analyses, network of 26 psychological attributes, analysis of network ties, centrality analysis, correlations between four centrality measures in full network and in MST, the MST with different distance measure, the effect of reverse coding on the analyses, and participation coefficient based on empirical (data-driven) communities.

3.5 Discussion

This paper has demonstrated how the use of three metrics taken from network science can enrich our understanding about psychological networks. Given the effort invested in estimating the network structure, it is a missed opportunity not to use the information it entails more fully to gain deeper understanding of estimated network. This "omission" may be understood and partly explained by researchers in the field being preoccupied primarily with network estimation methods (Christensen et al., 2018; Williams et al., 2019) and replicability issues (Epskamp & Fried, 2018; Forbes et al., 2017, Borsboom et al., 2018) that arise from the fact that network structures between variables are considerably more difficult to determine, relative to e.g. internet links or electricity nets; after all, conditional association between variables are not observable, but must be estimated from data. Appropriately dealing with sampling error in estimating network structures, and assessing their robustness, has therefore been the priority in psychological network analysis.

The concise overview of the three methods in terms of hypothesis and research questions, and procedure is given in Table 3.4.

Table 3. 4 An overview of the three methods

MINIMUM SPANNING TREE	
Recommended for network	Dense network and/or network with many small edges
Important procedure steps	1. Selecting distance measure: i. Gower's distance ii. Distance inversely proportional to shared variance 2. Centrality analysis (by inspection or/and with standard centrality measures computed)
Output	MST – filtered network
Methodological considerations	Distance measures i) and ii) will produce different MSTs if network has negative ties*
Other analytical possibilities	Looking at MST branches as communities Using MST to test the robustness of network estimation of the most essential edges MST can include distance metric as weight for further analysis
Effect of reverse-coding variables	i) affected* ii) not affected
Hypothesis/ Research question	RQ: Which node is the most central? Which (overlapping) communities exist in the network?
PARTICIPATION COEFFICIENT *as a corrective*	
Recommended for network	1. Pre-existing differences in kinds of nodes 2. Network with communities
Important procedure steps	If 1. is true: a. Defining node groups b. Calculating PC c. Choosing centrality measure to be corrected with PC (optional) If 2. is true: a. Data-driven detection of communities b. Calculating PC c. Choosing centrality measure to be corrected with PC d. Comparing the rank order of chosen centrality measure before and after the correction
Output	PC values for each node (in 1.b and 2.b); Corrected centrality measure (for 1.c and 2.c)
Methodological considerations	Communities should not overlap (1 and 2) 1.a Group affiliations may be ambiguous 2.a Decision about appropriate community detection algorithm
Other analytical possibilities	PC version that treats positive and negative edges separately
Effect of reverse-coding variables	Not affected if signs are not taken in the account when calculating PC
Hypothesis/ Research question	H_0= A centrality measure is not affected by (pre-existing or data-driven) communities
MOTIF ANALYSIS	
Recommended for network	1. Not for networks with small number of nodes and/or very low density 2. Has negative and positive ties 3. If weighted, additional steps in the procedure
Important procedure steps	a. Defining motifs of interest and the null model b. Motif identification and frequency c. Significance testing of motif frequency If 3. is true: d. Motif intensity (and coherence) e. Significance testing of motif intensity (and coherence)
Output	Identified motifs; Motif Frequency; P-values for frequencies; Motif intensity (and coherence); P-values for intensities (and coherence)
Methodological considerations	The definition of the null (reference) model
Other analytical possibilities	Other motif structures, e.g. that include more nodes
Effect of reverse-coding variables	Identified motifs and motif frequency will be different*, but onclusions about significance (of frequency, intensity, and coherence) will tend to converge
Hypothesis/ Research question	Many research questions and hypotheses possible. In this study: *Signed edges will tend to cluster in line with is observed is social networks and correlational networks (balance theory, forbidden triads, imbalanced triplets):* H_1= P0P, NNN, and PPN will be less frequent than expected by chance. RQ1 = Do same pattern of results holds true when only relatively stronger motifs are considered? RQ2= Are Intensity and Coherence measure following the same pattern of results as frequency of motifs?

* This should be the case, but there is a possibility that distances related to the negative edges are present in a network in such a way that will not affect the MST construction, e.g. a weak negative tie that exists among two peripheral nodes that have ties to other more central nodes

We demonstrated on an illustrative dataset how each of the methods proposed here adds new information about the network structure. First, the MST can help us in shedding light on the topological arrangement of psychological attributes in the network. Specifically, in the current example, the MST suggests that Empathy is the most similar to all other traits and plays the role of a "network connector" – it is the most central trait when centrality is based on the network filtered down to its most essential ties. In the network which also includes Big Five traits, it was somewhat surprising to see that Empathy has such important standing. This could be due to the questionnaire used for this trait (the Empathy Quotient) which captures affective and cognitive aspects (see Table 3.1). The authors (Baron-Cohen & Wheelwright, 2004) of the questionnaire state that the cognitive component of Empathy is closely related with an individual's "Theory of Mind" – a cognitive process that allows people to understand others and oneself. It might, thus, be plausible that cognitive processes related to Theory of Mind serve as a central hub in the system. In addition, it is tempting to see the analogy and state that the trait which is seen by some to hold society together, may also holding this network of different psychological attributes together. This finding is worth of further attention due to an implicit and misguided notion that Big Five traits are the best representative of psychological differences between individuals. If true, in network terms that would imply that they are expected to be in the top five most central nodes, which is the case only for some of them. In fact, Openness is among the peripheral nodes. Nonetheless, further theoretical consideration and research is needed. The MST provided an additional insight into possible clusters of attributes, and showed that clusters – that is, different branches of the tree, for the most part do not align with different kinds of psychological variables. For example, Big five traits and Schwartz's values span over different branches, suggesting that the grouping of variables is based on specific content rather than "nature" of a psychological variable (e.g. whether it is a trait, value, or interest). Furthermore, we used the fact that MST preserves the information of edge signs to employ it for robustness test of network estimation.

Second, by including information about the participation coefficient based on pre-defined communities, which also included "communities of one", we highlighted the specific role of some nodes based on their equal importance to the structure of different parts of the network. We found that Intelligence, although weakly connected to other traits, and by all centrality measures quite peripheral, does seem to have an interesting property of being relatively equally associated with all different kinds of nodes in the network. Based on this finding we can hypothesize that cognitive ability relates to personality: not in terms of substantial effect sizes but because it relates at a constant strength to most "parts" of psychological system. In other words, the question about relation between cognitive ability and psychological individual differences could be better answered if instead of looking at the "size" of that influence (operationalized with some statistical measure), researchers refocus their attention to the "broadness" of that influence. This agrees with the suggestion of Salovey and Mayer (1994) that instead of looking at pairwise correlations, a more complex analysis that looks at many connections at once should be preferred. Likewise, network ties of Intelligence seem to imply a different relation with Big Five model than reported in the recent review (Stankov, 2018). When 24 other relevant individual differences (26 minus 2 variables whose connection is under the consideration here) are controlled for, the strongest tie is not with Openness, but with Agreeableness and Extraversion (both negative and around 0.10).

We used PC together with the Participation Ratio to arrive at more sensible centrality measure, which showed that different centrality indices converge to Extraversion, Emotional Stability and Empathy as the three most central nodes in this network. Centrality of Extraversion and Emotional Stability would be expected since they are one of the traits that have been recognized as important psychological dimensions and systematically studied from early on in psychological science. Empathy taking the "third place" is somewhat surprising, but as discussed before, could be related with this trait capturing cognitive processes that are essential and fundamental in many social interactions (Ahmed & Miller, 2011).

Finally, we used motif analysis to research possibly interesting three-node configurations and investigate whether this psychological network "behaves" as a social network regarding its balance of negative and positive ties within triads – and the results showed this is not the case. We learned that some configurations that are challenging to interpret exist in the network at a higher frequency than would be expected in the reference system; most notably, this was the case for NNN triads. Identification of strong motifs revealed that these triads originate mostly from one group of nodes – Schwartz's values, possibly revealing negative feedback or (implicit) conditioning on a common effect of some or all of the variables. NNN triads are also significantly stronger than expected, but otherwise intensity and coherence do not seem to be related with frequency of motifs.

3.5.1 Methodological considerations related with the reverse coding of variables

An important issue related with network modelling of relationships between continuous variables which probably did not receive enough attention so far is the effect of reverse coding of variables on the results of network methods. It becomes an even more pressing issue when nodes are aggregations of more complex concepts – not easily described as positive or negative (e.g., some values), or when variables present dimensions which are interpretable on both ends (e.g. emotional stability – neuroticism, extraversion – introversion), and often coded arbitrary. This is the case for many continuous variables in psychology, and probably for all variables in our dataset to some extent. For example, Emotional stability (ES) is often coded negatively as Neuroticism (N), begging the question what would happen with the results of analyses if we used N instead of ES? To find out we repeated most of the analyses reported in this paper with the network that had N instead ES, and several other networks with some of the variables recoded. The results are presented in detail in Appendix 3 (section 12), while here we will highlight just the most important conclusions. The estimated network will have the same structure and absolute values of weights, but all the edges of reversed node will change their sign. Weight distribution of network is affected too, due to the changes in signs of some of the weights. The most affected are the results of MST, but only if the preferred distance measure (equation 1) is used. Otherwise, with the distance measure that is inversely proportional to shared variance, MST results are unaffected. This situation brings up the dilemma of which distance metric to use: the more rigorous one that is affected by variable coding, or the one which leads to a possibly substantial loss of information, but is immune to reverse coding? We do not provide an answer, because as usually, it will depend on the specific network, variables included and the research question. Nevertheless, researchers need to be aware of this issue. In contrast with MST, PC that takes only absolute value of weights is not affected by reverse coding. Motif analysis will produce different motif frequencies, intensity and coherence values, but the results of significance testing will not be affected to a greater extent and will tend to converge for the same network with differently coded some of the variables.

A logical conclusion following from the previous section is that the three methods discussed in this paper require an effort to be applied to a psychological network, as some additional decisions need to be reached that are in accordance with research questions/goals (also explained in sections 4.1, 4.2, and 4.3). Each decision has its repercussions. In the case of MST, one needs to consider the presence of negative ties and what is achieved by deciding to look at two negatively associated nodes as more dissimilar than two nodes that are not connected at all. For PC, the nature of nodes included in the network needs to be carefully looked at, while for motif analysis some notion about which specific configurations may reveal interesting patterns in the network should be formed. The common ground of all three methods is that they look at direct, local ties, but in the contrast to the degree centrality they provide more fine-grained information. This presents a potential for a deeper understanding of any network but is also a very convenient feature for networks that do not have well defined boundaries. By boundaries, we refer to two issues: The first issue is the possibility that some node(s) which are part of the system are not included in the network analysis. This is an issue for our network where selection of variables was atheoretical – since a "global" theory that describes all psychological attributes does not exist. The selection was further constrained by data availability. For example, we can think of some potentially important attributes that are not in the network, e.g., self-efficacy, need for cognition, narcissism. While acknowledging this, the limitation had its advantage in indirectly pre-selecting some of the currently most studied/used (and therefore, it could be argued, important) concepts. The second issue is related to the first one and refers to the nature of the investigated network. Some networks are more easily influenced by "externalities", e.g., for a psychological network this may include some important life events that can bring about the change in the network by directly or indirectly influencing one or more nodes. Hence, global properties of such network, and measures relying on all ties in it, may be less useful.

The fact that the whole system is not represented and that it is an "open" system, as is the case in probably many psychological networks studied so far, was the motivation for introducing these three network methods that rely more heavily on the local than global network structure.

To conclude, the added value of more information provided by more complex network tools comes at the price of less straightforward procedures and making more decisions (hopefully informed by theory and previous research). However, we believe that those elements are just more salient when using these three methods, than when using typical centrality analysis based on different centrality indices, where many assumptions are implicit (e.g., that all nodes are equally likely to be connected to any other node). Therefore, we look at this requirement for higher deliberation as a good practice in general when applying any network analysis to psychometric data, as it challenges researchers to think more about nature of nodes, ties, and smaller network configurations in the network. Nevertheless, that is not an easy task. Understanding these "new" methods may be at first somewhat less straightforward and difficult for researchers not heavily involved in network analysis. This is especially true for motif analysis, which is by far the most complex of the three. Given that network approach is relatively new in psychology, it will take some time for network ideas and methods to "sink in". Unfortunately, it also lacks strong theories. Be that as it may, better understanding of its analytical tools and exploratory (and that sometimes means under-theorized) potential will greatly facilitate the development of such theories. William James's argument that "a degree of vagueness can be beneficial to science when attempting new research directions" (Brandimonte at al., 2006: p.2) nicely captures the point we are trying to make. This holds true not only for network theories, but for any kind of theories which aim to integrate many small ("local") theories in psychology.

The methodology presented offers interesting possibilities for applications to other areas. For example, it would be informative to see how equally distributed ties are of depression symptoms among different groups of symptoms (e.g., thoughts, physical symptoms, behaviours, feelings), and which symptoms are most central when that information is taken into account. We are not suggesting that all methods should be used in every analysis. The most appropriate methods and its specific procedure should be established based on a careful consideration of the data at hand, research questions and theory behind it, and knowledge of existing network science tools. Our goal was to expand the latter.

The network approach is often compared to other multivariate methods more commonly used in the field of psychology, e.g., structural equation modelling (SEM), confirmatory factor analysis (CFA), mediation analysis (MA), hierarchical clustering (HC), multidimensional scaling (MDS). Although detailed comparison is out of the scope of this paper, we will proceed with a general overview with a highlight on three most notable differences between the network approach and often used multivariate methods in psychology that are more closely related with the three specific methods we introduced in this paper. Firstly, the network approach is less directly guided by researcher's assumptions about the connections between variables than most other methods (e.g., CFA). That is – except for the decision about the variables that will be included in the network. In reality, the decision about which variables will be included in the network is constrained with data availability. In this regard, using PC can help in indirectly controlling for some aspects of that constraint, acting as a corrective measure for possible bias in the selection of nodes that have been included in the network.

Secondly, in comparison with SEM, and MA, network analysis usually deals with a greater number of variables at once, implying that SEM and MA may be more appropriate for smaller set of variables, especially if a clear theoretical expectations exist about relationships between the constructs.

Finally, other approaches are not trying to look at the set of investigated variables as a system, and reveal the properties of that system – they rarely go beyond the micro-level of examining specific connections. In that sense, MST and motif analysis are valuable tools within network approach. MST can be used, among other reasons (mentioned in this paper), to filter the most important connections in the system and to provide answer about the most central variables/nodes on a more general level than specific centrality measures. One part of the output of motif analysis – the identification of motifs – can be viewed as a counterpart to MA (or SEM if configurations tested with motif analysis include more than three variables/nodes) among network methods. However, other outputs of the motif analysis, significance of motif frequency, intensity/coherence analysis and its corresponding significance testing aim at insights that use aggregated information about micro-level to inform about the properties of system as whole.

In conclusion, at this rather early stage of its application in the field of psychology, network analysis is mostly an exploratory approach, but that is likely to change with the introduction of more sophisticated methods that may provide additional insights. In turn, this will enhance the development of specific network theories that can be explicitly tested, resulting in unique contributions to our knowledge about psychological phenomena.

If we view network approach as a different way of thinking about psychological constructs, then exploring networks more "deeply" may lead us to interesting and important findings that would otherwise be missed. Those findings can lead to new questions, generate new specific hypotheses, and help form truly progressive network theories of psychological phenomena.

3.5.2 Limitations of the study

Our goal was to demonstrate the three methods by applying them to an illustrative dataset. The dataset, however, has some limitations that are important to note. Although we had an atypically large sample (for psychological research), it featured considerable amount of missing data, and how exactly to deal with this problem in network modelling is still an open question (Epskamp, 2017). Another open issue in psychological networks is measurement error, which is not accounted for. On an interpretative level, since nodes in network are entities, it is not clear whether their associations can be interpreted as conceptual overlap. To the list of open questions that fall beyond the scope of this paper, we may add the common method variance, that could be responsible for observing some of the edges. However, given that we used partial correlations in the network construction, we believe that most of common method variance (except those unique to a pair of variables) is in that way excluded. Furthermore, one of the sources of common method variance, social desirability, is explicitly included in our network because Self-disclosure is used as an indicator of proclivity to give socially desirable answers (the higher the trait, the smaller the proclivity). Finally, although we had a relatively big sample (pairwise), we do not know how selection-bias may influenced the results. The trade-offs of "big data" in general is that on the one hand it provides more diverse and bigger samples, but on the other hand, a self-selection bias can affect results in many different and unexpected ways. This can play out at multiple levels. For instance, FB users may be unrepresentative regarding some of the traits or due to demographics (McAndrew & Jeong, 2012), or FB users who used the *MyPersonality* application, could be, on average, psychologically different. For example, it could be argued that the sample consists of people who are more interested in psychological aspects of reality and in understanding themselves and others when compared to the general population. In line with this possibility, general self-selection may have influenced our findings about the important role of Empathy in the network. Lastly, individuals chose freely to fulfil certain questionnaire(s). Insomuch as the choice was not random, there is always a possibility that individual psychological attributes influenced that choice (e.g., more depressed individuals could be less likely to fill in an intelligence test).

In the context of those limitations, the findings we arrived at while demonstrating three methods are presented as tentative and their value is in generating new and interesting hypotheses. Furthermore, in our tentative interpretations, due to our network made of well-studied and diverse psychological attributes and due to the scope of this article, we just scratched the surface of many more interesting "small" findings (e.g., each identified triad in Table 3.3 would be a good starting point for a discussion and for generating further hypotheses). That being noted, harvesting an already existing dataset, which contains information about many psychological attributes of big number of people, and repurposing it to demonstrate "new" methods and while doing so addressing some new and some old questions (network of psychological attributes and cognition-personality relationship) presents a potentially useful exploratory research.

3.5.3 Future research

Regarding specific questions related to our dataset, future research would benefit from more theoretically guided inclusion of psychological attributes in the network, including different types of intelligence measures that capture more than g-factor. More objective (behavioral) measures of attributes would enhance the validity of findings. Longitudinal data (within-subjects networks) and data on specific populations (e.g., regarding mental health, age, gender, culture) would in addition enable answering questions about network dynamics and network structure. Future research can use simulation studies to determine how exactly each of the methods is affected by differences in network density, size, number of groups, structure, weight distribution etc. This would be especially interesting for MST, as we explicitly mentioned that it could be used to check the robustness of network estimations. We used PC on what we called “pre-defined communities”, but when there are no differences between nature of psychological attributes PC might be used in a typical way as well, which starts from empirically determined communities (such example is given in Appendix 3, section 13). Likewise, the PC measure can be extended in such a way that one could calculate it for positive and negative links separately. In the motif analysis, we looked only at triads, future work can include higher-order configurations, motifs that involve more than three nodes (e.g., bow tie).

Finally, we selected three network metrics for this article, but there are other measures and techniques that could be fruitfully used in the analysis of psychological networks (e.g., coefficient of intra-module activity, missing link prediction). The message is that network science methodology develops rapidly, and psychologists using network analysis would do well to embrace the possibilities these methods offer in both, analysis and stating new research questions, hypotheses, and even theories.

Chapter 4

The importance of the network meso-level:

The associations of structural and compositional properties of adolescents' peer groups in schools with their substance use and wellbeing

4.1 Prelude

In research over the past decade, it has been empirically supported that in addition to individual level factors, multiple and interdependent contextual factors have a powerful influence on individual health behaviour (Sallis et al., 2008). Social relationships, often conceptualised through social networks, represent one of the contexts that have been found to affect individual health outcomes (Smith & Christakis; 2008). This is especially relevant for the period of adolescence, when young people start to navigate their independence and autonomy from adults and spend increasing time with their peers. Thus, their interactions with peers become an increasingly more important source of influence for adaptive behaviours, attitudes and values, but also for risk behaviours and some behavioural problems (Veenstra & Laninga-Wijnen, 2021; Long et al., 2020; Moody et al., 2010). It is not surprising then that one of the consistent findings in the recent adolescence and relationships literature is that adolescents similar in many behaviours and attitudes (e.g., see Laninga-Wijnen & Veenstra (2021), Barnett et al. (2014)) tend to cluster within peer groups.

Clearly, adolescents' health behaviours are simultaneously shaped with many other sources of influences (e.g., family, neighbourhoods), described within frameworks such as Bronfenbrenner's ecological systems theory (1992). In recent decades, the influence from various social media platforms has become increasingly relevant (Keles et al., 2020). Nevertheless, given that adolescents spend large amounts of time in school and school related activities, their peers in school seem to be of special relevance. The relevance of the school environment was recognized by some governmental initiatives that provide guidance for a whole school approach to support students' mental health and wellbeing (Scottish Government, 2021). However, for a student, not all peers in the school are equally relevant, and the ones that belong to the same group within a school are likely to be more relevant and influential. As such, a peer group has a potential to be used as a powerful mechanism

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in interventions. It also suggests that instead of having a uniform intervention on a school level, a better approach could be to make tailor-made interventions for peer groups. The pervading importance of peer groups is supported by recent research that employed multilevel analytic approaches and social network analysis to simultaneously examine the effect of several contexts on different levels (e.g., peer groups, schools, neighbourhoods). It was found that school's peer group membership is an important predictor for health-related outcomes such as body mass index, and sexual behaviour (Evans et al., 2016; Barker et al., 2019), even after controlling for other, wider contexts and some individual factors.

4.2 Importance of network meso-level (communities)

Due to well-documented relevance of peer groups in schools, we focus on that particular network meso-level. What is considered as a meso-level in a given study is flexible, relative, and depends on the application and what it is contrasted with (Ylikoski, 2012). In this study, it is a level that goes beyond the micro-level of an individual student, and usually extends beyond dyadic relationships and localized network structures (e.g., triads). Although peer groups – the components of meso-level – are usually defined by analysing the whole school network which represents a macro-level, they are a level that is in-between network micro and network macro level. In network terms, the peer groups in a school are communities within a network that are often bigger than triads and as such are considered as larger meso-level structures (Robins, 2009). The focus on different network levels is related to different types of research questions, analytical methodology, and research goals. Furthermore, network theories, that is, the mechanisms that are used to explain network effects can differ.

It is important to note that utilizing network meso-level (communities) does not imply a competing but rather a complementary approach to one focusing on more micro or macro level, especially since these levels we will consider analytically and theoretically. Smith et al. (2020) recognized that network communities are underused in health research. If a health outcome is not evenly distributed over a network (school), but rather shows community clustering, this could inform school health interventions.

4.1.2 Peer groups within schools

Peer groups in adolescence are naturally occurring groups of two or more individuals (Kindermann & Gest, 2011). There are several notions of groups. For example, the term "crowd" is often used to describe a group of students with common reputations, and shared behavioural patterns and values (e.g., "Nerds") that do not necessarily interact or know each other. The latter implies that to define such groups no relational data is needed, as it can rely solely on self-perceptions.

Other notions of groups require relational data used by different methods to uncover groups (group detection algorithms – GDAs). Sociometric groups detect groups of individuals that have a similar pattern of ties with others but they are also not necessarily connected with each other (e.g., “Popular”) (Kindermann & Gest, 2011) and that can be achieved with block-modelling methods. The third notion of a group is operationalized via a community detection algorithm (CDA) applied to network data [20]. A CDA uncovers groups (communities) that consist of peers that nominate each other as a friend (cliques), but these groups can also include[21] others that may not nominate each other (that are not directly connected) but are indirectly connected through mutual friends – only a few “steps away” in the network. In other words, a community goes beyond the immediate social connections of an individual and considers a wider social environment, but smaller than the whole network. The peers in the same community, directly or indirectly connected, are likely to share social norms, to socialize together, to be similar due to the process of social selection, to influence each other and together shape their social environment.

In other words, the school network is partitioned in several smaller parts of the original network[22]. These communities themselves can be viewed as small(er) networks and are likely to differ in their network properties such as size, density, etc. We hypothesize that these global features of communities can be relevant for health outcomes of their members, independently or in interaction or of the social influence that arises from the direct contact with other community members. Yet, theorizing about this network’s meso-level and its effects on individuals has been underdeveloped in health research of adolescents. On the one hand, the idea that network properties at macro level are associated with individual wellbeing can be found in the classical work of Durkheim (1952) and has been applied and supported in studies of school networks (e.g., Pescosolido, & Georgianna, 1989; Gauthier et al., 2022). On the other hand, numerous studies of whole school networks employing statistical models for network data (e.g., exponential random graph models, stochastic actor oriented models) which look at relatively smaller (“micro”) network structures (dyads, triads, etc.) to investigate the existence of network effects on macro level, also found support of social selection, influence, contagion (and convergence) for many health-related outcomes (e.g., Mercken et al., 2012; Kiuru at al., 2012; for a review see Montgomery et al., 2020). Their finding could be extrapolated to imply that health-outcomes cluster within network meso-level structures. But those models do not investigate the network meso-level directly. While many studies in recent decades have found that adolescents and young adults with similar health-behaviours and outcomes cluster together (Ennett & Bauman, 2000; Barnett et al., l2014), the novelty of our approach is that we address the knowledge gap by explicitly examining whether the characteristics of those smaller parts of the networks

[20] Network data that can represent dyads of interactions or friendships.
[21] Depending on the CDA used, Clique Percolation methods detect smaller groups (cliques) that have members that are mostly directly connected.
[22] Depending on GDA they can be overlapping communities or not.

(network meso-level) to which individuals belong to are associated with their health behaviours.

Specifically, our aim is to explore the association between some compositional (gender ratio) and structural characteristics of peer groups (e.g., transitivity - tendency of friends of friends to be friends, etc.) with the health outcomes of individuals who are part of these groups. However, to answer the question about the relevance of the network's meso-level for individual health properly, we recognize its dependence on how the behaviours of interest and the meso-level are operationalized.

Firstly, before investigating our main question, and differently from most previous network research of health-related outcomes, instead of using a more narrowly defined health-related behaviour(s) and/or concept(s) as dependent variables, we employ a method that reduces the dimensionality of data to capture only the most important dimensions of health-related variables. Our rationale is that when investigating clustering on a community level it may make more sense theoretically to look at less specific behaviours, to focus instead on clusters of behaviours that co-occur. Within a peer group, peers may not have information about more specific behaviours or internal states of all members, for example, for those with whom they have no direct contact. Moreover, the social influence and resulting clustering may not operate neatly over specific behaviours, but rather on a more general level, on clusters of behaviours that usually co-occur. Therefore, viewing the *bundles* of behaviours instead of single ones, may be more appropriate for investigating the network's meso-level effects. Related to this, is the issue of the overall "visibility" or social functions of the behaviours that also may affect the degree of clustering.

Secondly, to define the network meso-level (identify peer groups) many different group detection algorithms (GDAs) could be potentially used, and they will not provide identical results. Therefore, we address this methodological gap by checking the sensitivity of our findings with ten different GDAs.

The paper is organized as follows: firstly, we further explain the rationale of using composite scores as dependent variables in the context of this study, after which we turn to our central topic – importance of network's meso-level for individual health. In the third section, we discuss the potential relevance of GDA choice when conducting a network meso-level study. The sections about analyses and results are presented in the same order, and followed by the general discussion.

4.1.3 Clusters (bundles) of health behaviours and their visibility

Most social network studies of peer social influence on health behaviours focused on single behaviours (such as alcohol drinking, smoking, using marijuana) or constructs (depressive symptoms), with some notable exceptions (Long et al., 2017, Adams et al., 2022). However, different health behaviours and outcomes are known to co-occur (Jackson et al., 2012). Their co-occurrence seems to show some regularity. Internalising and externalising problems are the two main dimensions used to describe the structure of mental health in children and adolescents (Cicchetti & Toth, 2014) and how behavioural and psychological problems tend to cluster together. Internalising problems are negative behaviours and emotions directed inwards, for example feeling sad or anxious (e.g., Bongers et al., 2003; Leadbeater et al., 1999).

Externalising problems refer to behaviours directed outside, towards others in the environment, and may include substance use, along with not health-related behaviours such as aggressiveness, delinquent behaviour, risk-taking, norm-breaking behaviours). Additionally, different kinds of substance use tend to co-occur (Halladay et al., 2020)[23].

Social influence is an umbrella term for several complex, simultaneous, dynamic, and possibly interdependent processes. Some of the most examined in the literature are: selection and deselection, peer pressure, imitation and norm conformity. These processes, if present for a certain health outcome, will result in social clustering within school according to the health outcome of interest. Social clustering means that peer groups will tend to be populated by individuals that are more similar regarding the outcome than expected by chance.

Since different health outcomes cluster together (within a person), it is possible that mechanisms of social influence operate on behavioural patterns rather than single behaviours, as Laninga and Vaneestra (2021) suggested in their recent review. For example, an individual may be influenced by their peers' general tendency to use substances rather than specific substance use (e.g., alcohol). In other words, if an adolescent observes that peers who drink are more likely to smoke or that social settings that include drinking also include smoking, this can create expectations that in that social environment both smoking or drinking are accepted. That is, through a process that Laninga and Veneestra called

[23] For adults, substance use is considered as an externalizing problem, but for adolescence it is sometimes mentioned as internalizing, or not classified as either. However, since it does not necessarily need to be directed towards others or related with others in a direct way – we will refer to it just as substance use (not as externalizing problems) in the following text.

"interpreted abstraction", "individuals may perceive and interpret *bundles* of behaviours of their peers, rather than simply adopt the specific behaviours of their peers."(2021; p. 21).

This taken together with studies that show predictable co-occurrence of internalizing problems on the one hand and substance use on other hand, naturally leads to the question whether the social influence processes are the same and equally powerful for different clusters of behaviours.

Possibly important for the process of social influence, different clusters/bundles of health behaviours can also differ in their visibility to others. Their difference in "visibility" comes mostly from the different roles they play in social activities, social functions they serve, and their perceived benefits for young people.

Internalizing problems are by their nature less visible or readily observable than substance use behaviours, or other health-related behaviours such as physical activity or eating habits[24]. Due to this difference in visibility, the mechanisms of social influence and resulting social clustering may be different[25]. Although substance use behaviours are usually done in secrecy from adults (e.g., family members), this is not necessarily the case when it comes to peers. Many forms of substance use behaviours require or are facilitated by certain social settings or activities, may involve specific objects (e.g., cigarettes, drinks) and often other peers may create access to some substances. Moreover, for some peer groups, engaging in substance use may be considered as desirable behaviour. So, although some individuals may be using drugs completely alone and in secrecy, for the majority it could be assumed that that behaviour will include peers in some way, and therefore be more visible to their friends than internalizing problems. Internal states (such as anxiety, depression) of individuals are generally less easily visible to most people, and usually do not serve group functions. Furthermore, adolescents may be less likely to discuss them outside very close friendships or may even try to hide them due to the stigma associated with having mental health issues. Therefore, peer influence and imitation may not be as powerful mechanisms of social influence when internalizing problems are considered, making clustering of adolescents based on it less strong.

In summary, we look at whether different bundles of behaviours cluster to different extent and whether the degree of clustering is associated with visibility of the behaviours.

[24] In general, but there are exceptions, e.g., for individuals with eating disorders.

[25] In addition, their strength could be different and may also differ during the lifespan of a community.

4.1.4 Network meso-level, community properties and individual health

The most central aspect of this research is moving from a question whether clustering of health-related outcomes exist within peer groups in schools to whether the individual differences in health outcomes are associated with some characteristics of the communities in schools that adolescents belong to. The answer to the latter question can provide insights on some mechanisms through which the network meso-level can affect individual wellbeing, and help generate hypotheses for future research on how and why it happens.

A peer group in school, or in network terms – a community – can have a role in the development and maintenance of health-related behaviours of individuals. Different mechanisms, possibly interdependent, can operate at community/network meso-level. For example, direct and indirect exposure to the behaviour can provide an opportunity to engage in certain behaviours, via peer pressure imitation, or conformity to shared norms. Importantly, adolescents can cluster together based on other attributes, e.g., gender (McPherson et al., 2001; Goodreau et al., 2009), socio-economic status (Block & Grund, 2014), ethnicity (González et al., 2007) that themselves can be related with higher risk for certain unhealthy behaviours and health outcomes. In this study, we focus on mechanisms related to community properties. Communities[26] that are found via a GDA will vary in their structural and compositional properties (e.g., size, gender composition) and these differences may contribute to the explanation of health outcomes of members in different communities. In theorising about how meso-level properties affect individuals (and vice versa), a useful framework can be found in the micro-macro approach developed in analytical sociology (Coleman, 1987). The difference is that the "macro" level in the context of our study is the network's meso-level. A rough sketch of our "micro-meso" approach that shows the interplay between the health of community members and community properties is presented in Figure 4.1.

[26] Since in this study peer groups are defined via GDAs, we use terms peer group and community interchangeably.

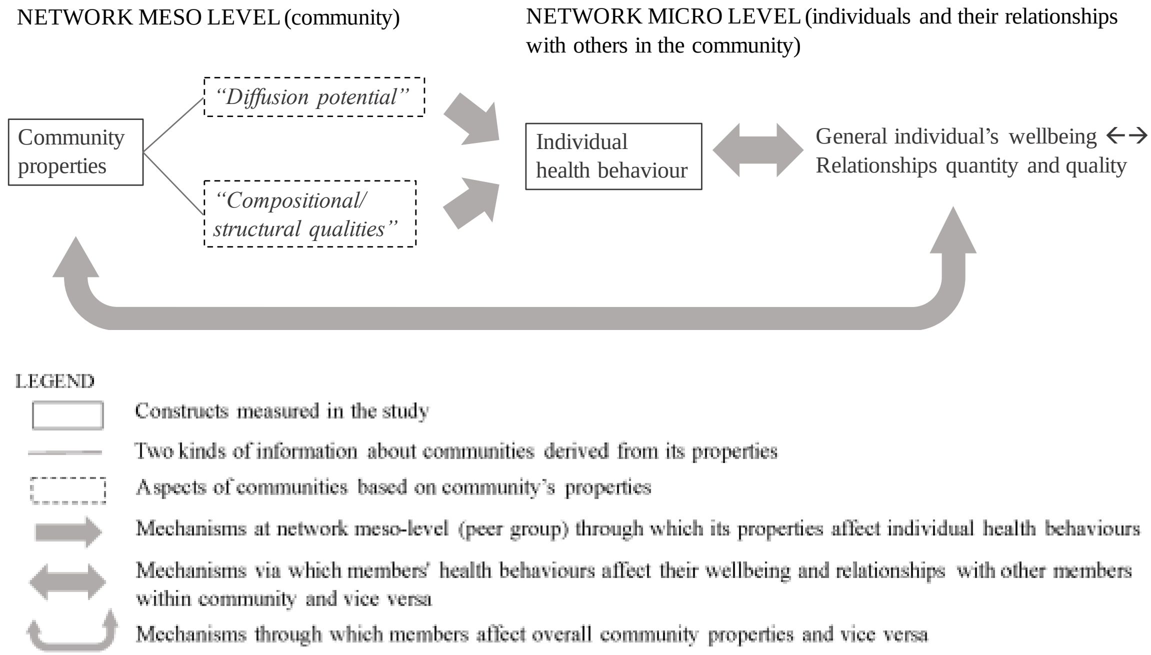
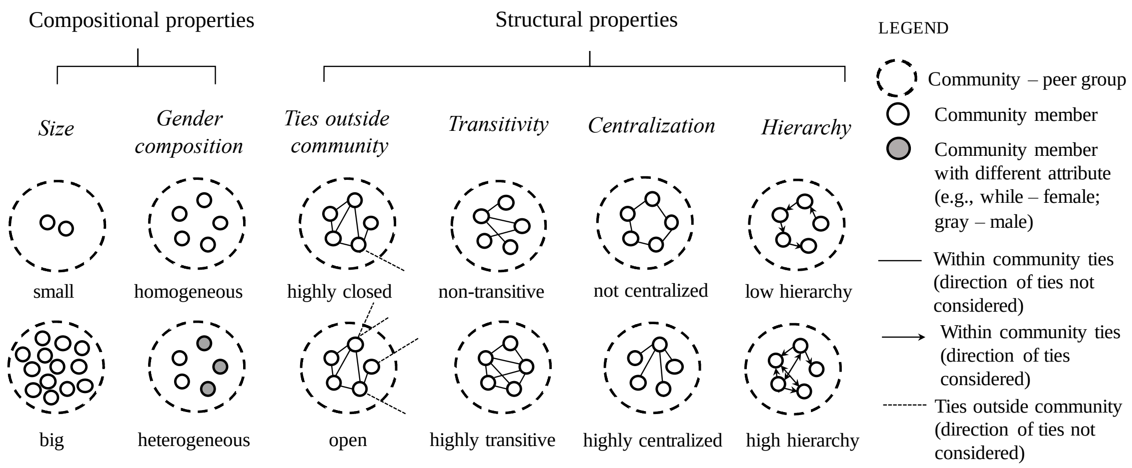


Figure 4. 1 The micro-meso loop: the interplay between the health of community members and community properties

As Figure 4.1 shows, community properties may affect the health of individuals, and vice versa, in two different ways: i) community properties may facilitate the diffusion of health-related behaviours ("diffusion potential"). E.g., in more transitive communities the spread of specific health behaviours is faster than in less transitive communities (Centola & Macy, 2007); and ii) community properties may influence individuals' health ("compositional/structural quality"), for example, a higher transitivity is associated to higher social integration and higher wellbeing (Wray et al., 2011) or/and individuals with high wellbeing may tend to create more transitive relationships and therefore communities. This notion is also supported by research showing that individuals with more transitive personal networks tend to score higher on psychological measures related to better mental health (Kalish & Robins; 2006, Maya-Jariego et al., 2020).

The two ways correspond to different views on networks, as pipes or prisms (Poldony, 2001). Aspect of "diffusion potential" corresponds to viewing network ties as "conduits"/ "pipes" through which something – e.g., a health-related behaviour - "flows" among individuals and can be spread via simple or complex contagion. Aspect of compositional/structural quality views networks as relational patterns around an individual that may have its own effect on and be affected by an individual (Moody et al., 2010), – through structural (pattern of ties) or compositional (attributes of people) effects. Those patterns can be related to the quality of social relationships in the community overall. It is important to note that cross-sectional design cannot disentangle the effect of micro level on meso level and vice versa.

Since each community is examined as a network, there are as many possible community properties as there are measures of network properties. We identified six community properties of interest (toy examples are shown in Figure 4.2). The choice of properties that we investigate was partly atheoretical as we aimed to choose network measures that are not highly interdependent and that describe a community's most basic properties (size, ratio of outside community ties, and transitivity). We also included some properties that were highlighted as generally important by research (e.g., McFarland et al., 2014) on adolescents' networks in schools (gender composition, centralization and hierarchy).



Notes: All examples for community properties are shown for a community of five members, except for the property size. Ties between members are not shown for compositional properties because they are not relevant for their calculation. Examples of structural properties with low and high values do not necessary show the highest and the lowest possible values, but rather the examples of relatively low versus high values.

Figure 4. 2 Six community properties investigated in this study

Here we explain six community properties measured in this study:

1.) *Community size* - The most obvious difference between communities is their size – the number of students belonging to the community. Smaller communities are usually considered to be "cliques" (not necessarily aligning with the network definition of a clique) in which members can have very close relationships with each other and communicate frequently. Bigger communities[27] may consist of several "cliques", and have a very different network structure than smaller groups because they consist of close ties with some members and weak ties with others (Cotterell, 1996). In bigger communities, direct and close relationships could be of higher importance than in small groups (Giordano, 1995). Bigger communities provide more freedom for their members, but also more uncertainty (Simmel, 1950), due to less knowledge about others. While most of their members may interact, they do not necessarily like each other.

2.) *Community gender composition* – People of all age groups, including adolescents, prefer to make friendships with similar others - homophily. One of the most salient features for homophily is gender (Smetana et al., 2006). Friendships in adolescence usually start within same-sex pairs, and later expand to include opposite-sex friends (Cotterell, 1996). Therefore, communities can be mixed, male, or female. Stolle et al. (2008) suggested that communities with compositional heterogeneity make an uncertain context that raises issues around trust and group boundaries.
3.) *Ratio of outside community ties* – Community can be more or less "strong" or closed, meaning that its members have most of their ties with each other, in difference with "weak" or open communities whose members have most of their ties with members of other communities. A strong community would have a small ratio of outside community ties[28], while the opposite is true for weak communities.
4.) *Transitivity* – One of the most basic network properties besides its size and density[29], is its transitivity (sometimes called clustering). Community is transitive if there is a tendency for a friend of a friend to be a friend. Transitive ties are associated with strong ties and transitive networks are related with higher trust (Buskens, 1998), control, and faster information flow and spread of behaviours between the members (Centola & Macy, 2007).

Next two properties are related to status and hierarchy: centralization and hierarchy.

5.) *Centralization* – Most people have a desire for status compared to others and that is amplified during adolescence (Veenstra & Laninga-Wijnen, 2021). This measure partly captures the differences in status. It describes how uneven the distribution of ties in the network (community) is. If everyone had a similar number of ties with others, the centralization would be near zero, and that would imply that there is no status differentiation in the group.

[27] In some literature (e.g., Cotterell, 1996) they are referred to as "crowds" (not to be confused with the same term used earlier in text).

[28] In network science, a very similar measure, called the mixing parameter is used.

[29] Size, density, and transitivity are network level measures that are correlated. Size of a network usually correlates moderately to strongly negatively with density, and in lower degree with transitivity (also negatively). Therefore, the density of the community was not included in the models as one of community properties.

6.) *Hierarchy* – Centralization does not account for the status ordering provided by the direction of ties that gives more information about the hierarchy. "Pecking orders" tend to form within a network (Redhead & Power, 2022; Michell & Amos; 1997), and some asymmetry in relations is often preferred (McFarland et al., 2014). Therefore, we also use a more complex measure of hierarchy (or social dominance) that uses information about the direction of ties among all triads (subgraph of three nodes) in the community (more details in Appendix 4).

Except for the size and community gender composition ("compositional"[30] properties), all other measures are basically network measures ("structural" properties) – but calculated for communities – and for them the information about ties between individuals is needed. Additionally, the last three measures require the community to have at least three members. The properties are not expected to be independent. For instance, the size of adolescents' peer groups is found to be related with gender composition – bigger communities are less likely to be homogenous regarding gender (Cotterell, 1996). Also, some properties are usually correlated, e.g., transitivity is usually higher in smaller communities than in relatively bigger ones.

Due to lack of a theory, our approach regarding community properties is exploratory and we hypothesize that some of the six properties will be associated with individual health outcomes. However, hypothesising about the direction of effect is not straightforward because the two ways in which community properties can affect individual health may work in opposing directions. For example, the same property (e.g., transitivity) can be related with positive health outcomes, but may also facilitate spread[31] of some negative health outcomes over a network. Hence, the two ways in which community properties affect individuals may lead to conflicting hypotheses and it is not possible to disentangle them with a cross-sectional data.

4.3 Using group detection algorithms to identify peer groups

The research mentioned so far employed one or two community detection algorithms (CDAs) on friendship nomination data. A CDA identifies dense parts of the network – communities – characterised by a relatively higher density of ties. A CDA provides a relatively objective measure of group boundaries. While the information about direct friendship ties with others is based on self-reporting, the participants are not asked about all the members of their group or about the ties existing within their group – the information that they may not have. The boundaries of the groups are determined by an algorithm and

[30] We recognize that size can be also understood as a structural rather than a compositional property, but here we are using the term "structural" to emphasize that a measure is based on network data.
[31] This can be via, e.g., a unidirectional simple and complex contagion or convergence processes.

can therefore be considered as relatively objective. Furthermore, if a CDA considers the information about the direction of ties (who nominated who, e.g., Walktrap, Infomap), the information about (non)reciprocity of nominations is harvested when defining groups. However, many CDAs are implemented only for undirected networks (e.g., Clique Percolation, Leiden, Louvain, Label propagation), which means that they cannot use the information about the direction of ties. Another approach is the sociometric[32] approach to network partition which is not based on finding groups that are more tightly connected, but on identifying a subset of actors within a network with similarly structured relations. For that purpose, block-modelling methods are often used. The main idea is that people who occupy similar positions or similar roles will tend to behave similarly (Hawe et.al., 2004). In contrast with CDAs, this approach recovers groups within a network that are not necessarily cohesive or well-connected within and less connected between, but are instead populated with members who have similar positions ("role") in the overall network.

A disadvantage when using any group detection algorithm (GDA) is that the so-called "ground truth"[33] is usually not available. As a result, the accuracy of a partition often cannot be fully evaluated. Furthermore, the result of any GDA depends on the data quality. For example, if there is missing network data on some network members, they may be nominated by others, but there will be no information about who they nominate – their network data will be partly missing. That will result in nodes in the network with in-going ties that have no out-going ties. GDAs do not differentiate between such non-responders and individuals that are nominated by others but did not nominate anyone by their choice[34]. Having non-responders will generally distort the network structure (e.g., lower density, lower reciprocity of ties, lower transitivity due to impossibility to have information about ties between non-responders) which will likely be reflected in a less correct community structure. Another disadvantage that applies to all GDAs is that algorithms usually do not have an explicit lower or upper limit for the size of a community. This can be inconvenient when many groups containing just one or two members are recovered. "Groups" so small do not align with the definition of a group. In addition, the group sizes resulting from a GDA can vary; they can detect small and big groups (depending on the network structure). That means that qualitatively different groups can be detected. For instance, in the literature on adolescents' social networks it is well-established that memberships in small and big peer groups have different functions and are differently important for adolescents' social development (Cotterell, 1996). The exception is the Clique Percolation algorithm, which is based on detecting highly connected cliques, which are usually rather small. Another

[32] Sociometric approach is uses network data to allocate people in different groups based on their popularity.

[33] This phrase is often used in network science literature in the context of community detection algorithms, and it highlights that in most cases researchers have no independent data about true communities within a network. One of rare exceptions to this is a well-known case study about ties within a karate club ("Karate club").

[34] To the best of our knowledge there is no algorithm widely in use which is considering missing network data, but given the constant growth of the literature it is possible that such an algorithm has been developed.

specificity of that algorithm is that it allows for individuals to belong to more than one group, while most other algorithms produce exclusive group memberships. Finally, many of the available GDAs[35] are based on somewhat different rationales and produce different network partitions. To illustrate this point, Gest et al. (2007) applied three GDAs on peer-reported interaction groups and self-reported friendship data and found that agreement across different GDAs was modest for the latter. In research related to health outcomes and adolescence, some of the more often used GDAs are based on a notion of cliques using the Clique Percolation method (Barker et al., 2019) or a similar approach (Ennett & Bauman,1996). Also, different variations of approach based on sociometric groups have a long tradition in developmental research (Hatzichristou & Hopf, 1996). However, there is no algorithm that is optimal for all possible community detection tasks[36] (Peel et al., 2017), and some general guidelines about the choice of GDA in health research have been only recently introduced (Smith et al., 2020). This brings up the question about the robustness of findings related with communities to different methods used to detect them. To gauge the sensitivity of network meso-level studies to methods used for group detection, we will use an ensemble of ten GDAs available in R software and applicable to our dataset.

Given the fundamentally different notion of what constitutes a group, it could be expected that resulting partitions based on community detection algorithms and sociometric approaches will differ and that the latter will show lower clustering and presence of network meso-level effects. To ease the communication, we refer to all the methods we use as GDAs, as we will use eight CDAs and two block-modelling techniques.

Following from the sections above, we form four research questions and hypotheses.

1a. To what extent does the experience of poor health and wellbeing outcomes vary at the individual, peer group and school level? And do peer groups vary significantly in individual health outcomes while controlling individual and the school level?

Hypothesis 1a: Peer groups in schools vary regarding health-related outcomes of their members and will be associated with individual differences in health outcomes even after controlling for relevant individual factors and the school level variation.

1b. Do more socially visible outcomes (behaviours) exhibit higher peer group variation than less visible outcomes? That is, are more socially visible health

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[35] There is no "official" list of all available CDAs/GDAs, but the number of them is growing and in 2010 Fortunato described 50 groups of methods.

[36] This is known as "No Free Lunch" theorem.

behaviours better predicted by community membership than less visible (salient) ones?

Hypothesis 1b: While we hypothesise that adolescents with similar health-related outcomes tend to cluster together, we expect that clustering will be relatively higher for socially visible (salient) behaviours that are also often manifested as a part of social activity, like many kinds of substance use. In contrast, regarding mental health outcomes that are not necessarily immediately visible to others in a peer group, we hypothesise that clustering will be relatively smaller.

2. ***Are some structural and compositional properties of communities related with health outcomes of individuals?***
Hypothesis 2: Communities differ in many properties. We will investigate whether some basic community properties calculated using network analyses and attribute data are related to health outcomes of individuals. We frame the general expectation that some of the investigated properties will be associated with individual health-related outcomes, after controlling for relevant individual factors and school level variation.

3. ***How sensitive is the study of network meso-level in schools to the methodological approach (group detection algorithm)?***
Specifically, we will investigate how successful different GDAs are in partitioning school networks to communities predictive of individual health outcomes and whether their properties are associated with individual health outcomes.

Hypothesis 3: Different GDAs will uncover somewhat different communities that will differ in both clustering regarding health outcomes and the associations of their properties with individual health outcomes.

4.4 Methods

4.4.1 Data and participants

The dataset comes from "The Peers and Levels of Stress" ("PaLS") study that investigated the relationship between pupils' peer group status and level of stress. The data were collected from January to May in 2006 in 22 secondary schools in and around the city of Glasgow in Scotland, UK. The schools were in socially mixed and mainly urban areas (Sweeting et al., 2008). Ethical approval for the study was given by the University of Glasgow Social Science Ethics Committee (SSL/05/03), and informed consent was provided by students and their parents. The study design was cross-sectional. In each school, all students from one year group (S4, 15-16 years old) were invited to participate[37]. At the time of data collection, most of the students had attended the school for four years. Overall, the response rate was 81% (N= 3148), and 50.8% participants were girls.

4.4.2 Measures

4.4.2.1 Attribute data

Students completed a questionnaire about their socio-demographic information, family, health behaviours, wellbeing and their friendships.

Measures used in this study are:

Socio-demographics. Participants were asked to provide information about their gender (male or female), their year of birth, school year, and their ethnicity.

Family affluence. Family Affluence Scale based on the version used in Boyce et al. (2006). It contains four items (e.g., “Does your family own a car, van or truck?”). The total scores range from 0 to 7, higher scores signifying higher family affluence (internal reliability – Cronbach’s alpha was 0.49). Due to negative skewness (-0.56) of the distribution of total scores, in the analyses we categorised the values in one of the following groups: “low”, “medium”, and “high”, representing values 0-3, 4-5, 6-7, respectively.

Parental care and control. Parental Bonding Instrument brief form (Parker et al., 1979; Klimidis et al., 1992) was used. It contains eight items that ask participants to describe their parents or guardians. Four items are about parental care (e.g., “Are loving”, Cronbach’s alpha was 0.72) and four about parental control (e.g., “Try to control everything I do”, Cronbach’s alpha was 0.59), with possible answers “Almost always” (1), “Sometimes” (2), and “Never” (3). Scores for both care and control could vary between 0 and 8, and a higher score signifies higher care and control, respectively.

Smoking. Student’s own smoking status was measured by asking them to choose one of five statements (from “I have never smoked at all (not even a puff)” (1) to “I smoke regularly (1 or more cigarettes a week)” (5)) that describes them the best at the moment.

[37] In the UK, the students in each year are not divided in separate classes, rather they attend different subjects with different groups of students (subject-specific classes).

Drinking. Frequency of drinking was measured with the question "How often do you have an alcoholic drink (not just a sip)?", with the range of possible answers from "Every day" (1) to "I have never had an alcoholic drink" (8).

Using drugs. Students were asked how often they use the following drugs (not including drugs that the doctor or chemist has prescribed to them): cannabis, Valium, amphetamine, LSD, ecstasy, solvents, cocaine, heroin, and magic mushrooms. The questionnaire included colloquial (street) names for these drugs as well. For each drug, five possible answers ranged from "Everyday" to "Never". Due to overall low prevalence of drug use, the answers were recoded in such a way that if a participant had reported using any drug every day or weekly, less often, or never, the assigned values were 2, 1, and 0, respectively (higher values, more frequent use).

Drug effects. Recent drug-related experiences and dependence, referring to the last month, were measured with three items (e.g., "I forgot things I did due to drugs.", Cronbach's alpha was 0.79), with possible answers from "Every day" (1) to "Never" (5). The theoretical range of scores is from 1 to 15, with lower scores signifying higher dependence.

Self-esteem. The self-esteem was measured with a scale based on Rosenberg (1965). It contains ten items (e.g., "I am pretty sure of myself", Cronbach's alpha was 0.86), each with possible answers ranging from "Strongly agree" (4) to "Strongly disagree" (1). The possible range of total score was from 0 to 30, higher score signifying higher self-esteem.

General mental health. General Health Questionnaire (GHQ-12) based on Goldberg (1978) was used. It contains 12 questions about health in general in the past few weeks (e.g., "Have you recently been able to concentrate on whatever you're doing?", Cronbach's alpha was 0.85) with answers ranging from "Better than usual" (1) to "Much less than usual" (4). The possible range of total score was from 0 to 36, higher score signifying worse mental health.

Worries. Worries were measured with questionnaire that included a list of ten common worries for teenagers (e.g., "Doing well at school", "My looks", Cronbach's alpha was 0.78) and for each of them participants were asked to answer how much they worry about it, with possible answers "A lot" (1), "A bit" (2), and "Not at all" (3). The total score was based on the sum and ranged from 0 to 30, higher score signifying having less worries.

Descriptive statistics about all variables are provided in tables 4.1 and 4.2.

The sample consisted of predominantly white students, 15 and 16 years old (10 were 17 years old)[38]. Family affluence of most students was medium or high, while 16% had low family affluence.

Table 4. 1 Descriptives of categorical variables (N = 3194)

Variable	*Categories*			*N total**
Gender	*Female*	*Male*		
N	1622	1572		3194
%	50,8	49,2		
Ethnicity	*White*	*Other*		
N	2808	246		3054
%	87,9	7,7		
Age	*15*	*16 and 17*		3190
N	1615	1575		
%	50,6	49,3		
Family affluence	*Low*	*Medium*	*High*	
N	496	1280	1309	3085
%	15,5	40,1	41,0	3,4

N total –total number of all cases with no missing data; *N* – number of cases in each category; % - percentage of cases in each category

Table 4. 2 Descriptives of continuous variables (N = 3194)

Variables	*N*	*M*	*SD*	*Skewness*	*Kurtosis*
Parental control	3155	2,12	1,54	0,71	0,409
Parental care	3159	6,44	1,511	-0,962	0,662
Health-related variables					
Smoking	3164	2,29	1,501	0,933	-0,635
Drinking	3184	4,87	1,615	0,391	-0,649
Using drugs	3149	0,37	0,608	1,390	0,821
Drug effects	3115	14,76	0,948	-6,037	46,886
Self-esteem	3034	19,78	4,475	-0,367	0,733
General mental health	3044	11,07	5,477	0,962	1,021
Worries	3036	21,10	4,121	-0,177	-0,472

N - number of all cases with no missing data; *M* – mean; *SD* – standard deviation

[38] Due to the low number of students aged 17, for the analysis the age was dichotomized to 0 (15 years old) and 1 (16 and 17 years old).

4.4.2.1.1 Principal component analysis

To reduce the number of dependent variables, the principal component analysis was performed on seven health-related variables: smoking, drinking, using drugs, drug effects, self-esteem, general mental health and worries.

The analyses resulted in two components with Eigenvalues higher than 1, which explained 36 and 24% of variance in seven health-related measures, respectively. Horn's parallel analysis on 500 simulated datasets also suggested retaining the first two components. The first component (PC1) can be interpreted as substance use (SU) behaviours (smoking, drinking, using drugs, and drug effects), while the second component (PC2) captures mental wellbeing (MW; self-esteem, general mental health and worries). Since we did not want to create correlated outcomes and we wanted to use a high percentage of variance in seven input variables, we opted for a more complex weighting scheme for seven items to arrive at two component scores for each individual. SU scores include weights for items related with mental wellbeing and MW scores include weights for items related with substance use (see table 2 in Appendix 4). This reflects the fact that in our sample students who use substances more tend to have worse mental wellbeing and students who have better mental wellbeing tend not to use drugs.[39] Higher values on each component score were associated with a better outcome: higher SU score means less substance use, and higher MW score means less mental health issues. Table 4.3 shows descriptive statistics for principal component scores (PC) and raw composite score calculated as a sum of standardised values of variables for which each PC had highest loadings - smoking, drinking, using drugs and drug effects for PC1; self-esteem, general mental health and worries for PC2. PC1 scores were strongly skewed, while PC2 scores were moderately skewed. Gender differences were found: girls have significantly lower scores on both SU and MW than boys (p<0.001). It shows that in our sample girls engage in substance use more and have lower MW than boys.

[39] We address the issue of different approaches for calculating composite scores with post hoc sensitivity tests (Appendix 4).

Table 4. 3 Desriptive statistics for principal component scores

Principal component scores	*N*	*M*	*SD*	*Min*	*Max*	*Skewness*	*Kurtosis*
PC1 – Substance use	2729	0,04	0,977	-4,82	1,90	-1,03	1,24
PC2 – Mental wellbeing	2729	-0,01	0,988	-4,03	4,69	-0,17	0,63
Raw composite scores PC1	3037	-0,01	0,750	-0,92	4,51	1,49	3,04
Raw composite scores PC2	2807	-0,01	0,773	-1,89	3,04	0,51	0,23

N - number of all cases with no non-missing data; M – mean; SD – standard deviation; Min – minimum value; Max – maximum values

Due to the requirement for normal distribution of variables, we used cube transformation for the first component (PC1) scores (after adding a constant to avoid negative values) that resulted in almost symmetrical distribution and was highly correlated with the original PC1 values (Pearson's correlation was 0.96, skewness was 0.01). The second component (PC2) was moderately skewed, and given that it represents only a moderate violation of normal distribution, we did not perform transformation of its original scores. More details about principal component analysis can be found in Appendix 4 (section 2).

4.4.2.2 Network data

Friendship networks. A sociocentric approach was used to collect the data on friendships (peer relationships). The approach requires respondents to write the names of people from a predefined list (a roster) with whom they have a certain kind of relationship. The students were asked to nominate up to six individuals they considered friends. Although students could nominate friends from outside their year group, only ties with students in the year group were considered, to construct a network with well-defined boundaries (the same approach was used in Long et al., 2020). Friend nominations were used to construct a directed[40] friendship network for each school.

In total, 46 participants did not nominate anyone from their school and year group and were not nominated as friends by anyone. These 'isolates' were not included in this analysis (the analysis of differences between isolates and non-isolates is reported in section 3 in Appendix 4). Some students who did not participate in the study were nominated as friends by others (N = 501), and were therefore included in the network analysis and group detection methods. For those students, we had missing data on their attributes, but partly-missing network data – the data about in-going ties only, that is, when they were nominated by others as friends. We did not have their friend nominations (their out-going ties). The rationale was that

[40] Directed network means that if student A nominated student B it was represented as an arrow from A to B (A⟶B), if B nominated A it was represented as A⟵B and if both nominated each other the ties was mutual and represented as A⟷B.

excluding them completely would distort the true network structure more than including their partially missing network data, and that would lead to less valid community structures.

Table 4.4 shows basic network properties for 22 schools and friendship networks (figure 4.3).

Table 4. 4 Basic network descriptives of 22 schools

School	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*	*21*	*22*
N net. (without isolates)	115	113	173	190	145	73	348	132	218	162	159	115	263	282	57	278	107	132	86	143	222	136
N isolates	1	0	2	8	1	3	4	1	0	2	2	2	0	4	1	2	6	0	2	1	2	2
% Non respond.	12,2	12,4	17,9	22,1	15,2	28,8	18,1	9,8	8,7	19,8	12,6	13,9	12,5	10,6	7,0	10,8	23,4	14,4	10,5	11,2	10,4	3,7
Density	0,04	0,03	0,02	0,01	0,03	0,04	0,01	0,03	0,02	0,02	0,02	0,03	0,02	0,02	0,07	0,01	0,02	0,03	0,05	0,03	0,02	0,03
Reciprocity	0,67	0,58	0,49	0,47	0,58	0,58	0,55	0,62	0,56	0,55	0,52	0,60	0,56	0,59	0,60	0,56	0,50	0,53	0,62	0,62	0,60	0,6
Transitivity	0,49	0,43	0,42	0,40	0,40	0,50	0,37	0,34	0,35	0,39	0,46	0,42	0,33	0,34	0,43	0,39	0,42	0,38	0,42	0,51	0,41	0,33
% Big comp.	93,9	98,2	97,1	90	98,6	90,4	98,3	100	100	98,8	95	98,3	100	100	93	99,3	95,3	100	95,3	96,5	100	97,8
Centralization	0,036	0,035	0,027	0,031	0,038	0,054	0,014	0,044	0,027	0,025	0,031	0,059	0,023	0,02	0,06	0,022	0,034	0,044	0,069	0,034	0,025	0,035
Total degree	7,97	6,39	5,85	5,32	7,30	5,42	7,33	7,76	8,39	7,11	6,45	6,87	8,04	8,67	7,47	7,89	4,92	6,56	7,58	8,53	8,23	8,78
EI gender	-0,87	-0,94	-0,74	-0,82	-0,80	-0,89	-0,83	-0,70	-0,86	-0,76	-0,71	-0,74	-0,76	-0,76	-0,77	-0,83	-0,80	-0,88	-0,91	-0,95	-0,90	-0,75
Ethnicity (white)	0,99	0,99	0,99	0,85	0,97	0,98	0,86	0,98	0,85	0,90	0,99	0,99	0,90	0,96	0,95	0,92	0,74	0,96	0,88	0,97	0,89	0,89
Avg. FA	4,83	4,18	4,93	4,58	4,62	3,69	4,66	4,89	6,28	5,04	4,68	4,78	5,83	5,45	4,80	5,44	3,68	4,79	4,87	5,21	5,52	5,04
% Girls (net)	0,56	0,64	0,52	0,41	0,51	0,53	0,56	0,50	0,43	0,49	0,59	0,47	0,48	0,50	0,46	0,50	0,47	0,51	0,46	0,55	0,52	0,53

Abbreviations: net – network; % Big comp. – the percentage of students in the big component of the network – the biggest connected part; EI gender – EI index for gender; Avg. FA – average family affluence; % Girls (net) – the percentage of girls in the school network; Numbers in columns: 22 schools

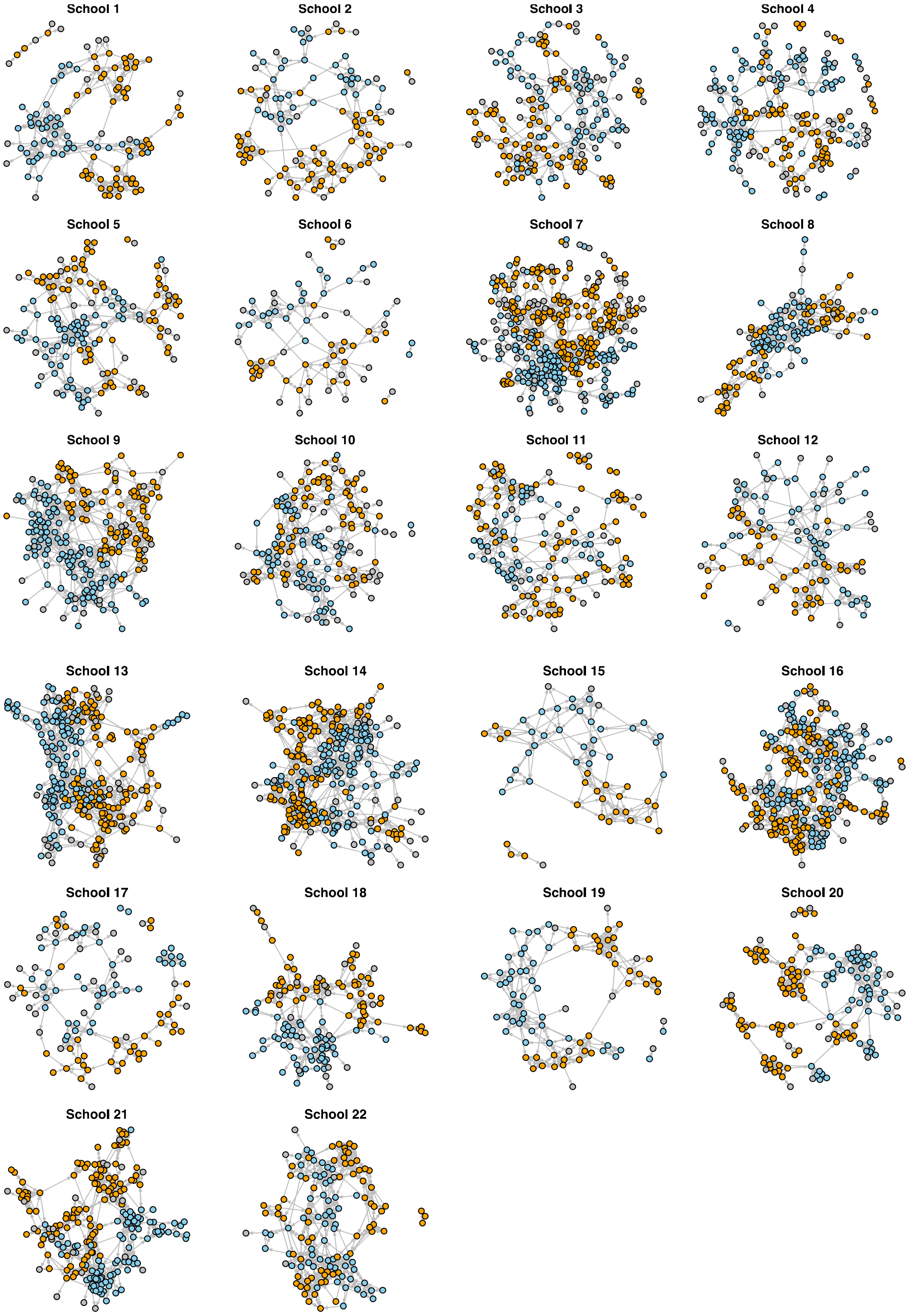


Figure 4. 3 Friendship networks in 22 schools

Colour of nodes in networks: orange – girls; blue – boys, grey – no data on gender

The number of non-responders[41] varies between schools, from only 4% to 29%. School networks show rather low density – only 1 to 5% of all possible friendship ties exist. However, relatively high transitivity (33 to 51%) shows a high tendency of clustering. High values of EI index indicate that most friendship ties (dyadic level) are between students of the same gender and the same ethnicity. Figure 4.3 shows that in most of the schools there is a strong clustering regarding gender.

4.4.3 Analytical strategy

To investigate the clustering of health outcomes within peer groups (RQs 1a, 1b, and RQ 2), the main analysis included a series of multilevel models (MLMs) for the two outcomes separately. Multilevel techniques partition variation in parts that can be attributed to differences between individuals (Level 1), as well as differences between communities (Level 2) and differences between schools (Level 3).

Before conducting the main analysis, the friendship network of each school was partitioned in several communities using ten group detection methods. To answer the first two research questions, the results for the Walktrap method were used. We chose the Walktrap community detection algorithm because it uses the information about direction of ties and previous work examining different community detection algorithms in health-related research (Smith et al., 2020) demonstrated it to be a good choice.

For each community, six community properties were calculated, and included as level 2 covariates in MLMs. Community properties were: community size, whether the community included only students of one gender (male or female) or both (mixed), the ratio of ties outside the community, transitivity, centralization, and hierarchy. Each measure is explained in more detail in the Supplementary materials. More details on procedures along with the results are provided in the following sections in the order in which they were executed, starting with the multi-level analysis based on results of partitioning by the Walktrap algorithm. Finally, the sensitivity of findings was checked with nine other GDAs.

We performed a series of additional analyses pertaining to different kinds of robustness checks, including assessing the sensitivity to partly missing network data. More details and results are reported in Appendix 4 (section 8).

We did not perform a correction for multi-testing (Models 5 on two outcomes) due to the exploratory nature of our study. It would lead to the loss of statistical power and reduce the probability of detecting existing effects. Other models, as well as models related with

[41] The term non-responders or non-participants is used for students in the school that did not participate in the study. The reasons for non-participation are not known.

sensitivity checks are complementary and address the same research question in a different way, so the correction was not needed (Rothman, 1990; Saville, 1990).

4.5 Analyses and results

4.5.1 Multilevel modelling

We used a bottom-up approach, starting with the models containing only random effects: community level variation (Model 1); and including school variation (Model 1.1). Since likelihood ratio test (LRT) comparing the two models indicated that adding school as a random effect did not significantly improve the model fit for both outcomes, the effect is not included in further models to avoid overfitting (over parametrizing) the models. We proceeded with progressively[42] introducing more complexity by adding fixed effects. Firstly, covariates at level 1 (Model 2, see table 4.5); then at level 2 (in three steps, Models 3, 4, 5) and finally adding the three level 3 covariates (Model 6). In the last, most complex model (M6), as level 3 covariates, we included school network size and percentage of females in schools. We also included modularity scores for each school[43].

Each more complex model was compared with the previous (ANOVA F test – reported in table 7, section 5 in Appendix 4). We compared all six models' performance using several indices and ranked them (tables 8 and 9 in Appendix 4). For both health outcomes M5 is ranked as the best model. Also, due to the lack of level 3 effects and our focus on the network meso-level (level 2 in MLMs), Model 5 is considered the main model in the following text.

Also, we ran Model 5 on several subsamples. Following the approach of Barker et al. (2018), we performed stratified analyses to check for effect modification by gender for models M1 and M5. To check the sensitivity of findings to community size, we ran Model 5 including only communities that had 30 or less members to assess whether the findings are similar when relatively big communities are excluded from the analyses.

[42] We added the community properties progressively instead all at once because some of them can be calculated only for communities that have at least three members, which results in models with smaller N and smaller statistical power.

[43] Due to high and positive correlation between modularity score and school size, instead of using the exact N, we assigned value 1 for schools with less than 141 students, value 2 for schools with 141 to 219 students, and value 3 for schools with 220 or more students.

Table 4. 5 Multilevel models in this study

Parameters included	M1*	*M1.1*	M2	M3	M4	**M5***	M6
Random effects							
Schools		+					
Communities	+	+	+	+	+	+	+
Fixed effects							
Individual covariates (level 1)							
Gender (male, female)			+	+	+	+	+
Age (15 or older)			+	+	+	+	+
Ethnicity (white, non-white)			+	+	+	+	+
Family affluence (low, medium, high)			+	+	+	+	+
Parental control			+	+	+	+	+
Parental care			+	+	+	+	+
Community covariates (level 2)							
Community size				+	+	+	+
Community gender composition (male, female, mixed)				+	+	+	+
Ratio of ties outside community					+	+	+
Transitivity					+	+	+
Centralization					+	+	+
Hierarchy						+	+
School covariates (level 3)							
School/network size							+
Modularity (school)							+
Prop. F in school							+

*****M1 and M5 are also modelled separately on male and female subsamples, Model 5 in that case did not include Gender as an independent variable. Model 5 is also run on the sample excluding communities that have more than 30 members.

We conducted multilevel modelling using R packages lme4/lmer (Bates et al., 2015). The missing attribute data was imputed with multiple imputation methods (40 iterations, mice package (van Buuren & Groothuis-Oudshoorn, 2011)). For both dependent variables, SU and MW, we estimated identical linear mixed-models, using the restricted maximum likelihood method (REML) and Nelder-Mead optimizer. Multicollinearity was not present (VIF <3, see figures 25 and 26 in Appendix 4).

Is there clustering regarding substance use and mental wellbeing within peer groups? Figure 4.4 shows how substance use and mental wellbeing scores are distributed over communities for one school (school 19, for all schools see section 9 in Appendix 4). Figure 4.4 suggests that clustering exists in the school, and it is more pronounced for substance use.

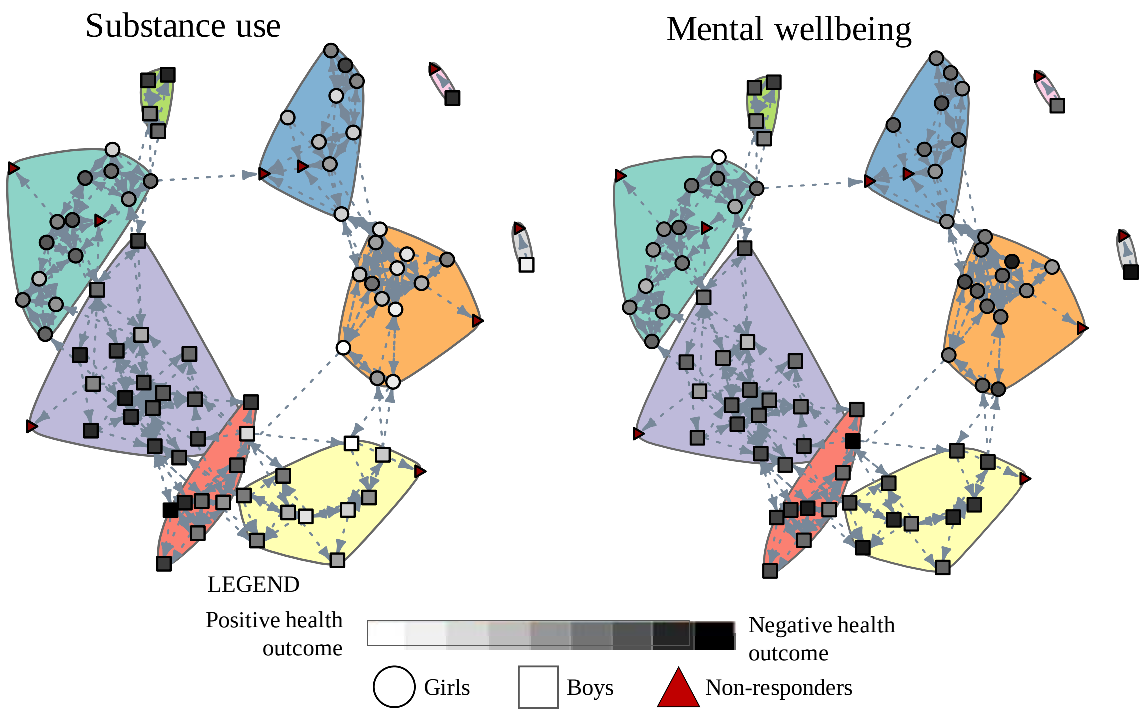
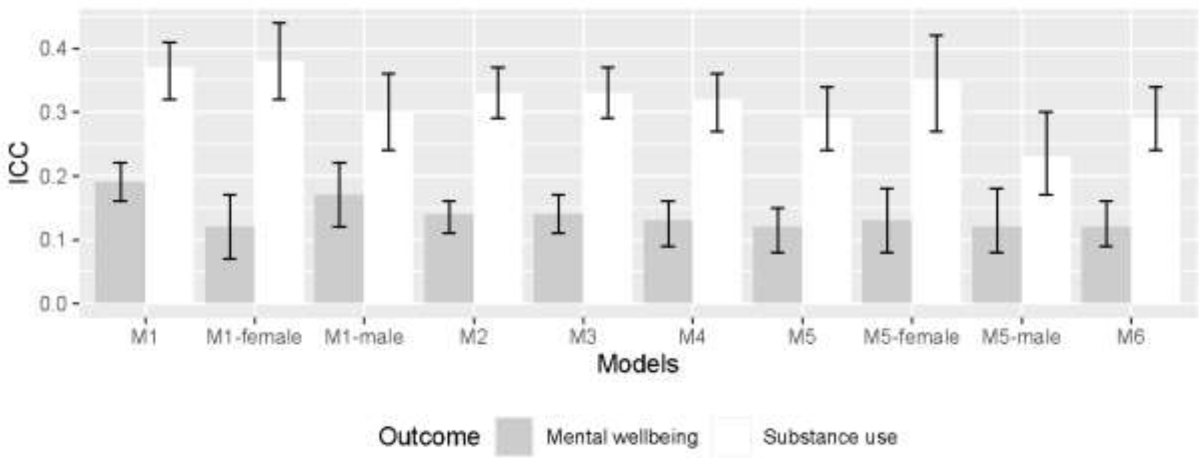


Figure 4. 4 Communities and health outcomes in one school (19)



Lower limits of confidence intervals are at 2.5 percentile, upper limits of confidence intervals are at 97.5 percentile.

Figure 4. 5 Adjusted ICC values for two health outcomes across six models (including M1 and M5 on subsamples by gender)

To answer research questions 1a and 1b, the main statistics of interest are Intraclass correlation coefficients (ICC) (sometimes called Variance Partition Coefficient – VPC). The ICC is the correlation between the values in a dependent variable of two randomly selected individuals from the same group. ICC is for two-level multilevel models equal to VPC and can be interpreted as a proportion of the total variance explained by the grouping structure of the population. It ranges from 0, when grouping does not convey any information, to 1, when all observations within a group are identical (Gelman & Hill, 2007, p. 258). Since we are interested primarily in random effects, we used the adjusted ICC which only relates to the random effects, in difference with the conditional ICC that also considers the fixed effects variances (Nakagawa et al. 2017). Adjusted ICC values and their confidence intervals for the two outcomes and models 1-6 are shown in figure 4.5.

The complete summary of results of all multilevel models for SU and MW, using Walktrap algorithm, are presented in Tables 4.6 and 4.7, respectively.

Table 4. 6 Dependent variable: Substance use - results for Walktrap community detection algorithm

Parameters/ Models	M1	M1.1	M2	M3	M4	**M5**	M5 (female)	M5 (male)	M6
(Intercept)	-0.07 (0.04)	-0.07 (0.04)	0.26 (0.08) ***	0.29 (0.09) **	-0.16 (0.20)	**-0.54 (0.24) ***	-0.15 (0.32)	-0.63 (0.31) *	-0.70 (0.92)
Level 1 covariates									
Gender (male)			0.24 (0.04) ***	0.21 (0.05) ***	0.21 (0.05) ***	**0.19 (0.05) *****			0.19 (0.06) ***
Age (dich)			-0.08 (0.03) **	-0.09 (0.03) **	-0.08 (0.03) **	**-0.08 (0.03) ***	-0.07 (0.04)	-0.09 (0.05) *	-0.08 (0.03) *
Ethnicity (white)			-0.48 (0.06) ***	-0.48 (0.06) ***	-0.47 (0.06) ***	**-0.48 (0.06) *****	-0.40 (0.09) ***	-0.54 (0.09) ***	-0.48 (0.06) ***
Family affluence (medium)			0.08 (0.04)	0.08 (0.04)	0.07 (0.04)	**0.10 (0.05) ***	0.09 (0.06)	0.12 (0.08)	0.10 (0.05) *
Family affluence (high)			0.04 (0.05)	0.03 (0.05)	0.03 (0.05)	**0.07 (0.05)**	0.05 (0.06)	0.10 (0.08)	0.07 (0.05)
Parental control			-0.11 (0.02) ***	-0.11 (0.02) ***	-0.11 (0.02) ***	**-0.12 (0.02) *****	-0.09 (0.02) ***	-0.15 (0.03) ***	-0.12 (0.02) ***
Parental care			0.23 (0.02) ***	0.23 (0.02) ***	0.23 (0.02) ***	**0.23 (0.02) *****	0.23 (0.02) ***	0.24 (0.03) ***	0.23 (0.02) ***
Level 2 covariates									
Community size				0.06 (0.04)	0.13 (0.06) *	**0.28 (0.07) *****	0.26 (0.09) **	0.31 (0.07) ***	0.30 (0.07) ***
Community gender comp.(male)				0.10 (0.09)	0.16 (0.10)	**0.18 (0.11)**			0.17 (0.11)
Community gender comp.(mixed)				-0.07 (0.09)	-0.06 (0.09)	**-0.11 (0.10)**	-0.38 (0.49)	-0.23 (0.10) *	-0.12 (0.10)
Ratio of ties outside community					0.08 (0.29)	**0.09 (0.36)**	-0.15 (0.10)	0.59 (0.46)	0.27 (0.43)
Transitivity					0.62 (0.19) **	**0.73 (0.27) ****	0.09 (0.42)	1.18 (0.32) ***	0.83 (0.29) **
Centralization					0.23 (0.30)	**1.59 (0.51) ****	1.65 (0.70) *	1.99 (0.65) **	1.54 (0.51) **
Hierarchy						**0.17 (0.37)**	-0.10 (0.53)	0.13 (0.48)	0.14 (0.38)
Level 3 covariates									
School/network size									-0.06 (0.05)
Modularity (school)									0.77 (1.07)
Prop. F in school									-0.74 (0.77)
Num. obs.	3148	3148	3148	3148	3079	**2698**	1351	1347	2698
AIC	8228.78	8230.78	7833.15	7845.94	7629.53	**6626.54**	3182.19	3466.65	6631.54
BIC	8246.95	8255.00	7893.69	7924.65	7726.04	**6726.84**	3260.31	3544.74	6749.55
Log Likelihood	-4111.39	-4111.39	-3906.57	-3909.97	-3798.76	**-3296.27**	-1576.09	-1718.33	-3295.77
Var: Residual	0.66	0.66	0.58	0.58	0.58	**0.58**	0.49	0.65	0.58
N groups: Community	387	387	387	387	339	**236**	152	158	236
Var: Community (Intercept)	0.38	0.38	0.29	0.29	0.27	**0.23**	0.26	0.19	0.24
N groups: School		22							
Var: School (Intercept)		0.00							
ICCadj./ICCcond.	0.37/0.37	0.00/NA	0.33/0.29	0.33/0.29	0.33/0.29	**0.29/0.24**	0.35/0.3	0.23/0.19	0.29/0.24
R^2mar./ R^2cond.	0/0.37	0/0.37	0.12/0.41	0.13/0.41	0.14/0.41	**0.17/0.41**	0.12/0.43	0.16/0.35	0.17/0.41

Abbreviations: Community gender comp. – community gender composition; Prop. F in school – proportion of females in the school; Num. obs. – Number of observations; AIC – Akaike information criterion; BIC – Bayesian information criterion; Var – variance; N groups – number of groups; ICCadj. – adjusted intraclass correlation coefficient; ICCcond. – conditional intraclass correlation coefficient; R^2mar. – marginal R^2; R^2cond. – conditional R^2; Age is dichotomized: 15 yrs = 0; 16 and 17 yrs = 1; Reference categories for factors: Gender – female; Ethnicity – all non-white; Family affluence – low; Community gender comp. – female

Table 4. 7 Dependent variable: Mental well-being - results for Walktrap community detection algorithm

Parameters/ Models	M1	M1.1	M2	M3	M4	**M5**	M5 (female)	M5 (male)	M6
(Intercept)	-0.00 (0.03)	-0.00 (0.03)	-0.38 (0.08) ***	-0.38 (0.08) ***	0.15 (0.16)	**0.36 (0.19)**	0.23 (0.27)	1.02 (0.26) ***	0.29 (0.70)
Level 1 covariates									
Gender (male)			0.56 (0.04) ***	0.55 (0.06) ***	0.56 (0.06) ***	**0.57 (0.06) *****			0.57 (0.06) ***
Age (dich)			0.02 (0.03)	0.02 (0.03)	0.01 (0.03)	**0.00 (0.03)**	0.01 (0.05)	-0.01 (0.05)	0.00 (0.03)
Ethnicity (white)			0.14 (0.06) *	0.14 (0.06) *	0.12 (0.06)	**0.10 (0.07)**	-0.11 (0.10)	0.24 (0.09) **	0.09 (0.07)
Family affluence (medium)			-0.04 (0.05)	-0.04 (0.05)	-0.04 (0.05)	**-0.03 (0.05)**	0.02 (0.07)	-0.10 (0.07)	-0.03 (0.05)
Family affluence (high)			-0.02 (0.05)	-0.02 (0.05)	-0.02 (0.05)	**-0.03 (0.05)**	-0.01 (0.08)	-0.06 (0.08)	-0.03 (0.05)
Parental control			-0.17 (0.02) ***	-0.17 (0.02) ***	-0.18 (0.02) ***	**-0.18 (0.02) *****	-0.17 (0.03) ***	-0.20 (0.03) ***	-0.18 (0.02) ***
Parental care			0.09 (0.02) ***	0.09 (0.02) ***	0.09 (0.02) ***	**0.10 (0.02) *****	0.13 (0.03) ***	0.08 (0.03) **	0.10 (0.02) ***
Level 2 covariates									
Community size				-0.02 (0.03)	-0.14 (0.04) **	**-0.17 (0.05) *****	-0.11 (0.07)	-0.21 (0.06) ***	-0.17 (0.05) ***
Community gender comp.(male)				0.02 (0.08)	0.01 (0.08)	**-0.02 (0.09)**			-0.01 (0.09)
Community gender comp.(mixed)				-0.03 (0.07)	-0.02 (0.07)	**-0.02 (0.07)**	-0.02 (0.08)	0.00 (0.08)	-0.01 (0.08)
Ratio of ties outside community					-0.14 (0.23)	**-0.32 (0.28)**	-0.54 (0.39)	-0.03 (0.37)	-0.39 (0.33)
Transitivity					-0.59 (0.15) ***	**-0.77 (0.22) *****	-0.15 (0.35)	-1.18 (0.26) ***	-0.82 (0.23) ***
Centralization					-0.59 (0.24) *	**-0.76 (0.39)**	-0.76 (0.58)	-1.03 (0.53)	-0.72 (0.40)
Hierarchy						**0.20 (0.29)**	0.38 (0.44)	0.00 (0.39)	0.22 (0.30)
Level 3 covariates									
School/network size									0.02 (0.04)
Modularity (school)									-0.36 (0.82)
Prop. F in school									0.63 (0.58)
Num. obs.	3148	3148	3148	3148	3079	**2698**	1351	1347	2698
AIC	8556.69	8558.69	8214.19	8230.98	8025.62	**6991.55**	3634.66	3369.22	6998.82
BIC	8574.85	8582.90	8274.73	8309.69	8122.13	**7091.86**	3712.79	3447.30	7116.83
Log Likelihood	-4275.34	-4275.34	-4097.09	-4102.49	-3996.81	**-3478.78**	-1802.33	-1669.61	-3479.41
Var: Residual	0.79	0.79	0.72	0.72	0.71	**0.70**	0.76	0.63	0.70
N groups: Community	387	387	387	387	339	**236**	152	158	236
Var: Community (Intercept)	0.19	0.19	0.11	0.11	0.10	**0.09**	0.11	0.09	0.10
N groups: School		22							
Var: School (Intercept)		0.00							
ICCadj./ICCcond.	0.19/0.19	0.00/NA	0.13/0.11	0.14/0.12	0.13/0.11	**0.12/0.10**	0.13/0.12	0.12/011	0.12/0.10
R^2mar./ R^2cond.	0/0.19	0/0.19	0.15/0.26	0.15/0.26	0.15/0.26	**0.16/0.26**	0.07/0.19	0.11/0.22	0.16/0.26

Abbreviations: Community gender comp. – community gender composition; Prop. F in school – proportion of females in the school; Num. obs. – Number of observations; AIC – Akaike information criterion; BIC – Bayesian information criterion; Var – variance; N groups – number of groups; ICCadj. – adjusted intraclass correlation coefficient; ICCcond. – conditional intraclass correlation coefficient; R^2mar. – marginal R^2; R^2cond. – conditional R^2; Age is dichotomized: 15 yrs = 0; 16 and 17 yrs = 1; Reference categories for factors: Gender – female; Ethnicity – all non-white; Family affluence – low; Community gender comp. – female

ICC values for Model 1 show that peer groups in schools, identified by the Walktrap algorithm, show substantial clustering regarding SU (ICC = 0.37), and a notable but smaller clustering in MW (0.19). 37 and 19% of the total variation in SU and MW, respectively, is accounted for by variations between peer groups. For both dependent variables, adding school variation (Model 1.1; tables 4.6 and 4.7) did not improve the model fit[44]. Since very low ICC values suggest a lack of clustering for health outcomes within schools (distributions of two outcomes per school are shown in figure 19 in Appendix 4) and to avoid overfitting, the school level is not included in further models. Therefore, all other models presented in this paper are hierarchical two-level with peer groups as a random effect.

When individual level 1 covariates are accounted for (in Model 2), the ICC values decrease for both SU (0.33) and MW (0.13). This pattern of results imply that the overall clustering can be partly explained away by clustering based on gender, ethnicity, family affluence and other level 1 covariates, relatively more for MW than for SU. Including all community properties as level 2 covariates (Model 5), ICCs further decrease (0.29 and 0.12 respectively). Finally, in Model 6, with school level covariates, ICCs for both outcomes stay almost the same. Gender-stratified models (M1), (figure 4.5), show that girls have higher clustering for SU than boys, but somewhat lower clustering for MW (values of adjusted ICC are 0.38, 0.30, 0.12, and 0.17, respectively).

To answer our central research question about the relevance of community properties we looked at the effects of six community properties in Model 5. Model 5 diagnostics are reported in Appendix 4 (section 5.1).

Effects of individual variables (level1) and community properties (level2) on health outcomes (Model 5)

Substance use

Model 5's total explanatory power is substantial (conditional R^2 = 0.41) and the part related to the fixed effects alone (marginal R^2) is 0.17. The effect of family affluence (medium versus low) is significant only after controlling for all community properties in Model 5.

Individual level 1 covariates (M5). The effects of gender, age, and ethnicity are statistically significant, suggesting that boys engage in less substance use than girls. Older students have higher SU than younger students, and non-white students have higher SU than white students. The effect of family affluence is statistically significant, pointing out that students from families that belong to either middle and high category of affluence have smaller SU

[44] We additionally run models with only schools as random effects. It resulted in ICCs smaller or equal to 0.01 for all GDAs. That means that approximately 1% of variation between individuals in the investigated health outcomes is attributable to schools.

than students from families that had the lowest affluence. The effects of parents' behaviours are both significant, and the direction of effects implies that higher control from parents is associated with higher SU, while higher care is associated with less SU. Due to cross-sectional data, we cannot assess to what degree parental behaviours are caused by students' SU and vice versa.

Community properties, level 2 covariates (M5). The effect of community size is statistically significant and positive, meaning that being in a bigger community is related to lower SU. Also, being in a more connected peer group (higher transitivity) and in a group with higher centralization is predictive of smaller SU. Community gender composition, how "strong" a community is (the ratio of ties outside the community), and how much hierarchy it has is not predictive of individual SU.

Model 6 fitted only for boys shows that all community properties that were significant for the whole sample stayed significant, with the gender composition of community being also a significant and negative predictor. The boys that are a part of communities that include girls tend to use substances more. For girls, the pattern of results is similar as for the whole sample but transitivity is no longer a significant predictor. However, overall clustering is higher for girls than for boys (0.35 and 0.23, respectively).

Model 5 in which level 3 covariates are incorporated does not show significant effects for any of the three covariates. That is in line with the finding that adding random effects of schools is not improving the model fit.

Mental wellbeing

Model 5's total explanatory power is moderate (conditional R^2 = 0.26) and the part related to the fixed effects alone (marginal R^2) is 0.16. The effect of ethnicity (medium versus low) ceases to be significant when all community properties are added to the model (M5), while centralization is not significant after controlling for hierarchy (but reaching almost significant *p*-value =0.054).

Individual level 1 covariates (M5). The effect of gender is statistically significant, showing that boys have a better MW than girls. The effects of parents' behaviours are both significant. Similarly, as with SU, results imply that higher control from parents is associated with worse outcomes, while higher care is associated with a better outcome.

Community properties, level 2 covariates (M5). The effects of community size and transitivity are statistically significant and negative, meaning that being in a bigger community and being in a more transitive community, is related with worse MW. Gender composition, how strong a community is, and hierarchy are not predictive of individual MW. The effect of centralization is nearly significant, and negative, showing a tendency of adolescents in more centralized groups to have worse mental wellbeing. All level 3 covariates in Model 6 were not significant.

The model fitted only for boys is similar to the model fitted on the whole sample, with the difference that ethnicity is also a significant predictor, while centralization is closer to significance level (*p*=0.051). For girls, neither community size, nor transitivity, are significant predictors, suggesting that for MW of boys the investigated properties are relevant, whilst for girls they are not. Overall clustering is rather similar for girls and boys (0.13 and 0.12).

4.5.2 Sensitivity to group detection algorithms

In addition to the Walktrap method, we used nine GDAs to check the sensitivity of meso-level findings to methods used for identifying peer groups in schools. As Walktrap (WT), seven methods were community detection algorithms (Clique percolation (CP), Edge-betweenness (EB), Fast greedy (FG), Infomap (IM), Leiden (LE), Louvain (LO), and Label propagation (LP)). Two methods were based on block-modelling approaches: block-modelling with indirect approach (BIA) and Stochastic block-modelling (SBM). The criteria for the inclusion of a GDA was their availability in R software and their applicability to the networks under the study[45]. Table 12 in Appendix 4 gives a short description of each GDA (partly based on Smith et al., 2020) used in this study, in alphabetical order (for more details on each algorithm see references in table 12 in Appendix 4). The basic description of community structure – the number of communities, their sizes, and modularity score of each GDA is provided in Table 4.8. The information about the number of gender-mixed, male and female communities per GDA and some other additional indices related with the partitions can be found in table 15 in Appendix 4.

[45] Some CDAs are applicable only to connected networks (e.g., Spinglass) – networks that do not have two or more members (not including the isolates) which are not connected with anybody else.

Table 4. 8 Community detection algorithms and communities found in 22 schools

GDA	BIA	CP	EB	FG	IM	LE	LO	LP	SBM	WT
N Com.	300	895	546	235	525	252	253	401	680	387
Avg. com. size	12.16	4.08	6.68	15.53	6.95	14.48	14.42	9.1	5.37	9.43
Min. com. size	1	1	1	2	1	2	2	1	1	1
Max. com. size	62	98	106	81	28	45	41	40	43	44
N size 1	37	514	214	0	5	0	0	1	78	1
N size 2	14	39	57	13	48	13	13	16	81	34
N size 3	10	61	46	13	50	10	10	32	98	39
N size 4-12	109	222	163	91	371	89	91	264	386	219
N size13-30	112	51	40	100	51	129	127	83	33	87
N size 31+	18	8	26	18	0	11	12	5	4	7
Mean Modularity	0.71	0.62	0.63	0.71	0.71	0.73	0.73	0.69	0.5	0.73

Abbreviations: GDA – group detection algorithm; N – number; Avg. com. size – average community size; Min. com. size – the size of the smallest community; Max. com. size – the size of the biggest community

As expected, communities found with ten GDAs differ (Figures 29 to 31 in Appendix 4 illustrate different partitions of the friendship network for three schools). Community structures between each pair of ten GDAs are compared with the adjusted Rand (AR) index that ranges between 1 (perfect overlap) and 0 (no overlap). The smallest overlap is between SBM and EB (AR=0.21), and the highest between LE and LO (AR=0.87; see figure 32 in Appendix 4 for more details).

For our data on friendship networks of 22 schools, CP[46] provides the highest number of communities that are on average the smallest, but it also gives the highest number of communities that consist of only one person. The GDAs that result in a smaller number of communities that are consequently bigger on average are FG, LE, and LO. They also have no one-member communities, while EB and CP result in many such communities. LE, LO and WT have the highest mean of modularity[47] scores over 22 schools (0.73), suggesting that, on our dataset, they provide communities that are more connected within and less between. The communities with more than 30 members are found with all GDAs except

[46] Even though CP method gives more than one community membership for some students, we employed the approach used by Evans et al. (2016) according to which if a student belonged to more than one community, they were assigned to the community in which they had more ties.

[47] Modularity measures the strength of partition of a network into communities. A high modularity score means that a network has dense connections between the people within communities and sparse connections between people that are different communities.

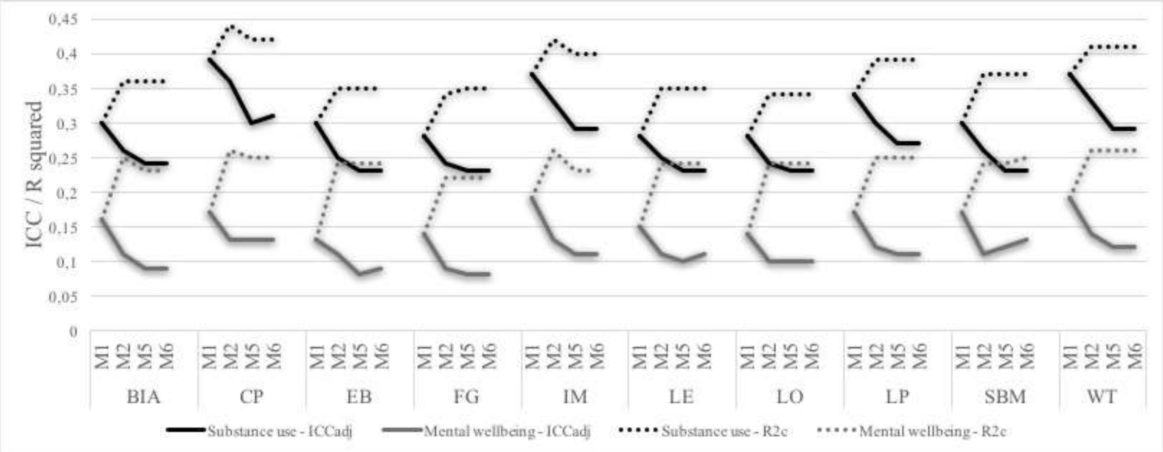
IM. Given the rationale of the SBM algorithm is based on regular equivalence[48], it is not surprising that SBM has the lowest average modularity (0.5), because the group members were not required to be connected but rather to have similar positions in the network. However, another block-modelling method – BIA based on structural equivalence – has relatively high average modularity (0.71). Relatively low modularity for CP is consistent with detecting many communities with just one member who does not belong to any clique. But, since they are not isolates, they will have ties with others, which will decrease the modularity score because their ties are considered as being between communities.

Sensitivity of clustering of health-outcomes to group detection algorithm

We rerun multilevel models in table 4.5 nine times, once for each additional GDA, using the community membership information it provided. For each community derived with each GDA, we calculated six community properties and included them as level 2 covariates in MLMs. Since each GDA returned a different partition, the communities and their properties were different from the ones used in MLMs models based on Walktrap. Likewise, one of level 3 covariates – average modularity – was also GDA-specific.

Figure 4.6 shows ICCs and R^2 for models M1, M2, M5, and M6, for each GDA. In addition to adjusted ICCs, pseudo-R^2s for mixed-effect models are reported. Specifically, we used conditional R^2 which is interpreted as a variance explained by the entire model, including both fixed and random effects (R package MuMIn (Barton, 2022)).

[48] Structural equivalence identifies actors that have the same ties to exactly the same others in a network, while regular equivalence identifies actors that have identical ties to equivalent, but not necessarily identical, others (Hawe et al., 2004).



Abbreviations: ICCadj. – adjusted intraclass correlation; R squared. – conditional R squared

Figure 4. 6 Intraclass correlation coefficients and R^2 (y-axis) for models M1, M2, M5, and M6 for two health outcomes and 10 GDAs.

Figure 4.6 shows that all GDAs in all models show higher clustering for substance use than for mental wellbeing. According to Model 1, between 28 and 39% (depending on a GDA) of variation in SU between individuals is associated with community membership, while for MW it is between 13% and 19%. We would expect that clustering would decrease as it would be explained away progressively more with each more complex model, showing a downward trend for each GDA in figure 4.6 As shown on figure 4.6, adding level 1 covariates (M2) decreases the community clustering in both outcomes across GDAs. Furthermore, for most GDAs adding level 2 covariates (M5) further decreases ICC, albeit not considerably. However, adding level 3 covariates (M6) does not decrease ICC further for most GDAs.

The R^2 values for the most complex models M5 and M6 (figure 4.6) show that models' explanatory power for SU is substantial (from 34 to 42% of explained variance), while for MW it is moderate (from 19 to 25%). R^2 would show an upward trend if more complex models provide a higher percentage of explained variance. However, that is not the case for most GDAs, as the R^2 values do not increase after Model 2, except for SBM with MW as the dependent variable. CP and IM for SU show decrease in R^2 after Model 5.

Sensitivity of effects of community properties on two health outcomes to group detection algorithm

Tables 4.9 and 4.10 summarise results of all GDAs for models that include community properties (from Model 3 to Model 6), for SU and MW, respectively. The tables show for each community property and each model the abbreviations of GDAs that yielded a significant effect, with the information about the direction of the effect in the brackets[49]. The tables also include results for gender-stratified models (Model 5) on only girls and only boys, and Model 5 including only communities that had 30 or less members.

Table 4. 9 Dependent variable: Substance abuse

Community property /Model	M3	M4	**M5**	M5-F	M5-M	M5-Com=<30	M6
Community size	CP(+)*, IM(+)*	LE(+)*, LP(+)*, WT(+)*	**BIA(+)*, LE(+)**, LP(+)***, WT(+)*** **	WT(+)**	CP(+)*, FG(+)*, LE(+)*, LP(+)***, WT(+)***	LE2(+)*, LP(+)***, WT(+)***	BIA(+)*, LE(+)***, LP(+)***, WT(+)***
Community male (vs. female)	EB(+)**, SBM(+)**	EB(+)**, SBM(+)*	**SBM(+)** **	/	/	CP(+)*, SBM(+)*	SBM(+)**
Community mixed (vs. female)	*No sig.*	*No sig.*	***No sig.***	*No sig.*	CP(-)*, SBM(-)*, WT(-)*	*No sig.*	*No sig.*
Ratio of ties outside community	/	*No sig.*	**CP(-)***	*No sig.*	*No sig.*	*No sig.*	CP(-)*
Transitivity	/	LP(+)*, WT(+)**	**LP(+)*, WT(+)** **	*No sig.*	LE(+)*, LP(+)*, WT(+)***	LP(+)*, WT(+)**	LP(+)*, WT(+)**
Centralization	/	LE(+)**	**BIA(+)***, LE(+)***, LO(+)*, LP(+)**, SBM(+)*, WT(+)** **	BIA(+)*, LE(+)*, WT(+)*	BIA(+)***, FG(+)*, LE(+)**, LO(+)*, LP(+)*, SBM(+)*, WT(+)**	BIA(+)**, FG(+)*, LE(+)**, LO(+)*, LP(+)**, SBM(+)*, WT(+)***	BIA(+)***, LE(+)***, LO(+)*, LP(+)**, SBM(+)*, WT(+)**
Hierarchy	/	/	***No sig.***	*No sig.*	*No sig.*	*No sig.*	*No sig.*

Abbreviations: *No sig.* - the effect was not significant; /- the effect was not included in the model.
In bold font: the main model – Model 5 on the whole sample.

[49] The effects of level 1 covariates and level 3 covariates are not shown as they were not of the central interest for this paper and the pattern of findings was similar across GDAs.

Table 4. 10 Dependent variable: Mental Wellbeing

Community property/ Model	M3	M4	**M5**	M5-F	M5-M	M5-Com=<30	M6
Community size	*No sig.*	LP(-)*, WT(-)**	**BIA(-)*, LP(-)*, WT(-)*** **	*No sig.*	BIA(-)*, EB(-)*, WT(-)***	BIA(-)*, LP(-)*, WT(-)***	LP(-)*, WT(-)***
Community male (vs. female)	*No sig.*	*No sig.*	***No sig.***	/	/	*No sig.*	*No sig.*
Community mixed (vs. female)	*No sig.*	EB(-)*	**EB(-)***	*No sig.*	*No sig.*	*No sig.*	*No sig.*
Ratio of ties outside community	/	*No sig.*	***No sig.***	*No sig.*	CP(+)*, LP(+)*	*No sig.*	*No sig.*
Transitivity	/	EB(-)*, WT(-)***	**EB(-)*, WT(-)*** **	*No sig.*	BIA(-)*, CP(-)*, EB(-)***, LP(-)**, WT(-)***	WT(-)***	EB(-)*, WT(-)***
Centralization	/	LE(-)*, LO(-)*, WT(-)*	**BIA(-)***	*No sig.*	BIA(-)*	BIA(-)**, WT(-)*	BIA(-)*
Hierarchy	/	/	**FG(+)***	*No sig.*	FG(+)*, LO(+)*	FG(+)*	FG(+)*

Abbreviations: *No sig.* - the effect was not significant; /- the effect was not included in the model.
In bold font: the main model – Model 5 on the whole sample.

A joint inspection of tables 4.9 and 4.10 shows that for SU a higher number of community properties are significant predictors than for mental health. For the latter, only after other properties in addition to size and gender composition are included in the model (all models except Model 3) some effects are detected. Excluding the communities that have more than 30 members from Model 5 shows that for all GDAs the direction of effects stays the same, but with a smaller number of significant effects, which could be due to any or all of the following: the smaller sample size, the smaller variation or the smaller relevance of those properties for communities with 30 or less members. Effect sizes and *p*-values for six community properties for two health outcomes and all GDAs (Model 5) can be found in Appendix 4, figure 33.

GDAs differ regarding significant effects that are found. However, we can see that for a given outcome, the direction of community effects is the same for all GDAs, suggesting that different GDAs tend to converge to consensus when the effect is found.

Additional robustness checks

Due to the novelty of our findings, we ran several post-hoc robustness tests. More details about the procedures and the results are presented in section 8 in Appendix 4.

A simulation of having more partly-missing network data – random deletion of out-going ties in school networks (Model 1 and 5, Walktrap). We ran simulations of having more partly-missing network data for each school network by randomly deleting out-going ties in the network to create additional 5, 10, 15, 30 and 40% new non-responders. On those "new" networks we performed community detection with Walktrap and used the membership data to rerun Models 1 and 5. The procedure is repeated only once for each specified percentage of additional non-responders. The results indicate that findings about clustering are fairly robust. Regarding estimates of community properties, their coefficients tend to change in both directions until 15% or more non-responders when they are mostly smaller, but their direction shows consistency. Given that sample sizes are progressively smaller when a bigger percentage of non-responders is added, the significant effects tend to cease to be significant. Findings show that in our dataset community properties effects are rather robust to additional missing network data, but only when its percentage is not too high (below 15%).

Other sensitivity test/robustness checks. Models with dichotomized DV (25% of students with worse outcome have a score of 1, others 0) show similar results for SU and MW for Model 1 with ICCs 0.39 and 0.13, respectively. In Model 5, clustering explains 31% of variance in SU, and only 6% in SU. For MW, community properties (Model 5) cease to be significant predictors when the outcome is to be among 25% of students with the lowest scores on MW. Thus, when the whole range of values is considered – a continuum from clinical and subclinical to normal and healthy, community properties are predictive of MW, but they are not predictive for being among 25% with the "worst" outcome. Clustering is 0.39 for SU and 0.13 for MW (Model 1). The results with factor scores are similar to the results found for principal component scores. Raw scores show a higher clustering for SU (0.44 - Model 1 to 0.37 - Model 5), and a small to non-existent clustering in mental MW (0.14; 0.03). Community properties (Model 5) show similar effects for SU as found for component scores, but no effects are significant for MW raw scores. Raw scores are often used in research because they are simple, straightforward to interpret and less dependent on sample characteristics (DiStefano et al., 2009). The downside is that it can obscure results when the structure of correlations between variables is more complex.

4.6 Discussion

Our study contributes to the body of research about clustering of health-related outcomes within adolescents' peer groups in schools.

To the best of our knowledge, this is the first study that expands previous research by exploring whether properties of communities found via a GDA contribute in explaining multiple individual-level health outcomes of adolescents. In line with our general expectation, we found that some community properties are significant predictors of individual health. More so for substance use (SU) than for mental wellbeing (MW).

Importantly, the found effects of community properties have the opposite direction for the two investigated outcomes.

Additionally, we addressed the methodological issue related to many available methods for identifying communities by using an ensemble of ten GDAs. We find that they differ regarding how much clustering they recover, especially for SU. However, all methods used show more success in finding a community structure predictive for more "visible" health outcomes (SU) than for less visible health outcomes (MW). Crucially, although overall some convergence is observed among GDAs regarding the significance of community properties, some GDAs give very different results.

We will revisit each research question and discuss results in more detail in the following sections.

4.6.1 Clustering of two health outcomes within peer groups

We used two clusters (composite measures) of behaviours as health outcomes of interest, rather than single behaviours. The rationale was that using a composite measure of behaviours that tend to co-occur is potentially better suited when the research interest is to investigate clustering in a wider community, rather than on a more micro network level that implies direct ties (e.g., dyads). Using narrowly defined behaviours or outcomes in such a case may not be in line with how mechanisms of social influence operate and may underestimate social clustering. For instance, imitation is one of the social processes that leads to higher similarity among peers in relevant outcomes (Veenstra & Laninga-Wijnen, 2022). Adolescents may not want or be able to copy their peers by manifesting the same behaviours or outcomes. Instead, they may use similar behaviours that have similar functions and symbolic value, that they observed as co-occurring, interchangeable, or coupled together. The two investigated outcomes based on principal component analysis scores, differ in how readily observable they are to others. Clustering is relatively high for SU, and moderate for MW. We find support for our hypotheses that the more "visible" health-related outcome (substance use) shows more clustering within peer groups in schools, but for both the clustering is found even after controlling for individual and school covariates. An alternative and not mutually exclusive explanation is that for MW the peer influence may be less important and that influence from others (e.g., family and peers outside the school) could be more relevant. Furthermore, substance use and internalizing states differ in how "contagious" they can be in general, for the former there could be more personal agency than in the latter that could be difficult to change even when one wants to (although at extreme cases that applies for addictions as well). It is possible that the potential social influence could be faster and stronger when the behavioural change requires less effort and time, given the opportunity and willingness to imitate. Also, it should be noted that data was collected in 2006. The visibility of internalizing behaviours may have shifted in recent years due to it being a more frequent topic of discussion in public arenas in the post-social media era, and therefore more visible.

Individual covariates investigated in this study are also better predictors of SU than MW. Finding that schools do not explain significant variation in health outcomes is in line with previous research by Long et al. (2021). Three level 3 covariates – school size, modularity, and the percentage of female students – are also not significant predictors of the two outcomes at the individual level. Previous research that used a similar analytical strategy found that variation between peer groups explains around 2% of variance in students' body mass index (Evans et al., 2016) and around 6.5% of variance in age of sexual initiation (Barker et al., 2019). We found that a considerably higher percentage of variance in the two outcomes is explained by variation between communities. However, the results are not directly comparable due to different kinds of predicted health outcomes, variations in the range of the outcomes, and the school level, which was present in the above-mentioned research.

4.6.2 The importance of the network meso-level: Associations of community properties with two health outcomes

In research studying social networks and health, data about some community properties is potentially available, but it was not harvested in previous research. In this paper, we argue that looking only at community level clustering and disregarding other potentially available information about communities is a missed opportunity to gain more understanding on how and why the clustering happens. This especially matters given a lack of theory development about network meso-level effects. Due to the explorative nature of this part of the analyses, our goal was to provide insights that will help generate more nuanced network meso-level theories and hypotheses in future research.

We find that some properties matter for individual health outcomes, when micro (level 1) and macro level (level 3) are taken into account. However, all significant effects are associated with a more positive outcome for SU, but with a more negative outcome for MW. Hence, the same community property can be associated differently with different aspects of health. This suggests that a community property cannot be considered as universally "good" or "bad" for all individual health outcomes. Rather, the same community property can be positively associated with one dimension of health and negatively with another.

Effect sizes for each significant effect in Model 5 for both outcomes and their interpretations are provided in section 5.4 in Appendix 4. Using Cohen's criteria, the effect size for community size is medium, and for other community properties effects are small, for both outcomes. All level 1 covariates that are significant are interpreted also as small, except for parental care's effect for SU which is medium. What is a large or small effect is highly dependent on a specific field of study, and in our context even a small effect can be theoretically important.

Given the cross-sectional data, we cannot make any causal claims about community property – individual health relationship. Any possible explanations of why or how certain properties influence health (Model 5, tables 4.6 and 4.7) would be very tentative. When thinking about the mechanisms of relation between community properties and individual health (the meso-micro loop), it is useful to consider the following questions:

1. How stable are communities and community properties?
2. Are individuals with the health outcome of interest expected to behave differently such that it will change the patterns of their ties; are they expected to join or leave communities with certain (structural or compositional) properties? (individual health behaviours→network change→community property)
3. Do we expect some community properties to have an independent effect on the individual health outcome? (community property →individual health)
4. Do we expect linear relationships between community properties and individuals' health outcomes?
5. Do we expect that community properties may have the same importance and direction of effects for individual health outcomes over the lifespan of the community?

At the time of data collection, most participants attended the same school for four years. Peer groups are fluid, they change over time, some people leave, others join. Despite that, groups are moderately stable and tend to show more stability in late adolescence (Brown & Larson, 2009; p. 78). Moreover, due to selection processes the psychological composition of groups shows some invariability even when the turnover in membership is high (Kindermann, 1993). Stability of peer groups' properties is not studied, but a reasonable assumption is that while they change over time, they also show some degree of stability. The relationship between a community property and individual outcomes is not necessarily linear. In some cases, it can be more intuitive to expect a curvilinear relation between a property and an outcome. Such relationship can explain inconsistencies in findings about some macro properties and individual outcomes (e.g., Mueller & Abrutyn, 2016). Also, the associations can vary, due to different moderating factors. Moreover, we do not know whether and how those effects change over the lifespan of the community.

Effects of community properties on individual substance use and mental wellbeing – possible explanations

Overall, Model 5 is less successful in predicting MW than SU. This is true for level 1, as well as for level 2 covariates. Given that we did not start with any explicit hypothesis about the direction of effects and their mechanism, four things are worth observing before we discuss possible explanations of community effects. First, the two outcomes are orthogonal on the individual level, but slightly negatively correlated on the community level (Pearson's correlation is -0.17, $p<0.001$). Second, some community properties are correlated significantly, albeit not highly (e.g., community size and transitivity are correlated -0.2/-0.3, see tables 12 and 13 in Appendix 4). The inherent interrelatedness of the properties makes an explanation of their effects challenging when other properties are statistically controlled for. For example, when interpreting the community size effect, one needs to think only at the aspect of size, and disregard that usually group size implies other structural properties. Third, the community size effects increase for both outcomes, when more community properties, including transitivity, are added in the model. Some other effects (e.g., centralization) also show changes in their significance when controlling for other properties. The changes could be due to the smaller sample in M5 (2698 versus 3079 in M4) that includes only communities that have more than three members or possibly due to one of the added variables acting as suppressor or mediator. Fourth, based on stratified models, there are indications that effects are moderated by gender.

Community size. Bigger communities, when controlling for other community properties, are related to smaller SU and worse MW. It could be more difficult to participate in risky health behaviours that may require smaller groups which can provide a higher discretion, that is, allow the behaviour to be secretive and not visible to someone who is less familiar. But since big communities also provide more anonymity, uncertainty and less opportunity to be visible, and are more likely to include people that one does not know or like, they may have a negative effect on individual wellbeing. Alternatively, drug users could be less likely to join big groups. Finally, for drug use to be acceptable behaviour, it may require a majority of peer group members to participate in that behaviour or comply with it. That majority is more difficult to reach in bigger groups.

Transitivity. Being in a more connected peer group (higher transitivity), controlling for other properties, is associated with less substance use and worse MW, at least for boys. In the more transitive groups, there may be higher control, closeness (structurally strong ties), and awareness of members' behaviours which could deter substance use. It is possible that those aspects or some other aspect of transitive groups have a negative effect on MW. Alternatively, boys that do not use substance or use it only rarely may be more prone to form transitive groups. Also, boys with worse MW may seek out more transitive groups that may provide more support.

Centralization. Being in a group with a higher centralization is predictive of smaller SU, when controlling for other properties. Only when hierarchy is controlled for, the effect emerges. The opposite is true for MW, centralization ceases to be predictive when hierarchy is controlled for. In more centralized groups some members have more in-going and out-going ties than others, implying that they have a higher social status or are simply more active members of a community. The communities whose members differ more in regard to that aspect have members that use substances less, possibly due to, in this case, positive influence of the members that are “in the centre”.

Gender composition of the group is a relevant predictor for SU for boys. Controlling for all other variables included in Model 5, boys in gender-mixed communities tend to use substances more than boys in male-only communities. Considering both outcomes, girls’ health behaviours and outcomes seem to be less related with the investigated properties of groups they belong to than for boys. Although overall community clustering is similar for girls and boys for MW, for girls no community property is a significant predictor, suggesting that for MW of girls the investigated properties are not relevant.

Taking into consideration Models 5 (for the whole sample and stratified by gender), and both outcomes, hierarchy and ratio of ties outside the community (ROTC) are two of six investigated properties that were not significant predictors of individual health. Hierarchy measure went through an additional transformation (see section 4 in Appendix 4). This, together with the fact it is conceptually related with centralization (both capture the concept of status differences in a group) probably affected its potential to add uniquely predictive information. The lack of importance of ROTC measure may be due to its significant albeit low correlations with other properties, transitivity, hierarchy and gender composition (see tables 12 and 13 in Appendix 4) and is still an important finding. Being in a more or less “strong” community (more or less connected with network members outside the community) is not related to the two health outcomes. However, we should not confuse it to mean that the community's centrality is also not relevant. Communities that have higher ROTC are not necessarily more central, since many outside ties can go to just one community.

4.6.3 Sensitivity of findings to GDA

In addition to Walktrap, we used nine other GDAs to investigate the sensitivity of the network meso-level study to methods used.

Sensitivity of clustering to GDAs

All GDAs show higher clustering for SU than for MW. Considering both health outcomes and Model 1, the GDAs showing the highest clustering within communities are CP, IM, and WT, while the lowest clustering is found for FG, EB, LE and LO. This is not surprising for FG, LE, and LO, considering that their average communities are bigger (table 4.8). However, the lowest clustering found for EB is surprising, especially because it is one of the most used and well-known algorithms. Overall, GDAs that show more clustering in SU also show more clustering in MW, suggesting that different GDAs did not lead to community structures that are differentially predictive for one of the two health outcomes. WT, IM and CP are similarly successful in predicting two health outcomes. From the analytical perspective, in our study using WT has advantages given that WT has a higher modularity than IM and CP, and produces less very small communities (having three or less members) due to which it had a smaller decrease in sample sizes for Model 5. WT was also found as the most optimal choice in Smith et al.'s case study (2020).

A higher clustering does not mean that the found community structure is more valid or closer to the ground truth. It is simply more predictive of a given outcome. Although the homogeneity of a group, regarding some attribute, is often taken as a validation of its existence, it would be unrealistic to expect that adolescents' peer group members do not differ in how well-adjusted they are, because homophily operates on many dimensions (Block & Grund, 2014). Therefore, the degree of clustering in the two outcomes should not be interpreted as an indicator of how correct the partition is, in the same way as we would not expect that true communities are homogenous regarding gender, although we know that there is strong gender-based clustering.

Our goal was to recover "true" communities, to be able to investigate what true clustering is in health outcomes. Furthermore, only for true communities it would make sense to expect that community properties will potentially matter. In this context, it should be noted that SBM and BIA also give communities that show considerable clustering. Given that the members of their groups have similar positions in the network, high clustering suggests that position in the overall network is relevant for the investigated outcomes. This is in line with research on adolescents that showed a relation between network position or the number of friends and some related health outcomes (Wang, 2021; Long et al., 2021).

Sensitivity of community properties effects to GDAs

Our findings demonstrate that while there is a convergence among findings from different GDAs, some GDAs differ considerably in regard to network meso-level effects. If we used only IM or EB, we would arrive at quite different conclusions than if we used only WT or CP.

We expected that methods that do not aim at finding tightly knit communities (SBM and BIA) will not find community properties to be related with individual outcomes. Given that the rationale of methods is based on detecting groups based on similarity of individuals' profiles of ties, and is not based on connections among members. This is reflected in low modularity for SBM (table 4.8), which reveals that communities have many ties to others outside the community and less ties within the community (in comparison to communities detected with other GDAs). Thus, it seems intuitive that the properties of such communities have a smaller informational value. If their groups are based on a different notion, how can their properties be related with individual outcomes? This could be due to some overlap in community structures between different GDAs, especially for BIA (figure 32 in Appendix 4).

A closer examination of tables 4.9 and 4.10 shows some differences across community properties and GDAs. All community properties are predictive for at least one GDA, one model or for one of the two outcomes. Hierarchy is not a significant predictor of SU for any of GDAs used (in any model), while it is a significant predictor for MW only when FG and LO algorithms are used. Both algorithms return, on average, bigger communities and have a high average modularity. It is possible that in such communities the hierarchy among members has negative aspects for adolescents' wellbeing[50] because there is less consensus about hierarchy or more opportunity for members with a worse status to be aware of status differences.

Gender composition is a significant predictor for a few GDAs in some of the models, and for both outcomes being in a gender-mixed community is related to a worse outcome. ROTC also has a significant effect for some GDAs. Being in a community with a high ratio of outside ties is related to more substance use and better MW.

Looking at gender stratified models reveals that overall the sample of boys shows a higher number of significant effects of community properties than the sample of girls for SU. The difference between the two subsamples is even more pronounced when MW is the outcome of interest. In that case, none of the community properties is a significant predictor for girls regardless of GDA used. That could be interpreted as a support of an interpretation based on the WT algorithm only, that the effect of community properties for individual well-being are conditional on gender and they appear to exist only for boys.

The IM algorithm shows no significance for any community property when predicting MW. For SU, only community size is a significant predictor but just for Model 3 which includes gender composition as another community property. Given that many indices suggest that IM has a partition of a relatively good quality (a high modularity of the IM's partition – table 4.8; the highest percentage of "cases" in "high-risk" communities – see section 6.2 in Appendix 4), the minimal number of detected effects seems puzzling at first. However, it should be seen as an example that high quality partition does not imply that the properties of found communities will matter for a certain outcome on the individual level, despite showing a high clustering within communities (figure 4.6). IM also has a relatively high number of small communities (with three or less members) which reduces the statistical power of more complex models. Moreover, IM's AR values (figure 32 in Appendix 4) suggest that IM is one of GDAs with a relatively more distinct community structure. Finally, IM's partition resulted in the smallest number of gender-mixed communities in comparison with other GDAs (see table 14 in Appendix 4), that resulted in higher variation inflation factors for gender and community gender composition (2.5 and 2.7 respectively) which

[50] Standard deviations and ranges of hierarchy values for the two GDAs seem to be similar to other GDAs or smaller, so the significant effect is likely not due to differences in variation of hierarchy.

could affect model's estimates even when not indicating a presence of a high multicollinearity.

EB, in addition to being among GDAs with lowest clustering for both outcomes and having relatively low modularity, is also among GDAs that gave the smallest number of significant community properties. No significant effects exist for model 5 for SU, and for MW only transitivity and community gender composition (mixed versus female) were significant effects. Given that it is one of the most used and well-known community detection algorithms (Fortunato, 2010), it highlights the importance of carefully considering the choice of GDA and benefits of using multiple methods.

4.6.4. Some guidelines for choosing a GDA

Bothorel et al. (2021) recently proposed a methodology for choosing a GDA consisting of several steps which resemble the procedure we used in this study. They demonstrated the procedure on the data about collaborations at a French crowdfunding platform using 11 GDAs. In addition to typically used validation metrics, they explicitly relied on the size of communities, and two properties they judged as showing interesting and relevant internal topologies for the analysed network (hub dominance - capturing a similar meaning as the centralization measure in our study, and transitivity). As we did in this study, they proceeded with the principal component analysis on several node attributes to measure homophily within communities. However, they use it as an additional indicator for the final choice of a GDA, while in our research context we caution against it. The difference of our approach is that our aim was not to decide which GDA is "optimal". Given that we do not know the "ground truth", we are not able to establish which GDA is the best. We focused on testing network meso-level effects and to gauge the sensitivity of network meso-level studies to the methods used. However, our sensitivity analyses allow us to make some observations regarding what is relevant to consider when choosing a GDA in a similar research context.

It is often noted that features of networks under study may be helpful for the selection of the GDA. For instance, some algorithms are not implemented for directed networks, so it would make sense to exclude them in situations when directed network data is available as it would lead to the loss of potentially useful information. However, as we can see in example of such GDAs used in this study (CP, FG, LE, LO, and LP), the information about the directionality was not essential for finding predictive partitions for our outcomes of interest. From figure 4.6, we can see that there is no clear pattern regarding clustering recovered in relation to whether the GDA used the information about directionality of ties. This is possibly because for the two outcomes we investigated, it is the mutual social influence processes and imitation that happens within communities that are relevant, and they do not require reciprocated or even direct ties. Possibly, we did not demonstrate that GDAs based on undirected ties "underperform" due to the presence of partly missing network data. Nevertheless, CP is one of the GDAs that resulted in highest clustering, even though it is implemented for undirected networks and we did not use the information about overlapping memberships that it provides.

Whilst we want to use our findings to inform school-based interventions, we are not using information about communities and individual health outcomes for planning an intervention, but as a part of a larger analytical strategy. Depending on how partitions will be used, whether the goal of finding communities is research-related (analytical) or practical (planning an intervention), different considerations and criteria related with GDAs should be important when choosing a GDA (Smith et al., 2020; Bothorel et al., 2021). There is a vast literature on comparisons of GDAs (e.g., Yang et al., 2016; Fortunato, 2010) in fields of network, computational, and data science. However, many of the comparisons are done on big or artificial networks, so it is not straightforward to translate the findings of such research to guidelines for a small-scale study with missing network data[51].

For analytical purposes, the optimal algorithms are the ones that *aim* to recover structure with a minimal number of ties outside communities (ties between communities) and communities that are strong (well-connected within). Smith et al. (2020) advise using LO[52] when GDA is a part of a wider analytical strategy (e.g., Evans et al., 2016). However, that can be data dependent. Based on modularity values in our dataset the best choices would be LO, LE, and WT, while SBM, CP and EB the worst (table 4.8). The mixing parameter[53] values calculated on the node level can be also used to provide information about nodes that have only ties with others in their community. The logic is that a GDA that gives the highest percentage of nodes that have all ties within their community is the best choice. Based on this criterion, FG is the best choice, while SBM is the worst (table 15 in Appendix 4).

Additional consideration relates to the size of communities. A definition of community or a group often mentions that it must have two members or more. A caution can be raised whether very small communities (<3 members), or even "loose" groups (with unconnected parts) should be considered. It is arguable whether very big communities (e.g., >30) could be considered as communities in the same way as smaller ones. In that case, it seems intuitive to choose a GDA that produces communities that deviate the least from a definition.

Another consideration relates to partly missing network data. As noted in the introduction, it is a rule, rather than an exception, that the network data collection, for whatever reason, will not include all network members. This will result in completely or partly missing network data for some network members. Consequently, proportional to the percentage of such cases, it will likely distort the network structure, resulting in less valid and stable

[51] We assume that this applies to most social scientists and practice-oriented researchers.
[52] In addition to Spinglass, which is not among the ten used GDAs in this study.
[53] Explained in more details in section 6.2 in Appendix 4.

partitions (e.g., less “strong” communities)[54], which may affect the findings about clustering and community property effects on health outcomes. In the context of our and similar research, robustness to missing data can be considered as an additional and important aspect of group detection robustness and stability. We addressed this issue in our post hoc robustness analysis only for WT (see section 7.5 in Appendix 4), but it could be expanded for other potential GDAs and help in making the decision about which GDA to use.

When the community structure is to be used for planning an intervention, other indices may be more informative. For example, Smith et al. (2020) defined high risk communities that can be potential targets of interventions. In our post hoc analyses we followed a similar procedure (section 6.2 in Appendix 4). The GDAs that seem to be most effective in detecting high risk communities are IM and LP, while EB is the least effective. The pattern of results is similar for both outcomes, but the effectiveness is notably higher for SU than for MW.

Different goals of using GDAs make some considerations more important than others and may lead to different choices of an “optimal” GDA. The caveat is that all considerations can be done only post hoc (after applying the methods and finding communities) and rely on using an ensemble of GDAs.

4.6.5 Practical implications

Since adolescence is the period of onset for many substance use and mental disorders (Kaltiala-Heino et al., 2011), it is a time in individual development when preventive efforts can potentially have a strong impact. In terms of improvements of adolescents’ health in schools, findings about clustering for both SU and MW informs that school level interventions may operate differently for some segments of the school population. Some GDAs could be used to identify groups of a specific interest which may benefit from more tailor-made interventions. Based on our findings, community properties of peer groups in schools are associated with individuals' health outcomes. What are community properties of peer groups with positive health outcomes? Our results suggest that the answer depends on the specific outcome (or clusters of co-occurring outcomes) of interest. Therefore, compositional and structural properties of peer groups in schools should be considered carefully and in relation with a specific health outcome.

From the analytical perspective, when the purpose is to plan interventions or when the research interest is to find whether there are network meso-level effects, the approach that uses an appropriate GDA to detect communities and then implements that information in multi-level modelling is a less time-consuming alternative to more sophisticated statistical

[54] There is even a possibility that network missing data will be associated with community membership. For example, members of a certain group could be less likely, for some reason, to participate in the data collection. In such a scenario, the distortion would be less pronounced for other groups, than for the group in question.

network modelling procedures (e.g., ERGM, ALAAM) that however have the advantage of disentangling social processes that lead to clustering.

4.6.6 Limitations of the study and future research

Limitations of the study also suggest potential avenues for future research. We acknowledge throughout the paper the limitations of cross-sectional data. Communities, in addition to not being static, are also overlapping. Since all GDAs except CP could detect only exclusive groups, we used an analytical approach (hierarchical MLM) that was best suited for nine GDAs, but not for CP. Future research using CP should use multiple membership multilevel models to appropriately test CP's community structure.

A certain constraint on relevance of our study comes from the fact that data was collected in the pre-social media era or just at its beginning when social network platforms and on-line communication were not as ubiquitous as today. Since they could be an important source of influence on adolescents' health and may have changed the meaning of peer groups, clustering of health outcomes, and visibility of different aspects of health, they should be addressed in future research explicitly.

Our analysis is restricted to friends at the same school and year. Although the majority of peer ties tend to be from the same school and year (Ennett & Bauman, 1996), adolescents may have peers of different ages and peers outside school who influence their SU and MW. Participants were in their late adolescence at the time of data collection and effects of socialisation are considered less strong/robust than in early adolescence (Steinberg & Monahan, 2007), so findings may underestimate the magnitude of clustering and properties of peer groups for younger adolescents.

Future research will benefit by integrating the information about the strength of ties and negative ties and by using algorithms that can harvest such information when detecting communities. We investigated six community properties, but there are other potential properties that could be relevant for individual health. For instance, centrality of community could be a relevant predictor. While it would be not optimal to include such measures of community in our models due to interdependence issues, it could be included as attribute data in ERGM or SOAM analysis. Future research can conceptualize network's meso-level in other ways besides using group detection methods. Cultural differences in clustering and relevance of community properties may exist, so research in different cultural settings is called for.

Finally, while we did not find macro-level properties to be relevant. That does not mean network macro-level has no influence on individual health. It is upon future studies to try to identify the important properties at macro level and investigate its effects and interactions with meso-level as well.

Chapter 5

Conclusions

The thesis consists of three studies, each applying network theories and methods to a different subfield of psychology. Our aim was to contribute to the integration of psychology and network science by using network concepts and theories while building on previous research and theory in psychological subdisciplines, to expand the existing theories and knowledge in the field.

5.1 Summary

In this section, we provide the summaries of three studies included in this thesis. The specific characteristics of the three studies are summarised in Table 5.1. From Chapter 2 to Chapter 4, studies show slightly higher complexity regarding methods used and research questions asked.

5.1.1. Study 1 (Chapter 2)

Study in Chapter 2 used an innovative approach to quantify structural aspects of personal ego-networks and analysed its relationship to well-known personality traits and one less-examined construct in related research – Sense of community. We acknowledged the possible interrelatedness of those personal attributes by applying a topological approach.
Both typologies and census of triads showed to be effective strategies for describing the structural properties of personal networks and exploring their relationship to individual psychological differences. Results indicate that more complex ego-network measures have a higher potential to disclose individual differences in personality traits. We observed that closed triads are positively correlated with Sense of community. When it comes to personality traits, emotional stability was positively correlated with strong closed triads and with the overall indicator of density; while agreeableness was associated with having less systematic clustering in personal networks.

The study of individual psychological differences in the structure of social networks is relatively new. So far, mainly the relationship between personality traits and the size, composition and connectivity of networks has been explored. However, there are other individual characteristics that a priori could be more directly related to the properties of networks, such as attachment styles and communication competences, as well as the skills for the initiation, development and maintenance of relationships (Bouchard & Maya-

Jariego, 2019). This is the case of Psychological Sense of Community, which has to do with the subjective experience of the local environments and the relational settings (Sarason, 1974). Overall, we found a higher number of significant associations of the structural properties of personal networks with the sense of community than with personality traits.

Two properties of personal networks showed an especially significant association with Psychological Sense of Community: transitivity and a greater relative presence of closed triads of weak ties. The first one is not a surprise, since transitivity is one of the basic processes in the explanation of social networks evolution (Holland & Leinhardt, 1976, 1977; Snijders, 2001; Stokman & Doreian, 1997) and integration of personal networks (Louch, 2000). However, the connection of Sense of Community with triads of weak ties is suggestive. Regardless of the value that small cohesive groups that provide support may have, the community seems to rely on a network of indirect ties between individuals which, without necessarily developing a strong personal relationship, can experience a shared sense of belonging.

Table 5. 1 The summary specificities of three studies

<table>
<tr><td>Study characteristics</td><td>Chapter 2</td><td>Chapter 3</td><td>Chapter 4</td></tr>
<tr><td>Type of network</td><td>Social</td><td>Psychological</td><td>Social</td></tr>
<tr><td>Theoretical background in psychology</td><td>Big Five Personality framework and Sense of Community</td><td rowspan="2">New network perspective on personality traits as a complex system</td><td>Peer groups in adolescence</td></tr>
<tr><td>Theoretical framework in network science</td><td>Theories related to triads (Simmel, 1950)</td><td>Effects of the network meso-level on individual outcomes; different measures of network communities</td></tr>
<tr><td>Specific methodological innovation</td><td>Use of new variants of a triadic based on measures on ego-centric data; typological approach in the analysis</td><td>Use of minimum spanning tree, participation coefficient, and motif analysis to describe psychological network</td><td>Use of network properties of detected communities as explanatory variables; checking the robustness of findings with ten group detection methods</td></tr>
<tr><td>Datasets</td><td>Primary</td><td>Secondary</td><td>Secondary</td></tr>
<tr><td>Method of data collection</td><td>Ego-network data (semi-structured interviews); attributes (a survey)</td><td>Psychological attributes (self-administrated on-line questionnaires)</td><td>Friendship nominations (socio-centric data); attributes (a survey)</td></tr>
<tr><td>Sample characteristics</td><td>Adults, Spain (2018, N=100)</td><td>Self-selected, part of a large international on-line study (2007 – 2012, N=1166923*)</td><td>Adolescents (high school students) living in Scotland, UK (2006, N=3148)</td></tr>
<tr><td>How are network methods used</td><td>Network measures as input variables for cluster analysis and correlational analyses</td><td>The use of network methods to describe the constructed (estimated) network based on psychometric data</td><td>Network measures as one of variables in multilevel models</td></tr>
</table>

Note: For Chapter 3, the theoretical background in psychology overlaps with the theoretical framework in network science.
* *N* of cases that had data about at least two psychological attributes.

5.1.2. Study 2 (Chapter 3)

Study in Chapter 3 was the most exploratory and methodologically oriented, while the other two chapters were driven by general research questions (Chapter 2) or hypotheses were formulated (Chapter 4). The study applies methods that are well-known within network science and proposes they could enrich analysis of psychological networks by demonstrating their use on networks of 26 psychological attributes (including personality traits, values, cognitive ability). This type of psychological network, where nodes are theoretically distinct concepts and span over different psychological domains are not often seen in the literature, due to the lack of the data that contains such a high number of different psychological variables. But more importantly, there is a lack of theory that justifies including those psychological concepts and not including some others. Therefore, we use the dataset for illustrative purposes and potentially to help generate hypotheses about a wider psychological system that includes different domains, but caution against making anything but tentative claims based on results of the analyses.

We used the Minimum Spanning Tree (MST) to map out the hierarchical structure of the network. The method allows for different directions, not only strength of association to be considered. Empathy is the most central node in the network filtered by MST, because it features the smallest distance to all other nodes.

We used Participation Coefficient (PC) together with Participation Ratio (PR) to arrive at more sensible centrality measures, which showed that different centrality indices converge to Extraversion, Emotional Stability and Empathy ("the three E") as the three most central nodes in the network. PC measure allowed us to consider the existence of theoretically different groups of constructs, as it specifically quantifies how the edges a node has are distributed to different communities. However, since the PC solely quantifies equality of tie distribution and disregards number and strength of ties, we proposed to use it in combination with PR measure that takes both into account. We demonstrated how PC and PR provide different information about the centrality of constructs in the network. Finally, we used motif analysis (of triads), investigating not only their occurrence but also their intensity. Investigating triadic configurations in psychological networks is useful because it provides a richer understanding of the network. Some triadic motifs are indicative as they either describe unusual finding(s) or they may point to the existence of methodological artefacts (e.g., NNN and PPN triads, and imbalanced triplets II T). In both scenarios, we benefit from knowing about their presence.

All "new" methods have a "local" perspective that does not assume flow in the network and are therefore adequate for use in psychological networks. We conclude that the methods provide richer data about network and nodes' position, but are more complex in comparison to other more often used metrics. That can be a benefit rather than a cost, since it encourages a more thoughtful consideration of data and theory.

5.1.3. Study 3 (Chapter 4)

Study in Chapter 4 advances previous research on clustering of health outcomes within adolescents' peer groups in schools and addresses the need for the development of meso-level theories of network processes influencing health. We set a general theoretical framework and made an exploratory investigation of network meso-level effects on two health outcomes - substance use and mental wellbeing – based on seven specific health-related behaviours and outcomes. We applied a data reduction method (principal component analysis) to define dependent variables. Doing so, we again acknowledged the complex relationship between specific measures of different constructs (behaviours or traits) as in Chapters 2 and 3. The novelty of our approach is that we apply the idea that the structure of social relationships surrounding individuals shapes their health at the network meso-level (communities), which was so far usually applied at network macro or micro level.

We used the Walktrap method to detect peer groups (communities) in schools and measured their six properties: size, gender composition, ratio of ties outside community, transitivity, centralization, and hierarchy. Meso-level variation is different for the two health outcomes: higher for substance use than for mental wellbeing. Using multilevel modelling to control for individual covariates, we found that some community properties are predictive of individual health outcomes, but the direction of significant effects for substance use and mental wellbeing is the opposite except for the property of gender composition. From an analytical perspective, since we were interested in investigating network meso-level effects, the approach that relies on a group detection algorithm and implements information about community membership in multilevel models provided a more direct way to test our hypotheses and a less time-consuming alternative than to use more sophisticated statistical models for network data (e.g., ERGM). To avoid the dependence issue, in multilevel modelling we did not use information based on relational data between communities (centrality of each community).

The chapter exposes the complexity of conceptualising and understanding network effects and highlights the importance of gauging the sensitivity to different methods available in rich network science’s toolbox. In this study, we find that findings based on ten group detection methods tend to converge. But we also find enough discrepancy between the methods to call for this kind of robustness checks in future studies of the network meso-level. We demonstrate that the network meso-level is worthy of more consideration in future research and development of network theories. We find enough evidence for existence of meso-level processes to warrant further studying and theorizing of meso-level effects on health. The processes we uncovered may have important implications for school-based intervention design, specific to the health outcome in question.

5.2 General discussion

In this section, we will address topics that are related to the three studies in this dissertation, but also go beyond any specific study and relate to general considerations, challenges and opportunities in network research in psychology.

5.2.1. Precursor of network approach in psychology

There are many commonalities of the three studies: they demonstrate an application of network theories and methods to psychological research, attempt to integrate network theories with the previous research and theories, use network methods that are innovative for the field, are based on cross-sectional and self-reported data, and are of interest for heterogeneous scientific audience. The most important common denominator of the studies is that their main focus is on the relational dimension, either between people or between constructs. In Brandes et al.'s words, "The potentially resulting dependencies are not a nuisance but more often than not they constitute the actual research interest. (2013, p.8)". But as the authors acknowledged, that interest – which is at the core of network science – does not start with networks, but with a perspective that focuses on interdependent relations. Similarly, in psychology, a precursor of the network approach can be found in the early 20th century in Gestalt (meaning "whole" in German) school of thought that is often summarised with the phrase "the whole is more than the sum of its parts" (Verstegen, 2010). Although in the beginnings the school dealt mostly with human perception, it was based on principles that later inspired an approach in psychotherapy. Importantly, this school of psychology formed research of Kurt Lewin and Fritz Heider, some of the most impactful figures in the early development of social network analysis (Doreian, 2017). Lewin emphasized the importance of the interdependence of individuals for understanding their behaviour and provided an interdisciplinary research agenda for studying group dynamics, while Heider developed balance theory. It is worth noting that within psychology there was already a perspective and a wider framework that provided a fruitful ground for network theory and methods, despite the simultaneous existence of other schools of thought that were not necessarily as conducive to network ideas (as noted in Introduction). Furthermore, in the last decade, psychological research also integrated "new" methods often aligned with computational social science, such as machine learning (Orrù et al., 2020) and agent-based models (Smith & Conrey, 2007), and it can be expected that such versatility in methods will contribute to a more diverse, interdisciplinary research environment in future.

5.2.2. The issue of self-reported nature of network data and parasocial relationships

All measures in all studies are based on self-reported data[55]. Regarding psychological variables, self-reported data is frequently used in psychological studies and defending their validity and reliability goes beyond the scope of this thesis. However, social network data is also based on self-reports, as participants have been asked about their contacts and friendships. The lack of objectivity and informant accuracy when reporting about interactions with others is well-documented (Bernard et al., 1984), and by using this approach we invariably introduce a subjective viewpoint. However, there is a value in having such a viewpoint, as addressed in Chapter 2. Nevertheless, we recognize that it raises the question of whether a finding about the association between network structure and a psychological attribute of an individual is the result of specific biases in network perception related to some psychological attributes or there are real correlations between psychological attributes of individuals and their network structure. Only a longitudinal research design that measures psychological attributes, networks and biases in network perception, or uses objective and valid measures of networks, can provide an answer to the question. Due to the theoretical and possibly practical importance of clarifying this issue, we expect that this line of research will be tackled in the future.

The issue of objectivity in self-reporting of social ties may be partly neutralised in socio-centric research because of the possibility to use information about the directionality of ties – if both people in a dyad agree they are connected (they nominate each other), the reciprocity can be understood as signalling higher objectivity of the information, while the lack of reciprocity itself could be used as an indicator of e.g., social status. However, due to constraints in study design (usually a maximum number of people to nominate is provided) and imperfect recall, it would be unrealistic to expect a socio-centric data collection to solve the issue. Nevertheless, when interested in friendship ties (as in study in Chapter 4) which implies a relationship quality that – for now – is best “judged” by people in that relationship, using data based on observations instead would not necessarily provide more valid and meaningful data, and would possibly inflict a higher cost and additional ethical concerns.

Chapter 4 raised an issue about the importance of connections that people form via social network platforms. On-line connections may represent a somewhat specific kind of relationships, with different dynamics and mechanisms of potential influence. This is especially the case when such relationships involve people or groups that are not necessarily

[55] The only exception is a measure of intelligence in study 2 (Chapter 3) that is based on performance on the cognitive ability test.

known to the individual or are not present in-person in their social world, and may not involve real reciprocity. They are called "*parasocial*" relationships and describe relationships in which one person is aware of the other, but vice versa is not necessarily the case (Beak at el., 2013). Although some early studies showed that that kinds of relationships are positively correlated with some negative individual outcomes (e.g., loneliness, Beak et al., 2013), in last decade they have become ubiquitous part of our social lives due to high exposure to social networking platforms (e.g., Facebook, Instagram). Therefore, one of future challenges is developing appropriate theoretical and methodological frameworks for integrating and investigating those different types of relationships in social network research.

5.3.3. Integrating different kinds of networks in psychology

The three studies investigated either social or psychological networks, but not both simultaneously. As noted in the Introduction, the two areas of network studies in psychology are rather unconnected with each other and other applications of network analysis in psychology, such as in neuropsychology (neuroscience) where network analysis is used to map the functional and anatomical connections in the human brain. These different applications are seen as "The Many Faces of Network Analysis" (Voss, 2011) in psychological research, rather than one unified network paradigm applied to psychology. However, from a network science point of view, we can recognize that the multifaceted aspect is more due to fragmented nature of psychology than to network methods and theories. While the progress on these different research fronts is promising, a theoretical framework that integrates them is currently lacking ("Networks within networks", Epskamp, 2019). There is still much theoretical development and research needed in these different types of network research and also in multilayer networks before merging them together. In an overview of the use of network analysis in psychology, Vitevitch (2016, p. 143) cautions that moving from one to another network involved in the same problem presents a very challenging task. However, some promising developments in attempts to integrate networks in neuroscience that consider the interaction between brain regions and psychological networks have been reported recently (Bathelt et al., 2022). Moreover, as one of the most influential psychologists Walter Mischel (Voss, 2011) concluded, network analysis in psychology "is necessary to gain a complete understanding how the social world truly functions" and will help connect various disciplines within psychology, but also, we may add, help connect psychology and other scientific disciplines. While systematic reviews of research of psychological networks in psychopathology (Contreras et al., 2019; Robinaugh et al., 2020) exist, reviews of social network reserach in psychology and more comprehensive systematic reviews of use of network analysis in all fields of psychology in several last decades are potential first step in trying to organize and connect different applications of network approach within psychology.

5.3.4. Practical implications for planning interventions

The social relevance of research, its potential to inform possible interventions and public policies related to important individual and group outcomes is a desired outcome for research in any scientific field, and is strongly emphasised in social sciences (Hidalgo, 2016) and psychology. On the one hand, in social networks research, "network interventions describe the process of using social network data to accelerate behavioural change or improve organisational performance" (Valente, 2012, p.42) and a recent systematic review and meta-analysis in health research (Hunter et al., 2019) suggested that they are associated with positive outcomes. For instance, if findings presented in this dissertation stand the test of replications in future studies, they can inform interventions targeting individuals with an unstable personality profile to be more aware of the pattern of social ties around them, their possible biases, or a heightened sensitivity to some specific patterns of social clustering and to support taking a more active role and agency in shaping their social surroundings (Chapter 2). Similarly, school level interventions could benefit from using different approaches with different peer groups in schools when targeting relevant individual health outcomes (Chapter 4). On the other hand, research on psychological networks applied to mental disorders holds promise for increasing treatment efficacy by identifying the most central symptoms as targets of intervention (Lunansky et al., 2022). The theory behind such interventions is still at the early stage, but there is possibility that if intervention efforts are focused on central symptoms, they may facilitate changes in other symptoms as well. Ideally, any intervention on individual level would be best informed with personalised network analysis based on longitudinal data. In Chapter 3 we investigated the network of different personality traits and other individual differences, but in general, a similar logic could apply. If an intervention is focused on changing the most central trait (e.g., empathy) that would possibly facilitate changes in other traits. Of course, given the relatively small strength of ties within the network, we would not expect the changes in other traits to be substantial.

To conclude, future research has the opportunity to translate research efforts into important practical implications by developing theories about the mechanisms of network dynamics and studying (and evaluating) the intervention potential.

5.3.5. Challenges of communicating with heterogeneous scientific audiences

Research goals in all studies were driven by both psychology and network science. This resulted in studies that can be viewed as interdisciplinary, but at the same time less representative of any of the fields they pertain to. We recognize that the work presented in the three chapters is likely to be viewed by a typical researcher in psychology as overly methodologically oriented and technical. Likewise, a network researcher with a natural

science background might view it as too theoretical. Those kinds of hurdles are expected in any interdisciplinary research. The question is how to address them. The answer in part relates to the style and strategies of research dissemination more than to research itself. We should aim at having straightforward take-away messages, but simplifying the narrative and reducing the complexity has its pitfalls and can even backfire (as the controversy around findings of a well-known research on health and social networks has shown). It may be helpful to apply some knowledge that network science acquired from well-established empirical findings about simple and complex contagion (Centola, 2018). This research line suggests that the best approach would be to start by communicating research findings to disciplines and audiences that are related and similar, instead of trying to get the message to more distant fields. In the context of our studies, this reasoning would imply that the target audience should be other social scientists, especially those interested in similar research questions. Researchers in those fields already use the network approach to some extent, and our research could encourage developments of more advanced research programs and agendas.
The future research should also look "at the other end of the tie" (psychology ←→ network science) – encouraging network scientists from other scientific fields to consider psychological theories and research when applicable. After all, those kinds of considerations resulted in substantial contributions to network science in the past. It is possible that other network researchers, especially those with background in "hard" sciences (e.g., physics) are reluctant to seriously consider research coming from "soft" sciences (e.g., psychology) since they have a different idea about what constitutes current trends in those fields. The idea of current research in one field is not necessarily correct and updated among scientists from other more distant scientific fields. It is not reasonable to expect from a researcher to know what is happening in other not closely related scientific fields, but it is important to be aware of this lack of insight and be open-minded to potential contribution from other less familiar scientific fields.

5.3.6. Questions that need to be asked before and after doing network research

We propose several questions to consider before and after doing network research in psychology as general guidelines when deciding and evaluating the choice of using the network approach.

Which elements make the three studies exemplary of the application of network science to psychology?

The studies in this dissertation use relational data (social network data or estimated psychological network) and are focused primarily on network concepts and methods. Although there may be a growing awareness, interest and acceptance of network approach within psychology, mainstream research rarely gives central attention to the relational dimension. Networks are more often a part of the story, not its focus. All three studies in this dissertation are not only based on network theories or concepts, but are also focused on methodological developments of network methods within the subfield of application.

Was it necessary to use network concepts and tools to answer the research questions?

This question addresses the necessity of using network theory and methods, given that, as mentioned in Introduction, such research often involves more effort in data collection and it is often more complex conceptually and analytically than most research in mainstream psychology. Thus, a justification of using the network approach instead of other simpler alternatives is needed. The only way to give a direct answer to the posed question is to include alternative non-network explanations and measures and test them in the same study. Study in Chapter 3 could not have been conceived without network theory and methods, since its aim was to introduce new network methods and it was based on previous network research in psychology. However, as noted in Chapter 3, investigating the associations between different psychological measures could have been tackled with use of other methods, (e.g., multi-dimensional scaling). The advantage of using network methods was that it also provides a wider theoretical framework within which investigating these associations would be of interest. Since the use of network approach to study relations among psychological constructs is still a relatively young area of research and often exploratory, its added value has been questioned and some concerns have been raised that it does not provide much more than "pretty pictures" (Schimmack & Gere, 2012). Yet, it is difficult to argue that it brought a long-needed creativity in the analysis of multivariate psychological data and has a potential to generate new hypotheses. Some aspects of research questions in Chapter 2 and 4 could have been tackled with methods that do not involve network data directly. For instance, in Chapter 2 in addition to eliciting ego-network data about 45 alters and ties between them, a Likert-type scale could have been constructed that contains items about how many different types of alters and ties (weak or strong) one has in their contact network and about their overall embeddedness. Similarly, in Chapter 4 we could have asked students how similar they are to others in their peer group regarding their substance use and mental wellbeing. These approaches would be clearly less optimal alternatives to using network data, given the raised concerns in the Introduction about the individual ability to report on less local features of their social networks (information that goes beyond triads in which they are involved), questionable ability to delineate members of their peer group in a consistent and objective way, and possibility of knowing the substance use and mental wellbeing of all others in one's peer group. Furthermore, including such measures would increase (already a relatively high) participants' burden or it would require a comparable sample for which these measures would have been used. Finally, both Chapter 2 and 4's research questions were based explicitly on network theories which would be challenging to translate to non-network terms. However, in a hypothetical case in which such an effort would have been feasible and that resulted in similar findings as its network research counterpart, we could conclude that network approach was not necessary. In case of the three studies in this dissertation, we argue that based on previous research and our findings, network approach was necessary and appropriate.

That being noted, it is important to recognize that doing network research is not always necessary and is both challenging and effortful. In research of psychological networks, where no additional "demands" in doing a study exist in comparison to a typical psychological study, it still requires a substantive knowledge of network theories and methods. If we assume that network analysis is not typically covered in much detail in undergraduate and postgraduate programs in psychology[56], that implies that it is not a part of a standard methodological and theoretical knowledge of a researcher in psychology. An effort to learn it adds to an already big list of required competences that a researcher ideally needs to have (Fried, 2017), and thus is not to be expected from a typical researcher in the field. In social network research, data collection is costlier to carry out, despite technological advancements. Additionally, there are important ethical and privacy issues that need to be considered. Moreover, the use of appropriate statistical methods for social network data such as exponential random graph models or stochastic actor-oriented models, requires expertise and experience that are considerable to acquire.
Finally, results of one network study are unlikely to generalize to other contexts and similar systems, instead they will need replications and they will lead to hypotheses to be tested in future research. As Robins (2015) pointed out, there is no *One True Study* that can provide a definite answer to a research question. More generalizable conclusions can be achieved with a research agenda across different research teams. Additionally, these teams are likely to be bigger and more interdisciplinary than ones responsible for a more typical psychological research.

Was it worth the effort?

Therefore, for both types of research, we can reframe "Is/Was it necessary?" question from Introduction to "*Is/Was it worth the effort?"* There is no simple and straightforward answer, and it can rarely be answered before the research is done. The answer will at least partially depend on the value that is assigned to understanding the specific research question and its potential practical implications, the additional effort needed to collect the data, expertise of, and openness of the scientific community. Many of those aspects are dependent on subjective judgments and the *zeitgeist*. While it seems that the current zeitgeist is favourable to network approach as well as to other methods related with computational social science, only a development of research programs that will work on building strong theories and their integration with existing body of knowledge will be able to sustain it and justify the excitement surrounding the use of network approach in psychology.

[56] This is an assumption (based on many anecdotal and non-systematic evidence) because we do not have the data about the courses available at undergraduate and postgraduate programs in psychology across the world.

The three studies in this dissertation contributed with new network methods, within the field of application, and with findings that opened new avenues for future research that could be of interest for research dealing with related research topics and not necessarily involving network approaches.

5.3.7. General conclusion

The last two decades have witnessed a great surge in network-related research in psychology. The network approach to interpersonal relationships and to relations between psychological constructs is believed to hold much promise across psychological research (Vitevitch, 2016). We undertook three studies in different subfields in psychology and applied network theories and methods to formulate and answer our research questions. Each study provided new insights and generated hypotheses and directions for future research. We conclude that the benefits of providing a more nuanced, albeit more complex, picture of the studied research topics and the potential of generating other relevant research questions, provide a counterbalance to the discussed challenges of the application of network theories and methods to different psychological subdisciplines.

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Appendices

Appendix 1

Supplementary Materials for Chapter 1

1 Search of the Web of Science database

In the Web of Science database, we searched scientific publications (articles, review articles, editorial materials and other) from 01/01/2000 to 01/06/2022 (date of search: 10/06/2022). The queries used and found results are presented in table 1.

Table 1. Results of queries made in Web of Science database

Query in the field “Topic” (from Jan 2020 to Jun 2022)	Results (*N* publications)
"social network*" AND "psycholog*"	12 756
“psycho* network*" OR "network psychometrics" OR "qgraph”	284
("psycho* network*" OR "network psychometrics" OR "qgraph") AND ("social network*")	12*

* Based on abstracts none of them integrated social and psychological networks in research, but rather mentioned both.

Note: Data included herein are derived from Clarivate Web of Science.

Figures 1 to 4 are derived from Report from Clarivate Web of Science.

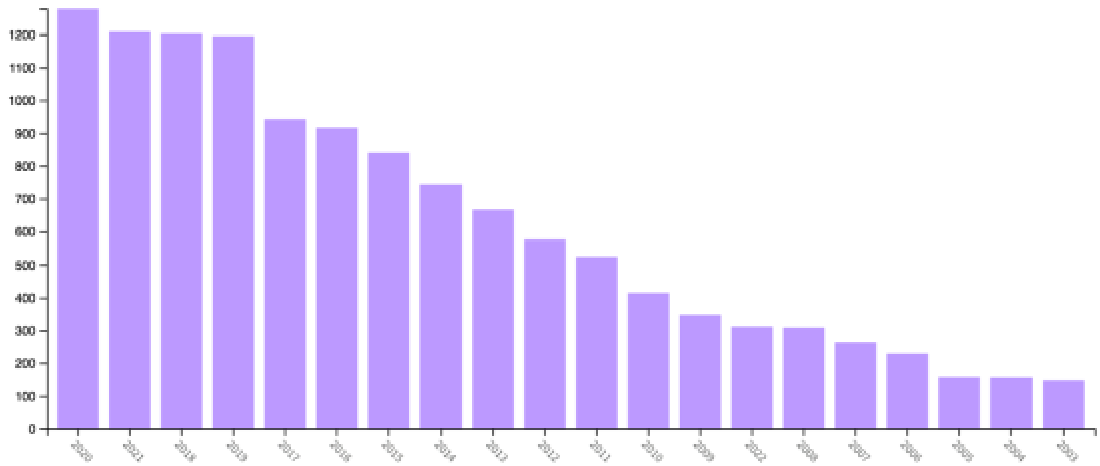

Figure 1. Number of publications per year (from highest number of publications to lowest) with both social networks and psychology as topic

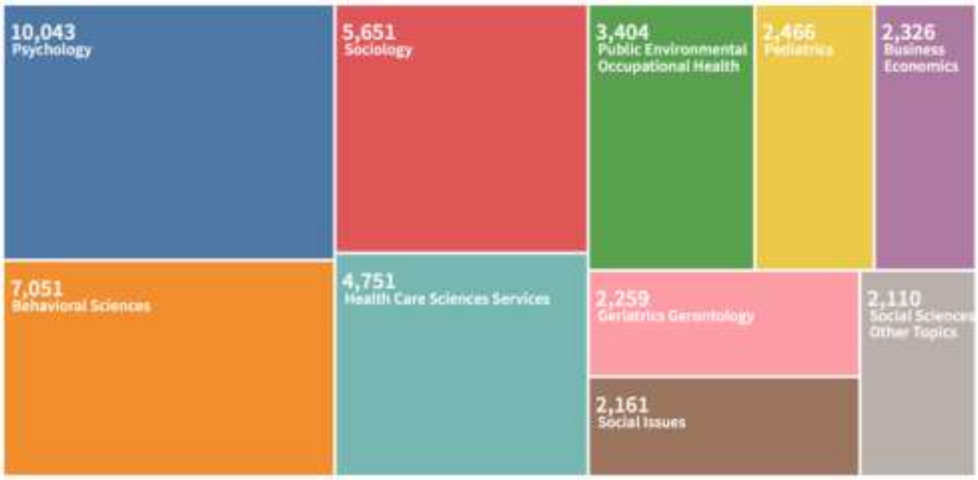

Figure 2. Research areas (as defined by WoS) of scientific publications with both social networks and psychology as topic

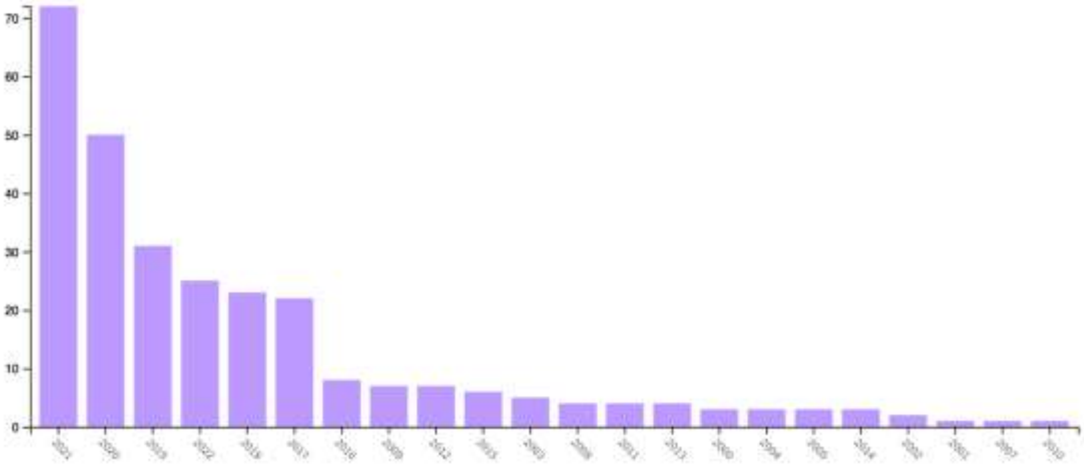

Figure 3. Number of publications per year (from highest number of publications to lowest) with psychological networks, network psychometrics or “qgraph” as topic

Figure 4. Research areas (as defined by WoS) of scientific publications with psychological networks, network psychometrics or “qgraph” as topic

2 Overlap of symptoms between mental disorders

We used the data about symptoms and mental disorders in ICD-10 (Tio et al., 2016; available at: http://psychosystems.org/publications/) to construct a network of overlap in symptoms between different disorders. Additionally, we performed a statistical validation, following procedure outlined in Miccichè & Mantegna (2019), to identify only the edges that appear more (are “overrepresented”) than it would be expect by chance given the bipartite structure of the network. The legend for 62 mental disorders (coded as F *xx*) in figure 5.1 is provided in table 2.

Table 2. Codes for mental disorders

Code	Disorder name
F07	Personality and behavioral disorders due to known physiological condition
F10	Alcohol related disorders
F11	Opioid related disorders
F12	Cannabis related disorders
F13	Sedative, hypnotic, or anxiolytic related disorders
F14	Cocaine related disorders
F15	Other stimulant related disorders
F16	Hallucinogen related disorders
F17	Nicotine dependence
F18	Inhalant related disorders
F20	Schizophrenia
F25	Schizoaffective disorders
F30	Manic episode
F31	Bipolar disorder
F32	Major depressive disorder, single episode
F33	Major depressive disorder, recurrent
F34	Persistent mood [affective] disorders
F40	Phobic anxiety disorders
F41	Other anxiety disorders
F43	Reaction to severe stress, and adjustment disorders
F45	Somatoform disorders
F48	Other nonpsychotic mental disorders
F92	Mixed disorders of conduct and emotions
F93	Emotional disorders with onset specific to childhood

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Appendix 2

Supplementary materials for Chapter 2

In this appendix, we explain in more details the three variations of KR triadic measures used in the analysis. As mentioned in Chapter 2, the purpose of designing these measures was twofold: i) to apply triadic analysis to ties between alters only, excluding the ego; and ii) to enhance the differentiation between networks of the same size. However, it should be noted that the following measures are equally adequate for triadic analysis that includes ego, and for ego-networks that differ in size.

1 Three versions of KR triads

Table 1 presents descriptive analysis of two global measures (density and transitivity) and other measures related with triadic closure.

Table 1. *Descriptive measures related with triadic closure and KR triads*

	Mean	*S.D.*	*Min.*	*Median*	*Max.*	*Skewness*	*Kurtosis*
Density	0,413	0,147	0,146	0,389	0,912	0,896	1,154
Transitivity	0,745	0,104	0,497	0,735	1	0,217	-0,194
Density of Strong Ties	0,144	0,086	0,017	0,134	0,443	1,089	1,221
Density of Weak Ties	0,269	0,119	0,087	0,244	0,779	1,417	3,324
Density of Missing Ties	0,587	0,147	0,088	0,611	0,854	-0,896	1,154
Average tie strength	1,901	0,288	1,275	1,905	2,601	0,024	-0,371
Ratio of All Triads	0,316	0,179	0,041	0,275	0,958	1,214	1,59
Tie Strength of 1 (fq.)	177,5	94,776	37	175	584	1,264	3,139
Tie Strength of 2 (fq.)	84,84	60,431	2	78	374	2,051	7,047
Tie Strength of 3 (fq.)	140,31	85,697	14	130,5	439	1,113	1,31
Proportion of ties of strength 1	0,444	0,158	0,076	0,457	0,788	-0,008	-0,357
Proportion of ties of strength 2	0,211	0,12	0,008	0,203	0,77	1,324	4,235
Proportion of weak ties (strength 1 and 2)	0,655	0,154	0,259	0,664	0,937	-0,316	-0,309
Proportion of strong ties (strength 3)	0,345	0,154	0,063	0,336	0,741	0,316	-0,309

fq. – frequency; S.D. – standard deviation; Min. – minimum score; Max. – maximum score

Operationalization of weak and strong ties – To calculate the percentage of seven triads in an ego-net, a decision about the cut-off value for strong tie had to be made. We decided to classify all ties with strength value of 3 as strong, in line with the analysis of frequency of all tie values in the whole sample (see table 1, the average strength of ties is 1.9), and ties of strength 1 and 2 as weak. Having a lower cut-off score would have resulted in too many strong ties, and hence smaller occurrence of configurations with weak ties (any of triads with letter W in figure 2.1 in Chapter 2).

1.1 Variant I: Triads as proportions of all possible triads

We started by identifying all unique combinations of three alters in each ego-network (triads of alters *ijk* is the same as *jki* and *kij*). Then we assigned them a three-letter code according to the strength of ties among the alters. We proceeded with the count of each of the seven configurations and divided it by the number of all possible unique triads, which was similar for all ego-networks (14190[57]).

Mean values and distributions of seven triads were similar. Triads with weak ties constituted most of the triads, especially weak structural holes (WWN triad), which could be attributed to the method of eliciting the network data that asked for 45 alters. The mean and variance were noticeably smaller for SSW and SSN, showing that weakly closed strong triads (SSW) and open strong triads (SSN, or strong structural holes) were less frequent. Among closed triads, the biggest variation is in the proportion of WWW, with several outliers. In line with the presence of outliers in most of the triads, distributions were mostly skewed. Therefore, in the analysis of relationship of triadic measures with all other variables, as an alternative to Pearson's coefficient, Spearman's rank coefficient was used that mitigates the effect of outliers and skewed distributions.

1.2 Variant II: Triads as proportions of all existing triads in the ego-net

The basic logic and one of the advantages of the KR census over other network measures was that it represents, not only a count of the different triad types, but rather the proportions of each type against the total number of possible triads given the number of alters in the ego network: in this way, egocentric networks of different sizes could be compared. However,

[57] This number was not the same for all ego-networks, as it depends on the number of non-isolated alters, that is the alters that have at least one tie with someone else in ego's network. In our sample of personal networks the number of non-isolated alters was in range of 37 to 45 (*M*=44.5).

in our study the network size, that is, the number of alters, is fixed to 45, meaning that this method will provide the same results as simple count of the motifs. Since the number of possible triads is methodologically induced, it does not describe the unique property of an ego-net and has no meaningful interpretation. In other words, we don't have information about true network sizes of our participants, which is crucial for meaningful interpretation of triadic proportions, as defined in KR method. On the other hand, using this calculation would give the same value for an individual with just one triad in his/her ego-net, e.g. SSS, and to an individual with complete ego-net with ties present between all alters, but where only one of those triad is the SSS configuration. We could argue that the meaning and interpretation of SSS triads in those two networks is very different. We wanted to consider the fact that the number of truly possible triads differs between individuals, and one straightforward way to achieve that is to use the information about existing triads in ego-net. Therefore, we decided to normalize the counts of each triad with the number of all present triads (open and closed - the total of all seven configurations) in the individual ego-net. In previously mentioned example, the first individual would score 1 on SSS triadic measure, while the second individual would score below 0.001.

1.3 Variant III: Triads as Z-scores in comparison to individual null model

We recognize that using the number of existing ties in the ego-net to compare the occurrence of triads in different ego-nets is just one of many possible ways. In fact, we could have used the number of all non-empty triads, some combination of both, etc. The ultimate purpose of not taking just the frequency of each triad in a network as a measure, is ability to compare triad occurrence among different networks, while controlling for some structural properties. The quantification of the occurrence of specific configurations in a network is frequently done by comparing the occurrence of certain configuration of interest (a motif) in network with the occurrence of the same motif in a null-model (for introduction see Milo et al. 2002), and we propose a way to generalize this approach to the comparison of ego-networks. As a null model, we defined for each ego-net its specific null-model as a random Erdős–Rényi graph (Erdős & Rényi, 1959) with the same density (number of links in the ego-net) and same proportion of weak and strong ties as individual's real ego-network. This means that any association of triadic measures of this kind with any attribute will not include the existing association of density and proportion of weak and strong ties with the same attribute. Subsequently, we made 100 such randomized graphs with the same specifications for each case (individual) and recorded the occurrence of motifs (triads) of interest in each graph. This results in the distribution of values for each triad/motif that is unique for each case/individual. The real number of triads in each ego-network is expressed as a z-score against that distribution: $\mathrm{Z} = \frac{(\mathrm{X}-\mathrm{M}_{\mathrm{rand}})}{\sigma_{\mathrm{rand}}}$, where X is the number of occurrence of the motif in the real ego-network, M_{rand} is mean of occurrence of the motif in 100 randomized networks with the same density and proportion of weak and strong ties as in the real individual network, and σ_{rand} is the standard deviation of those occurrences in the sample of 100 randomized networks[58]. The result of this procedure were seven z-values for each ego-net, one for each triad. Low or high z-scores (lower than -2.58, and higher than 2.58, corresponding to p-value of 0.01) indicate that the configuration appears significantly less or significantly more in real network than it would be expected by chance. This means it represents a motif[59] – an important characteristic of the real network. In other words, the configuration is less or more frequent than in the sample of random graphs that differ with individual network only in structure. Furthermore, we used the absolute value of a z-score as a proxy of the prominence of certain motif in the network.

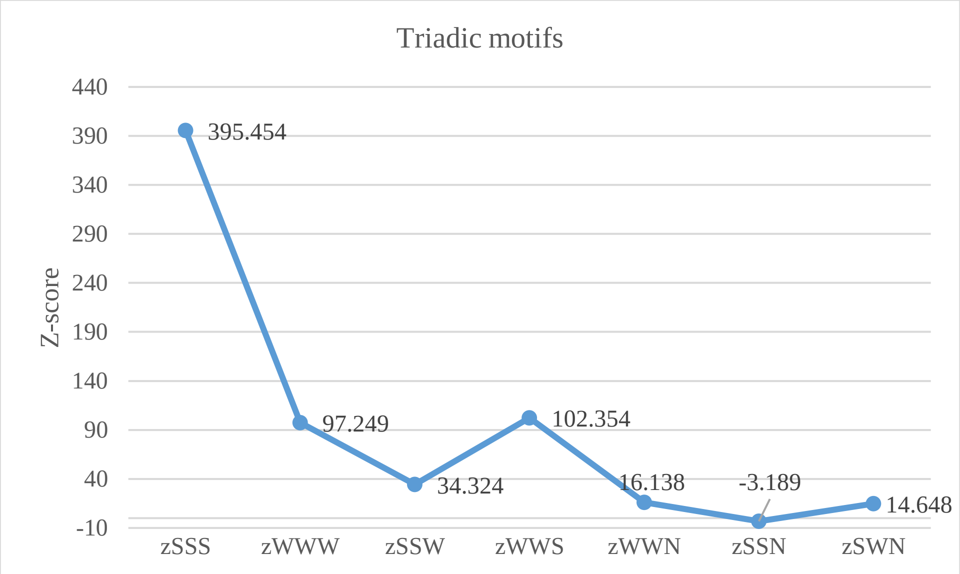

Figure 1. Average values of Z cores for real ego-networks in comparison with 100 random networks (tailor-made for each case)

The resulting average z-scores for each triad are shown in Figure 1. As it can be seen in the figure, on average all motifs are statistically significantly overrepresented in ego-nets, while open strong triad (SSN) is underrepresented. This implies that all closed and open triads are far more (or for one motif, far less) frequent than it would be expected by chance, that is, in the random network with the same density and ties composition. Strong closed triads (SSS)

[58] The distributions of average occurrences of motifs were normally distributed, allowing the use of z-scores.
[59] Use of the term motif can be slightly confusing, as some research prefer to address certain configuration as a motif only when analysis shows it to be statistically significant. While appreciating this distinction between motif and configurations that some researchers make, we will address all investigated configurations as motifs, and describe them as significant if their occurrence is found to be statistically significant.

are the most prominent motif. This is expected in real social networks as they are characterized by higher clustering than random networks. The next most prominent motif describes weak structural holes (weak open triads). This implies that even after we control for individual tendencies to assign strong versus weak ties, the finding that WWN is one of most frequent triads persists. The third most prominent motif is WWS, followed by WWW. The strong open triads (so-called forbidden triads) is the least prominent motif, and the only motif that occurs less frequently in real ego-networks than in their corresponding random networks. This is not a surprising finding, as it is well established in the social network research (e.g., Granovetter, 1983) that this configuration is underrepresented in social networks, as it naturally leads to triadic closure.

In addition to inspection of the specific motifs, we used seven obtained Z-scores for each individual ego-network to try to quantify the "randomness" of a given ego-network. We aimed to express the randomness of an ego-net by calculating the mean of the absolute values of seven scores:

$$(|\mathrm{Zsss}| + |\mathrm{Zwww}| + |\mathrm{Zssw}| + |\mathrm{Zwws}| + |\mathrm{Zwwn}| + |\mathrm{Zssn}| + |\mathrm{Zswn}|)/7$$

The higher score would imply less randomness as it shows that the network differs from a random network in higher degree; hence the measure is named Non-randomness. However, before averaging the scores, we did the min-max transformation that results in the range of values between 0 and 1 since the original z-scores showed to be extremely skewed and had noticeably different mean.

2 Relationship of triadic measures with psychological attributes

We have not preformed corrections for multiple testing, as it would lead to a considerate limitation of statistical power. Figures 2 and 3 show heatmaps of significant correlations between two groups of network measures (KR variant II, and KR variant III) and psychological attributes (Big Five personality traits and Sense of Community).

2.1 KR variant I and its relationship with psychological attributes

Weakly closed strong (SSW) and open strong triads (SSN) are not related with any of 11 investigated psychological attributes. In the group of personality traits, only Emotional Stability is positively correlated with strong closed triads (SSS), and with the triad with one strong and two weak ties (WWS). Composite measure of Mean TIPI10 is negatively correlated with "mixed" triad (SWN).

2.2 KR variant II and its relationship with psychological attributes

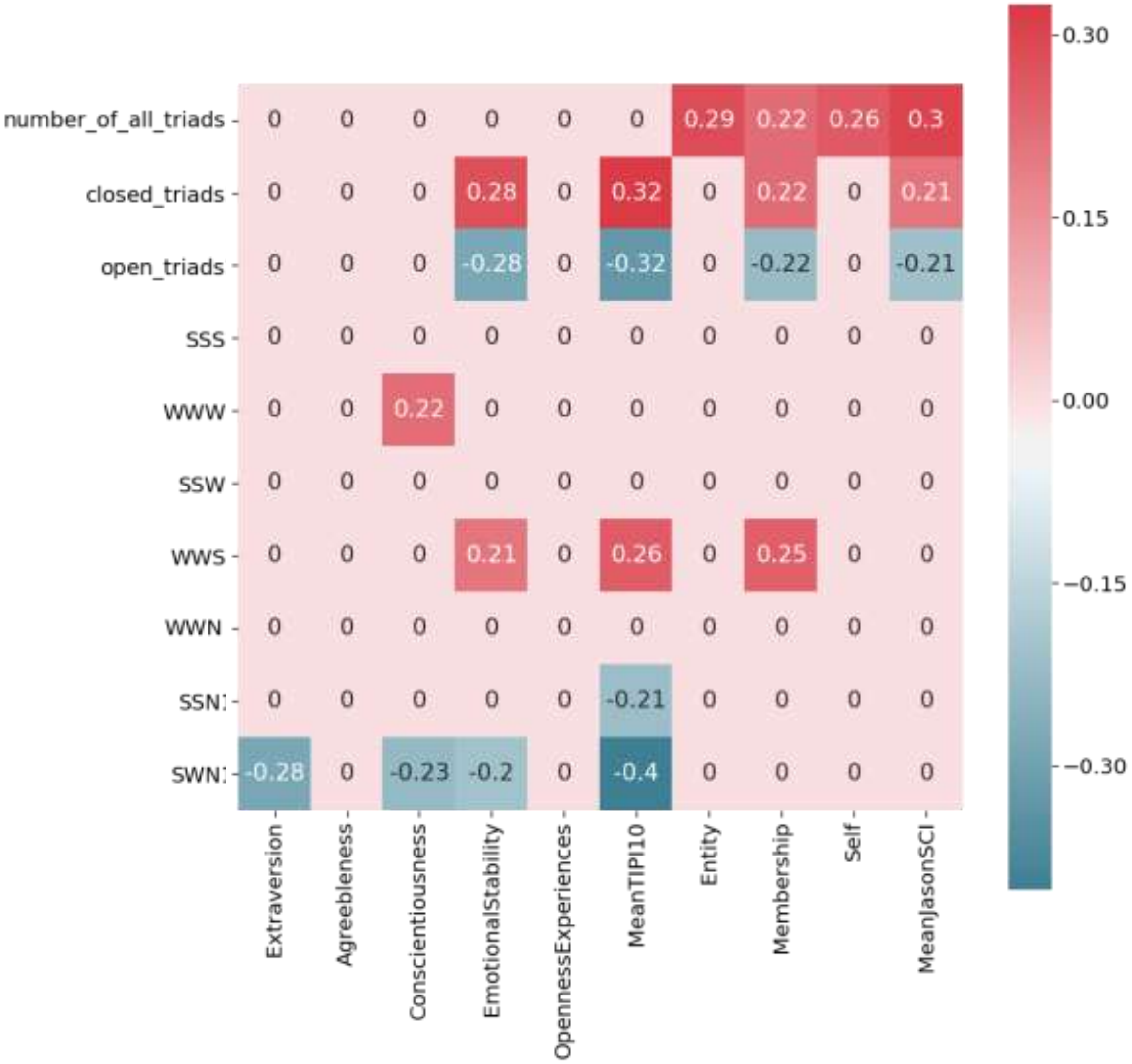

Figure *2.* Significant correlations between KR variant II measures and psychological attributes (based on 1000 permutations)

In Figure 2, correlation coefficients of KR triads of ego's alters as proportions of all existing triads are shown. In comparison with the first variant, we can see that significant coefficients have been shifted more from Sense of Community variables (right) to Big Five Personality variables (Figure 2, left side). We also found significant relationship between WWW and C, WWS and both Mean TIPI10 and Membership. As with the first variant of triadic measures, here we can also see that all psychological attributes have similar pattern (direction and strength) of association with a given triad.

2.3 KR variant III and its relationship with psychological attributes

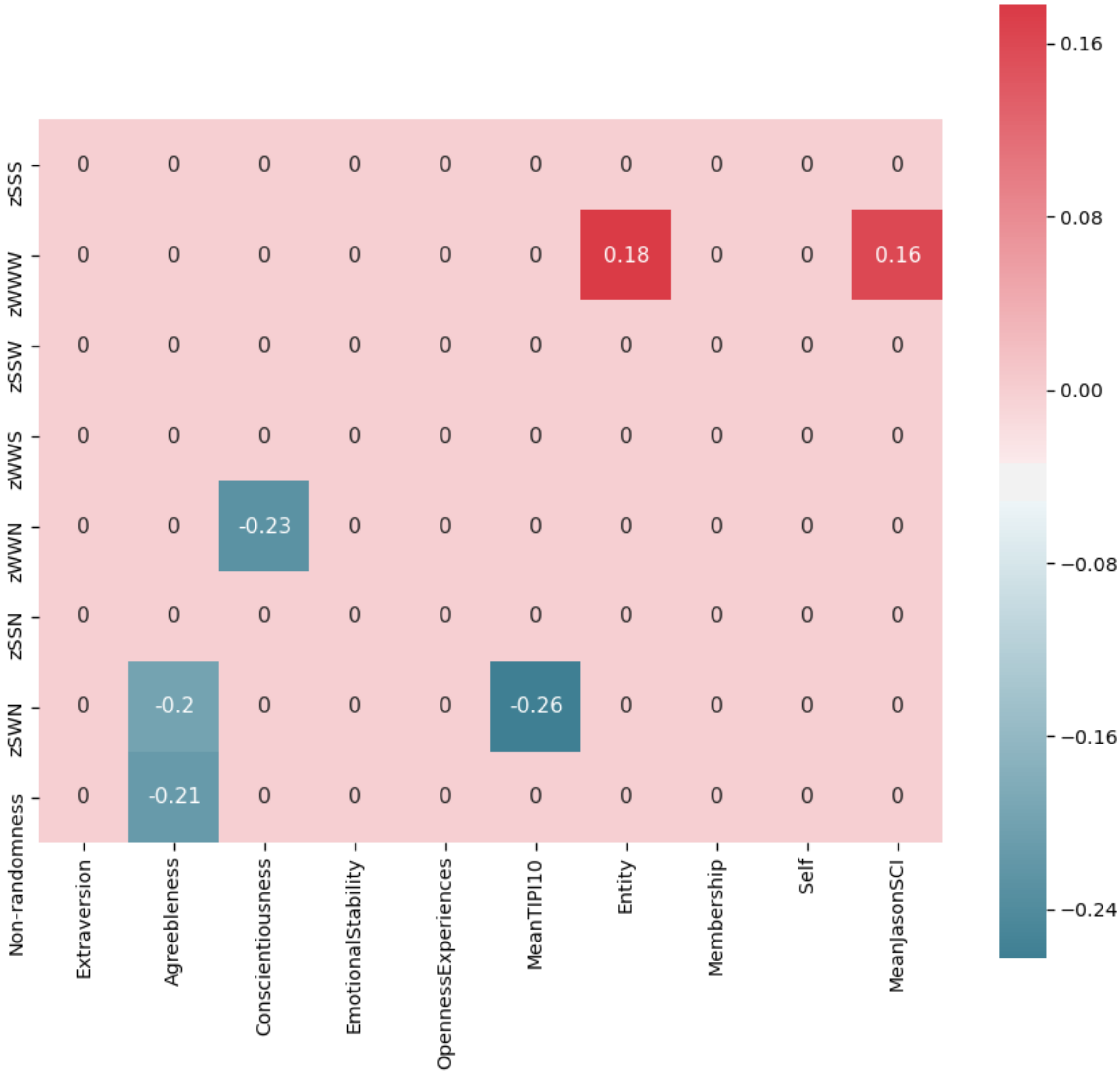

Figure 3. Significant correlations between KR variant III measures and psychological attributes (based on 1000 permutations)

The third variant, where we control for the density and individual tendency to assign ties as strong and weak, results in noticeably sparser significant correlations and clearer picture of two groups of attributes regarding their relation to specific triads. Entity and Mean PSC are positively correlated with WWW configurations.

C is negatively associated with WWN triad, suggesting that individuals with higher C are less likely to perceive, live in, or report on weak and open triads. Only in this variant of triadic measure, trait A shows any, in this case negative, correlation with a measure derived from triadic configurations – Non-randomness. Non-randomness was constructed in attempt to capture the relations of psychological attributes with non-random patterns among alters in social network. According to this finding, the more agreeable a person is, the more likely s/he lives in/perceives/reports being surrounded with random network of ties. This may be a result from different mechanisms acting simultaneously: it may be that more agreeable egos are more likely to have alters that are more heterogeneous (less like each other) and therefore less likely to show some systematic clustering; it may be that they are also more tolerant to non-structured social environment and less likely to induce or force some changes in it. This finding is in accordance with the result showing negative correlation between A and centralization and it is possible that the lack of centralization (an absence of an alter who is directly connected with many other alters – a hub) in ego's network contributes to apparent higher randomness of alters' ties of more agreeable people. Non-randomness showed no relation with Emotional Stability, indicating that this personality dimension is not related in any way with degree of randomness in ties between alters.

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Appendix 3

Supplementary materials for Chapter 3

1 Data processing

Data file of each questionnaire was processed in several steps: if only items scores were available (true for most of the measures), all cases with more than 15% missing data within a questionnaire were excluded. After recoding, the missing data was replaced with median of individual scores on all items of questionnaire, or a subset of questionnaire to which item belong to, before final score(s) were calculated. This strategy seemed more sensible than taking an average score of non-missing values, since some scores had to be calculated using slightly more elaborate procedure than taking a sum or average of scores (e.g. Schwartz's values). We used the mean instead of average value, to preserve the same level of precision (that is, not to induce scores with more decimals artificially). Then, we merged all the files based on the unique ID (a string of letters and numbers) in one dataset. Lastly, we excluded all cases that had data (a score) just for one of 26 variables, ending with in total 1166923 cases which had data about at least two psychological attributes.

2 Sample description

A separate data file contained demographic information for some participants, extracted from Facebook profile, if the data was available on the profile and if the participants gave their consent to use it. Data about age was available for 20,8% after re-evaluation of some cases as missing data due to a high chance of being inaccurate (all older than 89 yrs, *n*= 568, Table 2).

Table 1. *Countries with more than 1000 participants in the sample (in descending order)*

Country	*N*
USA	273138
UK	72747
Canada	36188
Australia	25499
India	9233
Singapore	6800
Philippines	6146
Ireland	4904
Spain	4872
Mexico	4410
France	3867
Malaysia	3751
Indonesia	3483
Sweden	2763
Pakistan	2543
Italy	2220
Germany	2121
Finland	1697
Netherlands	1565
Egypt	1495
Belgium	1354
Greece	1350
Colombia	1317
Romania	1217
Argentina	1199
Japan	1087
Portugal	1086
Brazil	1061
Denmark	1043

Table 2. *Descriptive statistics for age (for available data, N=242726)*

Mean	*SD*	*Mdn*	*Min.*	*Max.*	*Skew.*	*Kurt.*	*N*	*% of total sample*
26,13	6,663	25	14	89	2,465	10,459	242726	20,8

3 Descriptive of missing data

Table 3. *Number of not-available data (NA) on 26 psychological attributes per case*

	Mean	*SD*	*Mdn*	*Min.*	*Max.*	*Skew.*	*Kurt.*	*N*
Number of NA per case	20,76	1,462	21	0	24	-5,61	47,463	1166923

Table 4. *Matrix of sample sizes of complete observations (non-NA) pairwise*

Quest.	1	2	3	4	5	6	7	8	9	10	11
1.Body Consc. (*BCQ)*		4319	1480	6187	5158	9451	7903	2178	6758	2280	4771
2.Big5 traits (*IPIP*)			1743	5393	10583	46250	10634	3021	32412	2328	3981
3.Intelligence (*myIq*)				1423	1428	2556	1945	1177	1798	1066	1879
4. Awareness of physical symptoms (*Pill*)					6550	11458	9726	2028	8689	2159	4154
5.Integrity assessment (*Orpheus)*						17798	12120	2253	12967	1978	4107
6.Interests (*SIQ*)							22765	4131	61560	3615	7647
7.Self-monitoring (*SMS*)								2990	15726	2828	6120
8.Values (*SVS*)									2770	2447	2721
9.Life Satisfaction (*SWLS*)										2549	5143
10.Depression (*CES-D*)											2621
11.Empathy (*EQ*)											

Quest. – Questionnaire;
Acronyms in the brackets – usually used abbreviations for psychological instruments described in Table 1. in the main text;
Body Consc. – Body Consciousness.

The minimum sample size complete pairwise observation for 11 questionnaires was 1006 (Intelligence and Depression), and maximum size was 61560. However, the true maximum size for complete pairwise observations of 26 traits (measured by those 11 questionnaires) was 1048574 for all pairs of Big 5 personality traits (equal to the number of participants who had fulfilled IPIP questionnaire, see Table 5 below). When all 325 pairs of observations are considered, the median sample size was 4131 (Mean = 43776,99, SD=180530,616).

4 Descriptive statistics of 26 psychological attributes

Table 5. *Descriptive statistics of psychological attributes*

PA	*N*	*% of non NA*	*Mean*	*SD*	*Mdn*	*Min.*	*Max.*	*Skew.*	*Kurt.*
Agreeableness	1048574	89,86	3,55	0,692	3,60	1	5	-0,441	0,065
Conscientiousness	1048574	89,86	3,49	0,723	3,50	1	5	-0,169	-0,307
Emotional stability	1048574	89,86	2,77	0,802	2,75	1	5	0,165	-0,37
Extraversion	1048574	89,86	3,61	0,796	3,75	1	5	-0,442	-0,244
Openness	1048574	89,86	3,83	0,670	3,90	1	5	-0,516	0,083
Body competence	13735	1,18	4,44	0,809	4,50	1	6	-0,396	0,081
Private body	13735	1,18	4,32	0,833	4,40	1	6	-0,343	-0,038
Public body	13735	1,18	4,29	0,752	4,33	1	6	-0,31	0,195
Fair-Mindedness	33791	2,90	1,49	6,189	1,50	-19	20,5	-0,038	-0,418
Self-Disclosure	33791	2,90	0,23	6,713	0	-19,5	19,5	0,021	-0,645
Intellectual int.	144924	12,42	27,86	3,715	28	7	35	-0,663	0,824
Low militaristic Int.	144924	12,42	30,47	7,367	31	10	50	-0,073	-0,334
Low violent-occult int.	144924	12,42	20,27	5,508	20	7	35	-0,048	-0,416
Wholesome act. int.	144924	12,42	17,15	3,896	17	5	25	-0,414	-0,138
Awareness of physical symp.	14675	1,26	65,23	29,675	61	0	181	0,685	0,195
Empathy	9985	0,86	44,07	12,873	44,50	1	79	-0,183	-0,301
Intelligence	3829	0,33	113,77	14,399	116,3	64,7	138,6	-0,458	-0,275
Life satisfaction	76267	6,54	4,37	1,362	4,40	1	7	-0,3	-0,781
Low Depression	4973	0,43	45,52	12,692	45	20	80	0,176	-0,736
Self-monitoring	29635	2,54	148,44	16,462	150	100	200	-0,035	-0,364
Achievement	7930	0,68	0,17	1,041	0,21	-3,9	5,1	-0,177	0,365
Hedonism	7930	0,68	-0,12	1,465	-0,04	-5,8	5,1	-0,309	0,252
Power	7930	0,68	-2,15	1,478	-2,25	-6,6	3,6	0,361	0,075
Self-direction	7930	0,68	0,99	0,918	0,99	-2,7	5,9	-0,027	0,2
Tradition	7930	0,68	-1,36	1,182	-1,33	-6,1	2,8	-0,096	-0,207
Universalism	7930	0,68	0,37	0,942	0,40	-3,7	3,7	-0,247	0,375

M - Mean, Mdn - Median. SD – Standard deviation, Min. – minimum score, Max. – maximum score, Skew. - skewness, Kurt.- kurtosis, PA – psychological attribute

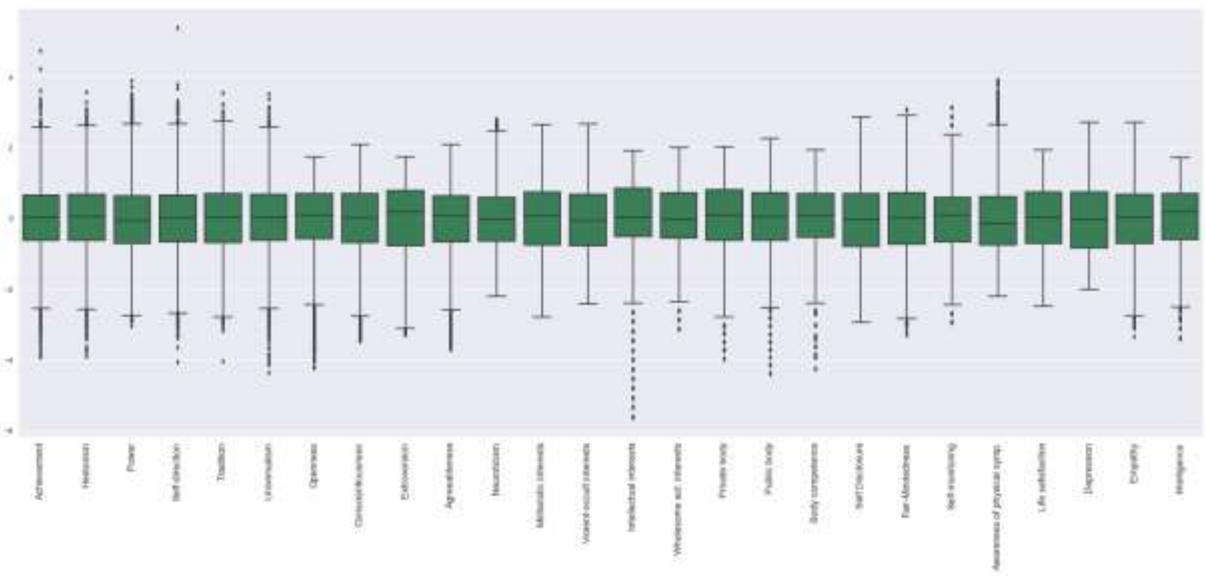


Figure 1. Boxplots of 26 standardized psychological attributes

5 The choice of the estimation method

In previous research that dealt with estimation of psychological networks with ordinal and continuous variables, the most popular procedure was partial correlation networks regularized with graphical LASSO technique (gLASSO) (Epskamp & Fried, 2018), applied from the fields such as neuroscience and genomics. Williams et al. (Williams & Rast, 2020; Williams et al., 2018) have recently pointed out that this procedure is not always optimal for high dimensional data in psychological research setting where number of variables does not exceed the number of observations. In the paper, authors also introduce a non-regularized method based on maximum likelihood estimations (used in our study), and demonstrate that it outperforms gLASSO technique regarding false positives and has overall more consistent performance. Epskamp and Fried (2018) reported lower specificity of gLASSO than expected for dense network structures with many very small edges as well.

Given the correlation network of our dataset and previous research on correlations between the concepts included in the network we expected that our network will have many very small edges. To that end, we had to consider those recent findings suggesting that gLASSO method may not be appropriate.

To find out which estimation method is the best for our data, we preformed simulations (following procedure described in Williams et al. (2019)) to compare the performance of the most popular models: (i) gLASSO, with tuning parameter (γ) set to 0.5, and (ii) gLASSO, with tuning parameter (γ) set to to 0 – the latter variation is added as it preserves more edges and as such provides a good comparison with the non-regularized method; with (iii) non-regularized method based on maximum likelihood estimation for covariance and precision matrix.

R package qgraph is used to fit the gLASSO models (Epskamp et al., 2012) and the non-regularized model was estimated with custom function provided in Williams and Rast (2020). The graphical lasso estimates the precision matrix with *l1*-based regularization, while non-regularized method estimates the precision matrix in two steps. Firstly, it is estimated with non-regularized maximum likelihood and then it uses Fisher Z-transformed confidence intervals (alpha set to 0.001) to determine non-zero relationships.

Next, the positive definite partial correlation matrix estimated with the non-regularized method (described above) was performed on our data. Afterwards that estimation was used to generate samples of different sizes from the corresponding standard multinormal distribution (M= 0, SD= 1; GeneNet R package (Schaefer et al., 2018). We simulated samples of size N ∈ {500, 1000, 1500, 2000, 2500, 3000, 3500, 4000, 4500, and 5000} to have N used in our estimation procedure included in the range (N = 4131). Each sample size was simulated 50 times. From those 500 samples, networks were estimated with three methods (described above). After the partial correlation matrix was obtained for all samples and with all three methods, absolute values less than 0.05 were set to zero.

Next, four performance measures were computed for each estimation to check the accuracy of the estimated partial correlations: a) sensitivity (SE) - the true positive rate; b) specificity (SP) – the true negative rate (1 − SP = the false positive rate), c) false positive rate, and d) Mathews correlation coefficient (MCC) – which calculates correlation between the true partial correlations and the estimated partial correlations, and ranges between -1 and 1. These measures were averaged across simulation trials grouped by sample size and the estimation method. The results of simulations are presented in Figure 2.

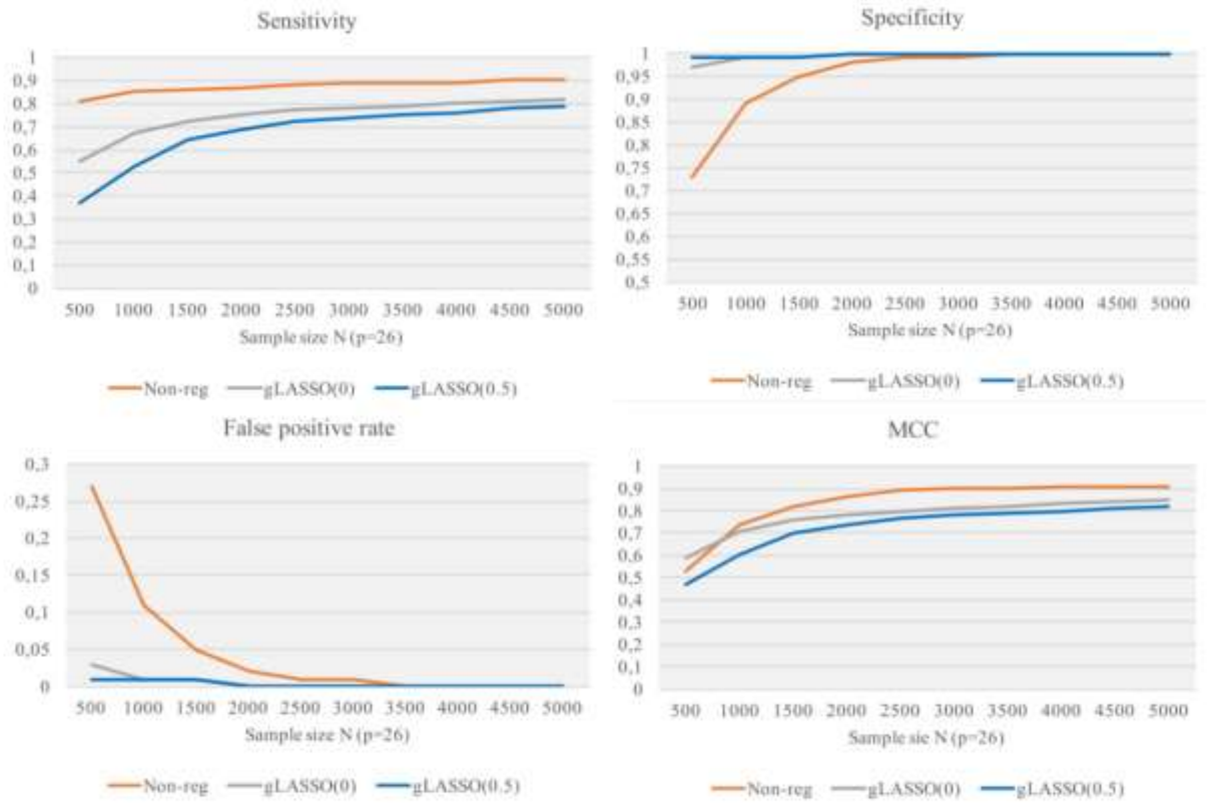


Figure 2. Simulation results comparing three estimation methods on four performance measures based on the average value of 50 simulations for each sample size (N)

In general, with the increase of N, all methods show an increasingly better performance. For the sample size below 2500 the performance of the three methods differ, and non-regularized method is inferior to gLASSO methods regarding specificity (and its reversed measure, false positive rate). For sample sizes over 3500, the non-regularized method shows equal performance as other methods in specificity (and false positive rate), but it outperforms two gLASSO methods when sensitivity and MCC are considered. These results informed us to choose non-regularized method to estimate our network.

Additional note on setting the *N* and alpha parameters: The *N* – sample size parameter used in every network estimation method, is set to median value of complete pairwise observations in the whole 26 X 26 matrix. This seemed to be the most sensitive choice since we had many missing values, and the treatment of missing values in network analysis is still an open question. For that reason, we had to make the decision which *N* to use for network estimation procedure. We decided that making *N* equal to number of all participants (more than one million) would be overly permissive, while *N* equal to smallest pairwise sample (1006) would be overly restrictive. Opting for the balance between two extremes the median value was chosen ($N = 4\ 131$). Alpha set to 0,001 presents a rather strict choice, in purpose of preventing false positive edges. As a side-effect of these two decisions the smallest absolute value of edge weight that could be detected in our dataset as significant was 0.05, which presents a reasonable cut-off score for interpreting a partial correlation coefficient as signifying the existence of a (very weak) connection between concepts.

6 Robustness analyses

Existing procedures for estimating the stability of estimated psychological networks (Williams et al., 2019) where not directly applicable on our data due to high percentage of missing data for each variable. In order to test the stability of estimated network, two kinds of robustness tests have been performed: 1) comparisons of the estimated network in 100 split-halves samples, and 2) comparison of estimated network on whole sample with 100 samples consisting of randomly selected 80% of all cases, as explained in the main text.

The networks in both analyses were compared by calculating Spearman correlations between samples for nine centrality measures, and Pearson correlations between network matrices as vectors. It should be noted that for Expected influence measures the rank correlations between absolute values are considered (as we were interested in the stability of the influence of node, not the direction of that influence).

We also looked at correlation between matrices of minimum spanning trees. Additionally, “Similarity Index” is calculated between each network pair and MST pair. This index takes only absence and presence of edges into account, it is defined as: the number of the edges present in both networks divided by all edges present in any of two networks. This measure has range of values from 0 to 1, where higher value indicates higher similarity.

When looking at the correlation and Similarity Indexes, it should be noted that minimum spanning tree contains only 0 and 1 weights and always has the same number of edges (number of nodes minus one).

6.1 Robustness analysis I: Split halves (100 random splits, size of each split-half sample was N≈583461)

For the calculation of partial coefficients, the size of the sample is set on 2075 – the median value of complete pairwise observations in one randomly chosen split-half sample. As in the estimation of the whole network, the alpha is set to 0.001.

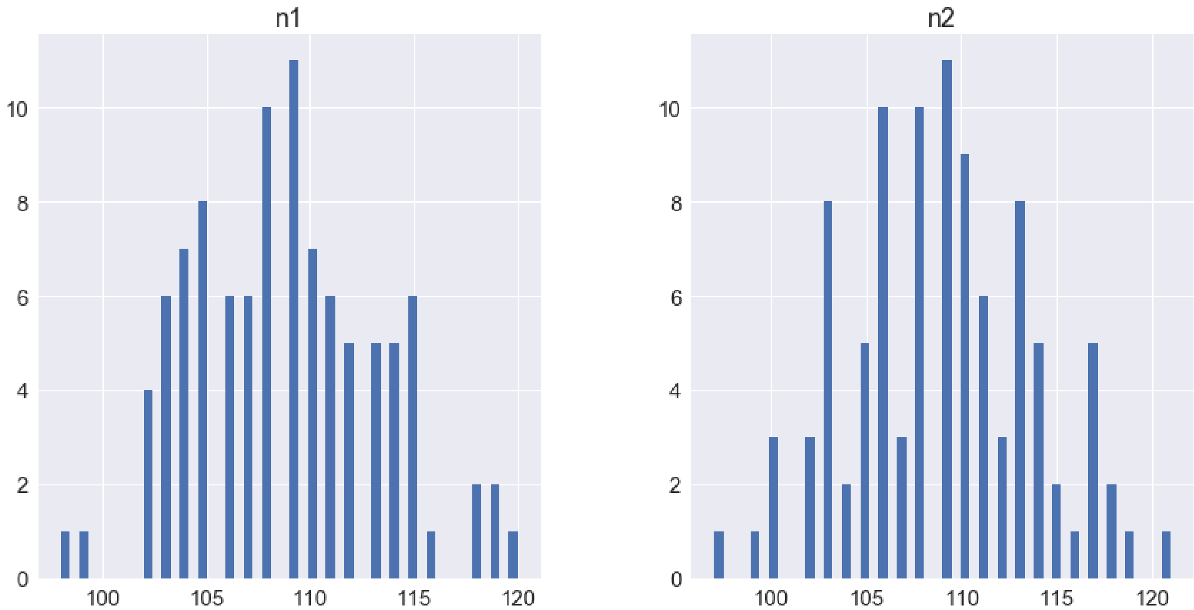


Figure 3. Number of ties in estimated network: first split-half (right): *M*=108,79; *SD*=4,55; second split-half (right): *M*=108, 92; *SD*=4,84

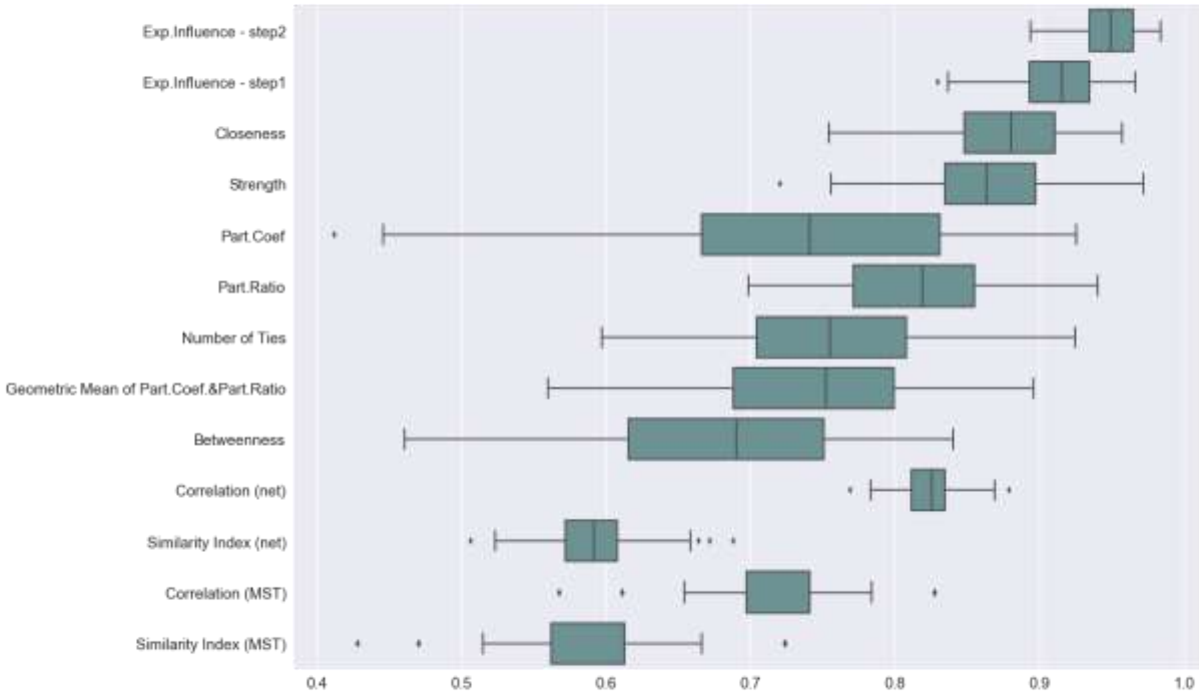


Figure 4. Boxplots of correlations for centrality measures, correlations and similarity indexes of network and MST matrices for each pair of split-half samples (*N*=100)

Table 6. *Descriptive of correlations for centrality measures, correlations and similarity indexes of network and MST matrices for each pair of split-half samples (N=100)*

	Mean	*SD*
Centrality measures		
Expected Influence - step2	0,95	0,019
Expected Influence - step1	0,91	0,032
Closeness	0,88	0,045
Strength	0,86	0,047
Participation Coefficient	0,74	0,110
Participation Ratio	0,82	0,058
Number of Ties	0,75	0,073
Geometric Mean of Participation Coefficient & Participation Ratio	0,74	0,080
Betweenness	0,68	0,086
Network and MST		
Correlation (network)	0,82	0,019
Similarity Index (network)	0,59	0,032
Correlation (MST)	0,72	0,056
Similarity Index (MST)	0,59	0,065

Table 7. *Descriptive of differences in networks estimated for each split-half pair (N =100)*

Difference between two split-half samples	*Mean difference*	*SD*	*Min. difference*	*Max. difference*	*Mdn difference*
Number of Ties	6,35	4,4139	0	23	5
Mean of absolute weights	0,005	0,0033	0, 00009	0,015	0,004
Sum of weights	0,024	0,0023	0,016	0,030	0,024
Maximal edge difference*	0,178	0,0263	0,1187	0,258	0,180
Proportion of Negative ties	0,021	0,0143	0,001	0,064	0,018
Sum of Negative weights	0,007	0,0045	0, 00008	0,020	0,006
Sum of Positive weights	0,006	0,0043	0,0000007	0,022	0,005

* The highest difference observed between two networks among all 325 edges

6.2 Robustness analysis II: 100 random samples (80% of total sample, N=933538)

As in the estimation of the whole network, the size of the sample is set on 4131, and the alpha is set to 0.001.

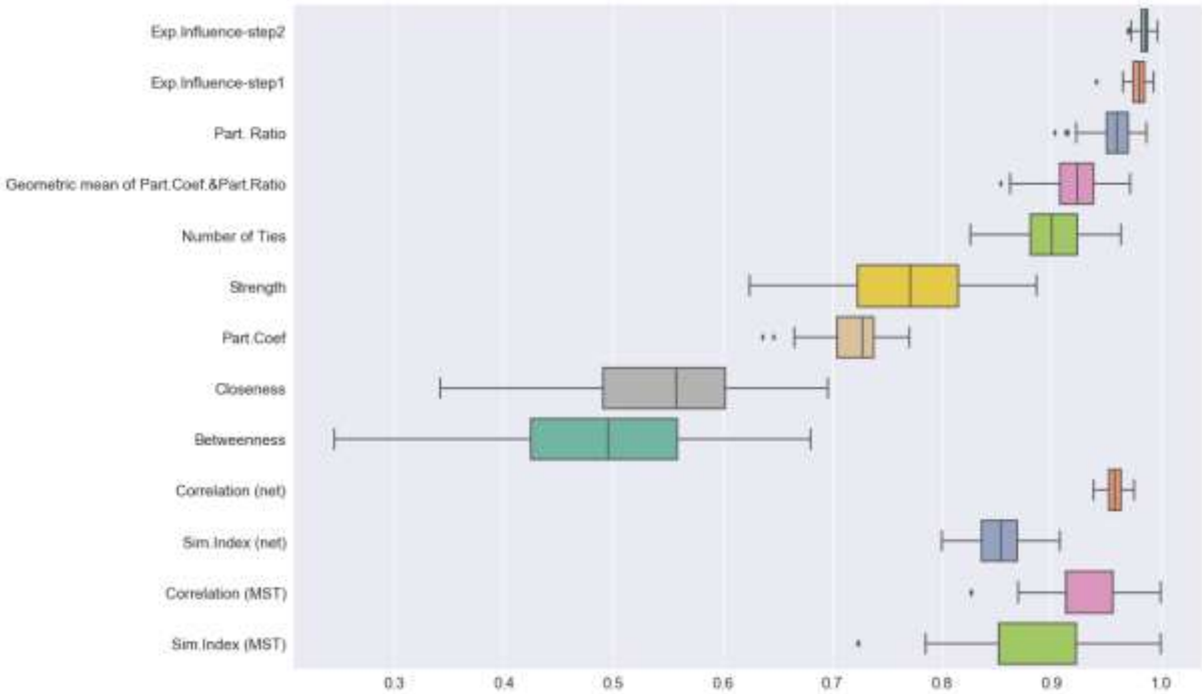


Figure 5. Boxplots of correlations for centrality measures, correlations and similarity indexes of network and MST matrices between total sample and each random sample (fraction=0.8, *N*= 100)

Table 8. *Descriptive of correlations for centrality measures, correlations and similarity indexes of network and MST matrices between total sample and each random sample (fraction=0.8, N= 100)*

	Mean	*SD*
Centrality measures		
Expected Influence-step2	0,98	0,006
Expected Influence-step1	0,95	0,011
Participation Ratio	0,96	0,017
Geometric mean of Participation Coefficient & Participation Ratio	0,92	0,024
Number of Ties	0,90	0,031
Strength	0,76	0,065
Participation Coefficient	0,72	0,028
Closeness	0,59	0,073
Betweenness	0,60	0,085
Network and MST		
Correlation (networks)	0,96	0,008
Similarity Index (networks)	0,85	0,024
Correlation (MST)	0,93	0,044
Similarity Index (MST)	0,89	0,071

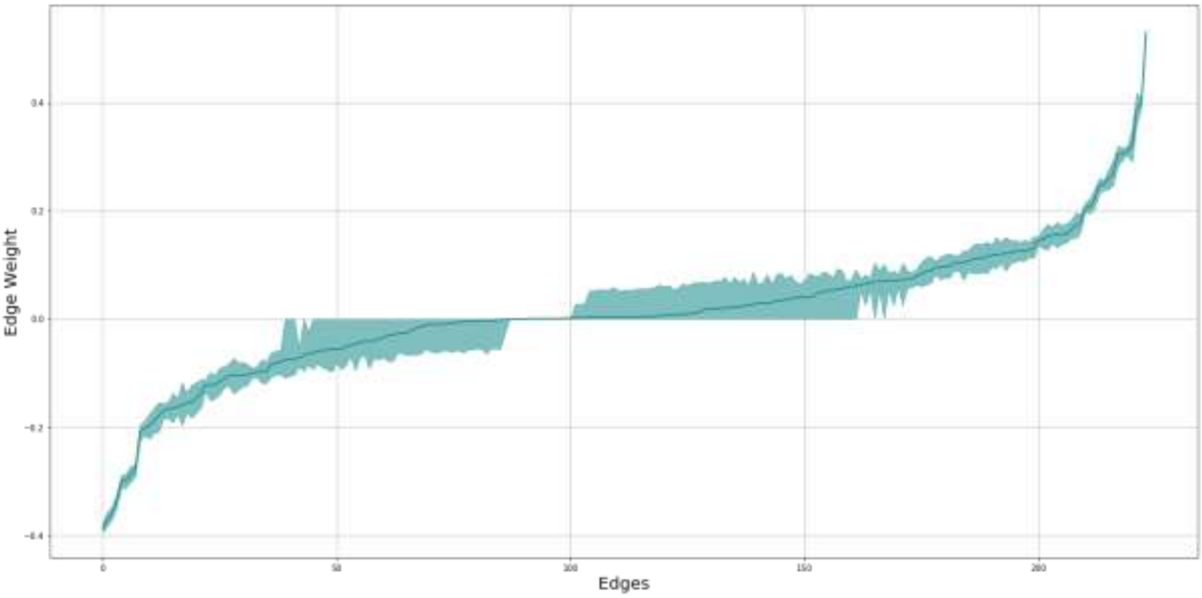


Figure 6. Means and confidence intervals of edge weights for 224 edges (out of 325) that had at least one non-zero weight in 100 random samples (0.8 fraction of total sample)

Network, and therefore each edge, is estimated in a sample consisting of 80% randomly selected cases 100 times. As noted before, in the calculation of partial correlations, *N* is set to be 4131, substantially lower than real number of cases (1 166 923). The purpose was to reduce statistical power due to the high presence of missing data. For all edges, average standard deviation of estimated edge weights was 0,011.

Out of 325 edge estimations for each network, 101 edges were always estimated as zero. Remaining 224 edges had been estimated as non-zero at least once, and they are shown in Figure 9 with confidence intervals (lower bound at 2.5 percentile value, upper bound at 97.5 percentile value), in order of the average weight. Among those 224 edges, moderately strong correlation is found between absolute weight and variations in estimations (r=-0,43), showing that stronger edges are more reliably estimated. As it can be seen from Figure 9, the signs of edge estimations are completely consistent in all 100 networks for each edge, showing very high reliability in the edge signs.

Due to difficulty in showing labels of 224 edges on one Figure, the edges with the highest standard deviation of estimates (the least stable) are presented in Table 9, and the most reliable (non-zero) edges with lowest standard deviation in Table 10.

Table 9: *Ten percent of all non-zero edges (23) with highest variation in estimations*

Edge	*Mean of weights*	*SD*	*Min. weight*	*Max. weight*
Empathy-Emotional stability	-0,047	0,034	-0,098	0
Life satisfaction-Intelligence	0,033	0,034	0	0,089
Empathy-Intelligence	0,040	0,034	0	0,092
Low Depression-Intelligence	0,030	0,033	0	0,092
Low Depression-Private body	-0,042	0,033	-0,099	0
Power-Extraversion	0,033	0,033	0	0,085
Power-Intelligence	0,026	0,032	0	0,091
Hedonism-Fair Mindedness	-0,031	0,032	-0,088	0
Universalism-Public body	-0,030	0,032	-0,082	0
Intelligence-Public body	0,054	0,031	0	0,106
Extraversion-Public body	0,038	0,031	0	0,086
Empathy-Openness	0,035	0,031	0	0,081
Power-Openness	-0,035	0,031	-0,080	0
Life satisfaction-Hedonism	0,042	0,030	0	0,092
Hedonism-Emotional stability	0,021	0,030	0	0,092
Self direction-Conscientiousness	-0,039	0,030	-0,088	0
Conscientiousness-Private body	0,038	0,030	0	0,082
Awareness of physical symp.-Conscientiousness	-0,026	0,030	-0,084	0
Low Depression-Agreeableness	-0,057	0,030	-0,106	0
Tradition-Low violent-occult interests	0,030	0,029	0	0,075
Tradition-Intelligence	-0,056	0,029	-0,103	0
Hedonism-Private body	0,025	0,029	0	0,077
Tradition-Private body	0,050	0,029	0	0,098

Table 10. *Ten percent of all non-zero edges (23) with smallest variation in estimations*

Edge	*Mean of weights*	*SD*	*Min. weight*	*Max. weight*
Low violent-occult int.-Conscientiousness	0,071	0,006	0,057	0,087
Intellectual int.-Public body	0,094	0,006	0,079	0,108
Fair Mindedness-Extraversion	0,001	0,006	0	0,059
Low Depression-Low violent-occult int.	0,001	0,006	0	0,057
Public body-Private body	0,304	0,006	0,291	0,319
Low violent-occult int.-Openness	-0,099	0,006	-0,115	-0,087
Achievement-Self Disclosure	0,001	0,005	0	0,054
Wholesome activities int.-Public body	0,001	0,005	0	0,054
Awareness of physical symp.-Extraversion	-0,001	0,005	-0,053	0
Universalism-Self Disclosure	0,001	0,005	0	0,053
Tradition-Wholesome activities int.	0,001	0,005	0	0,052
Awareness of physical symp.-Public body	-0,001	0,005	-0,052	0
Power-Low violent-occult int.	-0,001	0,005	-0,052	0
Self-monitoring-Awareness of physical symp.	0,001	0,005	0	0,052
Self-monitoring-Openness	0,001	0,005	0	0,051
Body competence-Private body	0,248	0,005	0,236	0,262
Body competence-Public body	0,400	0,004	0,390	0,414
Intellectual int. -Low violent-occult int.	-0,100	0,004	-0,110	-0,089
Wholesome activities int.-Low militaristic int.	-0,387	0,004	-0,399	-0,374
Intellectual int.-Openness	0,205	0,004	0,197	0,215
Wholesome activities int.-Low violent-occult int.	0,145	0,004	0,134	0,156
Wholesome activities int.-Intellectual int.	0,310	0,004	0,301	0,320
Low violent-occult int.-Low militaristic int.	0,530	0,003	0,522	0,535

7 Network of 26 psychological attributes

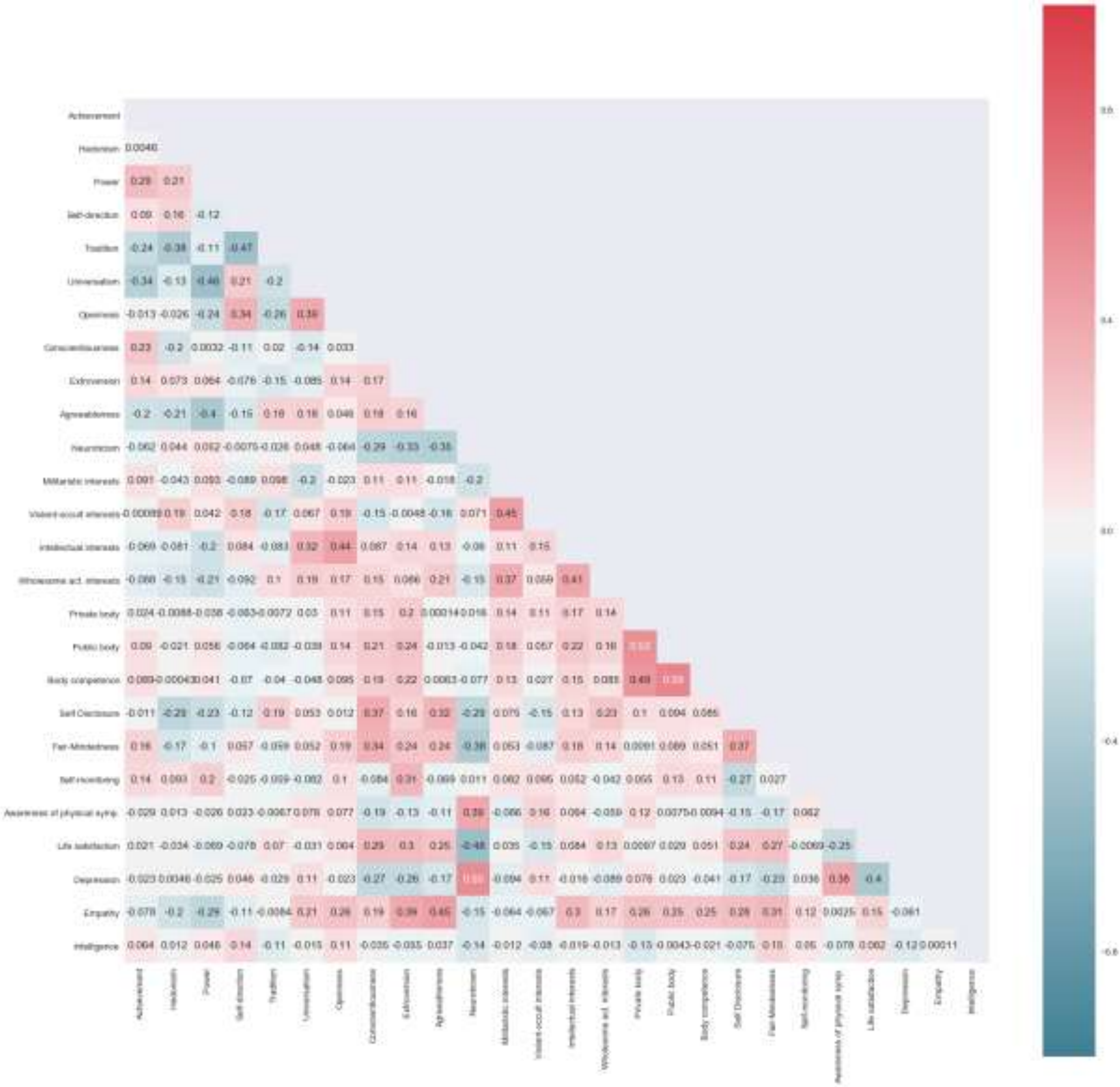


Figure 7. Pearson correlations between 26 psychological attributes

Table 11. *Descriptive of ties in correlation network*

	Signed ties	*Absolute weights*	*Positive ties*	*Negative ties*
Mean	0,04	0,14	0,15	-0,11
SD	0,17	0,12	0,12	0,10
Min.	-0,47	0,00	0,00	-0,47
25%	-0,07	0,05	0,06	-0,15
Mdn	0,03	0,10	0,13	-0,08
75%	0,15	0,19	0,21	-0,04
Max.	0,59	0,59	0,59	0,00
N. of ties	325	325	193	132

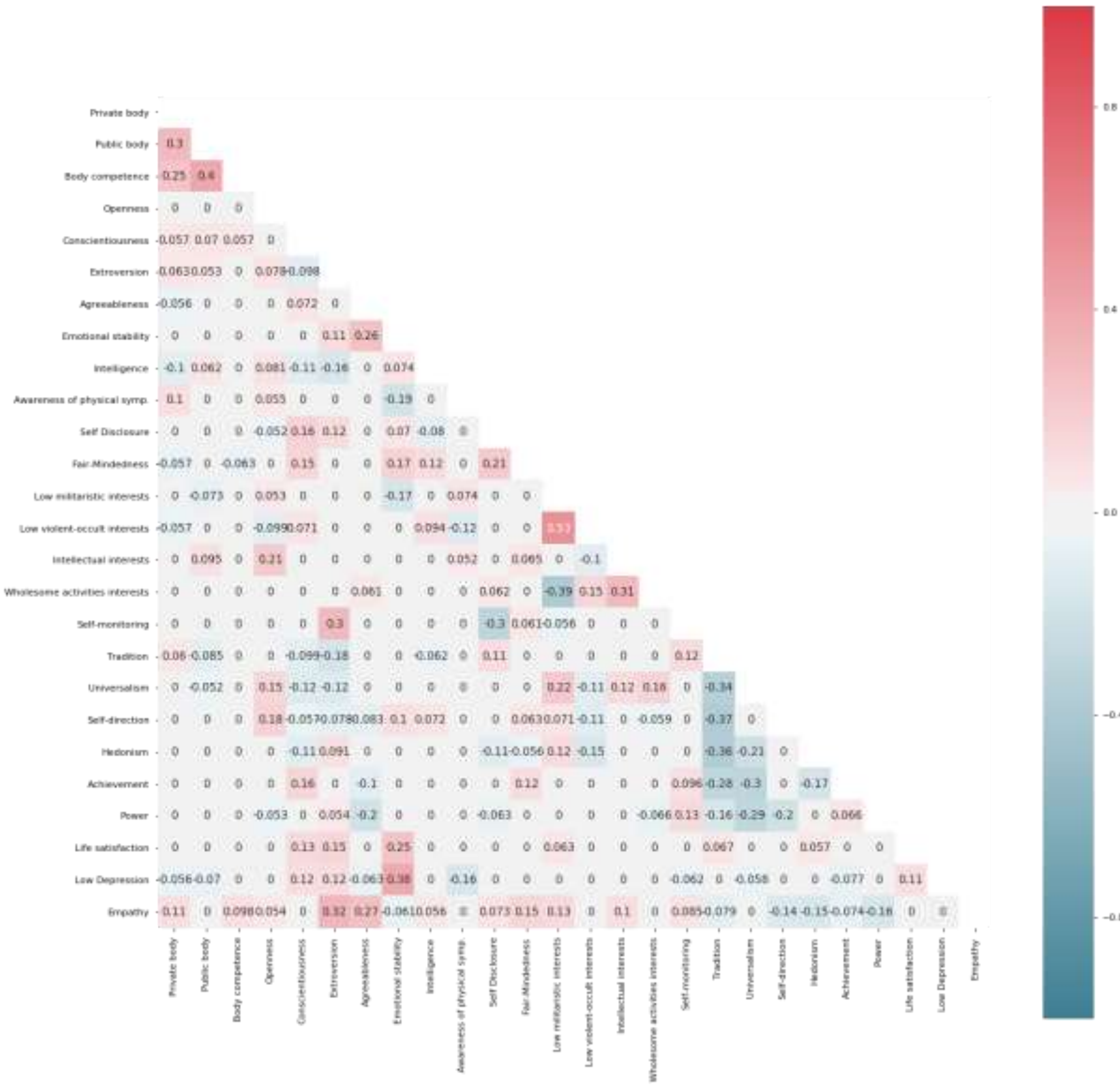


Figure 8. Non-regularized partial correlations between 26 psychological attributes

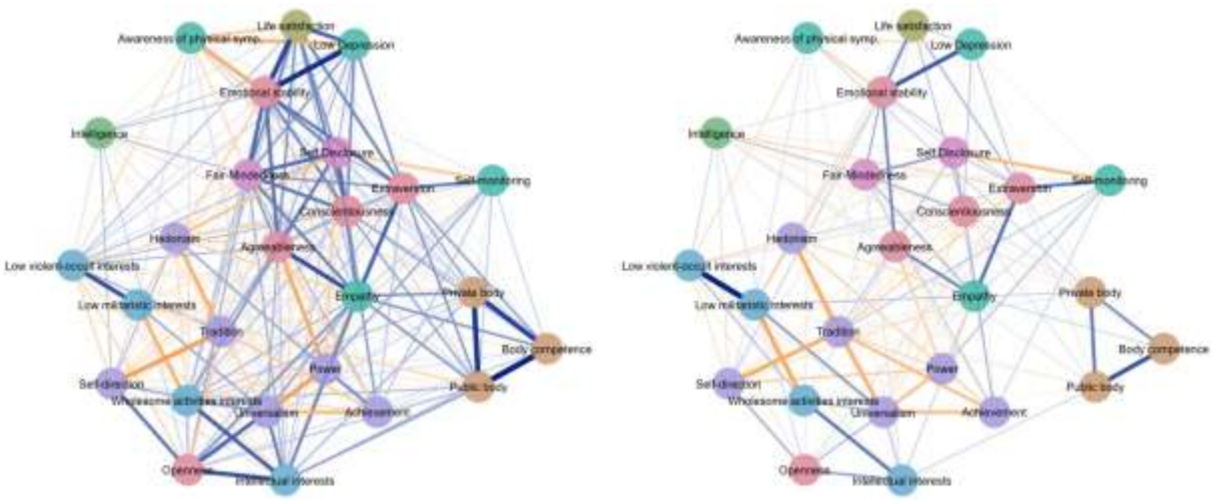


Figure 9. Correlation network (left) and partial correlation network (right) with the same layout

8 Analysis of network ties

In order to find out how positive and negative ties and their weights are related and distributed at the node level, for each node we calculated the number of positive and negative ties and the sum of their weights. Then we used Spearman's coefficient to check whether having negative and positive edges is correlated across nodes. Since we were not only interested in the correlation, but also in whether the number and strength of two kinds of ties tends to be equal at the node level, we additionally computed the Shannon entropy measure[60]. A negative rank correlation of (-0.40) between the number of positive and negative ties reveals a moderate tendency for nodes which have more positive ties, to have a smaller number of negative ties, and vice versa. This tendency is somewhat higher when weights are considered (-0.43).

Entropy of positive and negative ties is higher than entropy of signed absolute weights (medians are 0.94 and 0.88, respectively, after transformation of entropy scores on the same scale with range from 0 to 1). In other words, the number of positive and negative links of a node are more unequal (different) than the sum of positive and negative weights. The two types of entropy are highly associated (0.78). The node with the highest entropy when the number of ties is considered is Agreeableness (4 positive, 5 negative), closely followed by Intelligence and Self-disclosure (7 pos. and 5 neg. ties, both). Life satisfaction has the lowest possible entropy (7 positive links), followed by Intellectual interests (7 pos. and 1 neg.). Intelligence has the highest entropy, while Body competence has the smallest entropy, when considering weights. For more details see Table 12 and 13.

[60] Shannon entropy (H) is a diversity index defined as $H = -(p(neg) \times \log p(neg) + p(pos) \times \log p(pos))$, where p represents the fraction of positive or negative links (weights).

Table 12. *All edge and weights related information for each node*

Node/variable	*N (all) edges*	*Stre-ngth*	*N pos. edges*	*N neg. edges*	*Sum pos. edge weights*	*Sum neg. edge weights*	*H edges*	*H weights*
Achievement	10	1,44	4	6	0,435	-1,009	0,980	0,884
Agreeableness	9	1,16	4	5	0,663	-0,502	1	0,988
Awareness of physical symptoms	7	0,75	4	3	0,283	-0,468	0,994	0,957
Body competence	5	0,87	4	1	0,804	-0,063	0,728	0,378
Conscientiousness	16	1,63	10	6	1,044	-0,589	0,963	1
Emotional stability	11	1,84	8	3	1,420	-0,416	0,853	1
Empathy	17	2,11	11	6	1,448	-0,663	0,945	1
Extraversion	16	2,11	11	5	1,476	-0,638	0,904	1
Fair-Mindedness	12	1,29	9	3	1,110	-0,176	0,819	1
Hedonism	11	1,61	3	8	0,273	-1,332	0,853	0,659
Intellectual interests	8	1,05	7	1	0,950	-0,100	0,548	0,455
Intelligence	12	1,08	7	5	0,561	-0,514	0,989	1
Life satisfaction	7	0,82	7	0	0,825	0	0	0
Low Depression	11	1,27	4	7	0,728	-0,541	0,954	0,986
Low militaristic int.	12	1,94	8	4	1,263	-0,682	0,927	1
Low violent-occult int.	11	1,59	4	7	0,840	-0,754	0,954	0,999
Openness	11	1,05	8	3	0,851	-0,203	0,853	0,708
Power	11	1,45	3	8	0,252	-1,194	0,853	0,668
Private body	12	1,27	7	5	0,941	-0,330	0,989	0,827
Public body	10	1,26	6	4	0,984	-0,279	0,980	0,763
Self-disclosure	12	1,42	7	5	0,815	-0,608	0,989	0,986
Self-direction	13	1,58	5	8	0,487	-1,096	0,970	0,892
Self-monitoring	9	1,21	6	3	0,797	-0,418	0,927	0,930
Tradition	14	2,38	4	10	0,360	-2,018	0,871	0,615
Universalism	13	2,24	4	9	0,645	-1,600	0,899	0,866
Wholesome act. int.	8	1,25	5	3	0,735	-0,513	0,963	0,978

*H – Shannon entropy measure

Table 13. *Correlations between edge related descriptives on the node-level*

	2	*3*	*4*	*5*	*6*	*7*	*8*
1. N of pos. edges	-0,40	0,86	0,38	0,42	0,12	-0,09	0,001
2. N of neg. edges		-0,43	-0,90	0,62	0,70	0,25	0,24
3. Sum of pos. edge weights			0,43	0,27	0,17	-0,20	-0,07
4. Sum of neg. edge weights				-0,56	-0,76	-0,20	-0,28
5. N of (all) edges					0,79	0,11	0,17
6. Strength						-0,06	0,05
7. H of pos. and neg. edges (standardized)							0,78
8. H of pos. and neg. edge weights (standardized)							

9 Centrality analysis

In addition to number of ties (degree), strength, closeness, betweennes, Participation coefficient, and Participation Ratio (explained in Chapter 3), we used two centrality measures not commonly used in the network analysis: Expected influence – step one, and Expected influence – step two. We explain them in more details here.

Expected influence – The strength of node is calculated by summing up the absolute values of all node's edge weight. Hence, it is not differentiating between positive and negative weights. Robinaugh et al. (2016) introduced two measures of a node's influence in an undirected network addressing the presence of negative edges and therefore can differentiate nodes that may have little cumulative influence on network activation due to similar sum of negative and positive edge weights:

1) Expected influence 1(one step, EI_{1_i}) – measures node's influence on the nodes to which it is directly connected. The formula is the same as for the strength with the crucial difference that it preserves negative and positive value of the edge weight:

$$EI_{1_i} = \sum_{j=1}^{N} a_{ij}\, w_{ij}$$

   where a_{ij} is a binary adjacency matrix (presence and absence of ties), and w_{ij} is weighted and signed adjacency matrix.
2) Expected influence 2 (two step, EI_{2_i}) – measures the secondary influence of a node by taking into account the expected influence of their neighbours. The formula is:

$$EI_{2_i} = \sum_{j=1}^{N} a_{ij}\, w_{ij} + \sum_{j=1}^{N} a_{ij}\, w_{ij} \sum_{k=1}^{N} a_{jk}\, w_{jk}$$

   where $\sum_{j=1}^{N} a_{ij}\, w_{ij}$ is the expected influence – step one, plus the sum of those values for other nodes multiplied by edge weight between pair of nodes.

Table 14. *Descriptive statistics of nine centrality measures (N=26)*

	Mean	*Median*	*S.D.*	*Kurtosis*	*Skewness*	*Min.*	*Max.*
Number of ties	11,08	11,00	2,855	0,157	0,095	5,00	17,00
Strength	1,45	1,36	0,439	-0,402	0,535	0,75	2,38
Betweenness	12,35	7,00	13,691	-0,225	1,172	0,00	39,00
Closeness	0,004	0,004	0,0005	-0,823	-0,107	0,003	0,004
Exp.Iinfluence-step1	0,17	0,30	0,720	0,171	-1,003	-1,65	1,00
Exp.Iinfluence-step2	0,69	0,68	0,691	-0,450	0,079	-0,57	2,13
Participation Ratio	2,49	2,64	1,005	-0,346	0,079	0,72	4,81
Participation Coefficient	0,71	0,73	0,112	0,742	-0,870	0,42	0,88
Product of Participation Ratio & Participation Coefficient	1,78	1,92	0,790	-1,127	0,009	0,55	3,19

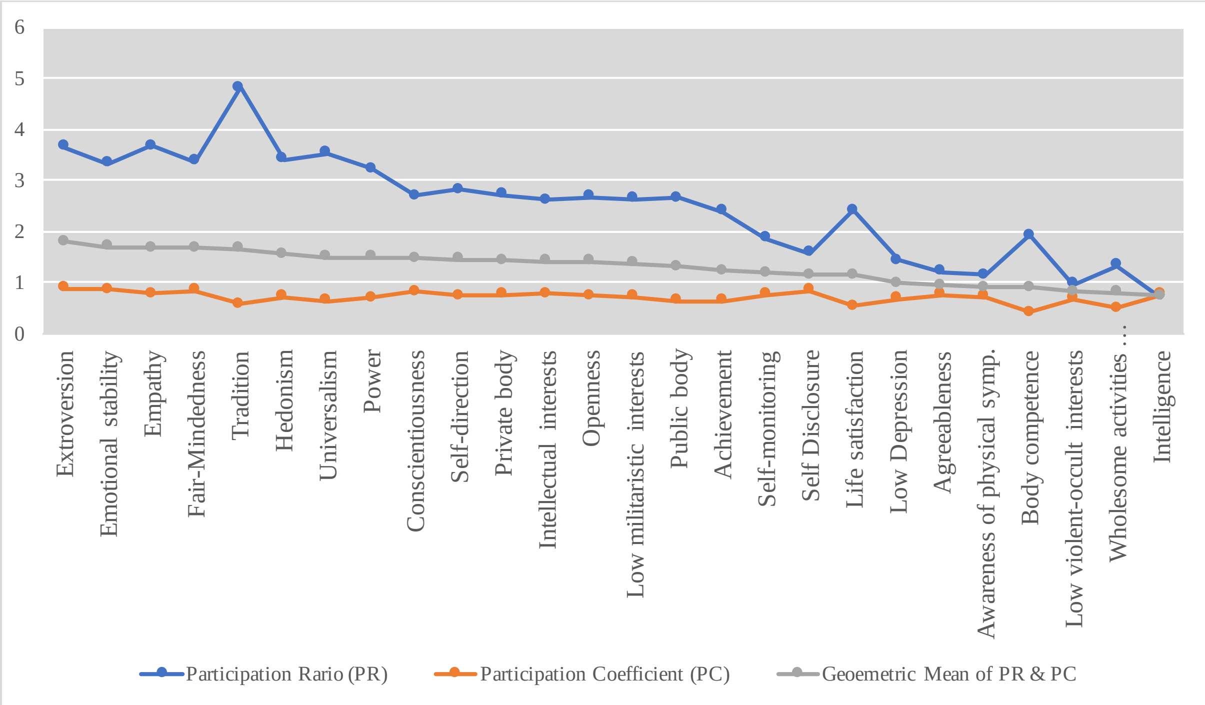


Figure 10. Unstandardized participation ratio, participation coefficient, and geometric mean

10 Correlations between four centrality measures in the full network and in the MST

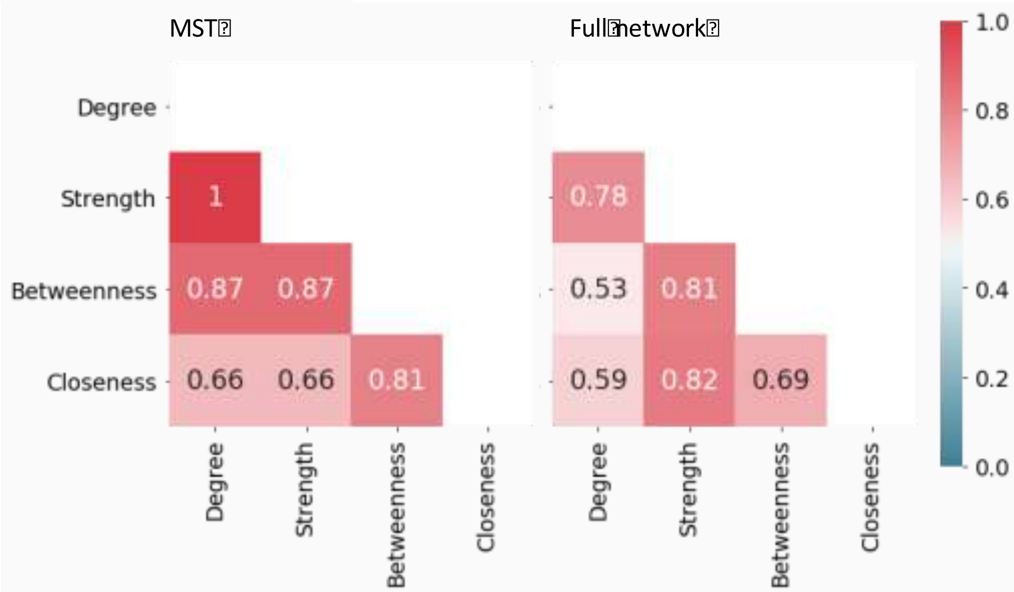


Figure 11. Correlation coefficients (Pearson's *r*) between four centrality measures for minimum spanning tree (MST) and the network (the "full" network)

Table 15. *Centrality scores of each node in MST (Gower's distance)*

node	*Degree*	*Strength*	*Betweenness*	*Closeness*
Empathy	4	4	224	0,011
Emotional stability	4	4	137	0,009
Low militaristic interests	4	4	137	0,010
Agreeableness	2	2	136	0,010
Fair-Mindedness	3	3	87	0,007
Universalism	2	2	84	0,008
Private body	3	3	68	0,009
Extraversion	2	2	66	0,009
Wholesome activities intrests	2	2	66	0,007
Self-monitoring	3	3	47	0,007
Intellectual interests	2	2	46	0,006
Self-disclosure	2	2	46	0,006
Conscientiousness	2	2	24	0,005
Openness	2	2	24	0,005
Public body	2	2	24	0,007
Achievement	1	1	0	0,005
Awareness of physical symptoms	1	1	0	0,007
Body competence	1	1	0	0,006
Hedonism	1	1	0	0,007
Intelligence	1	1	0	0,006
Life satisfaction	1	1	0	0,007
Low Depression	1	1	0	0,007
Low violent-occult intrests	1	1	0	0,008
Power	1	1	0	0,006
Self-direction	1	1	0	0,004
Tradition	1	1	0	0,006

11 MST with different distance measure

To convert the partial correlations to distances, different equations can be used. In the simplest application, correlations (partial correlations in our case) are converted to distances by disregarding the direction of the correlation and subtracting the shared variance from 1, leading to distances d ranging from 0 to 1, see Equation 1. Alternatively, one can take the direction of the correlation into account by assigning the largest distance to a perfect negative correlation, and the smallest distance to a perfect positive correlation (as we have done in Chapter 3), see Equation 2. The relationship between the (partial) correlation coefficient and the distance measure for both formulas are shown in Figure 12, and the distance computed for each tie are shown in Figures 13 and 14.

$$d(i,j) = 1 - pr_{ij}^2 \quad (1)$$

$$d(i,j) = \sqrt{2(1 - pr_{ij})} \quad (2)$$

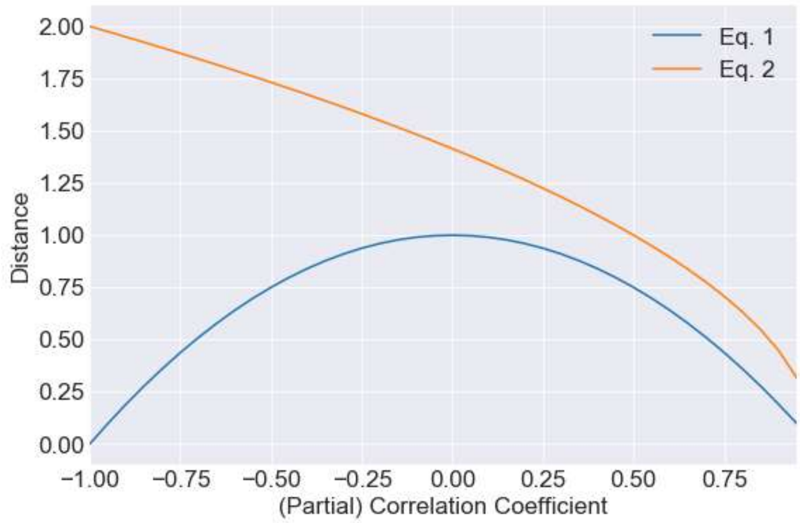


Figure 12. The relationship between *r* or *pr* with two distance measures

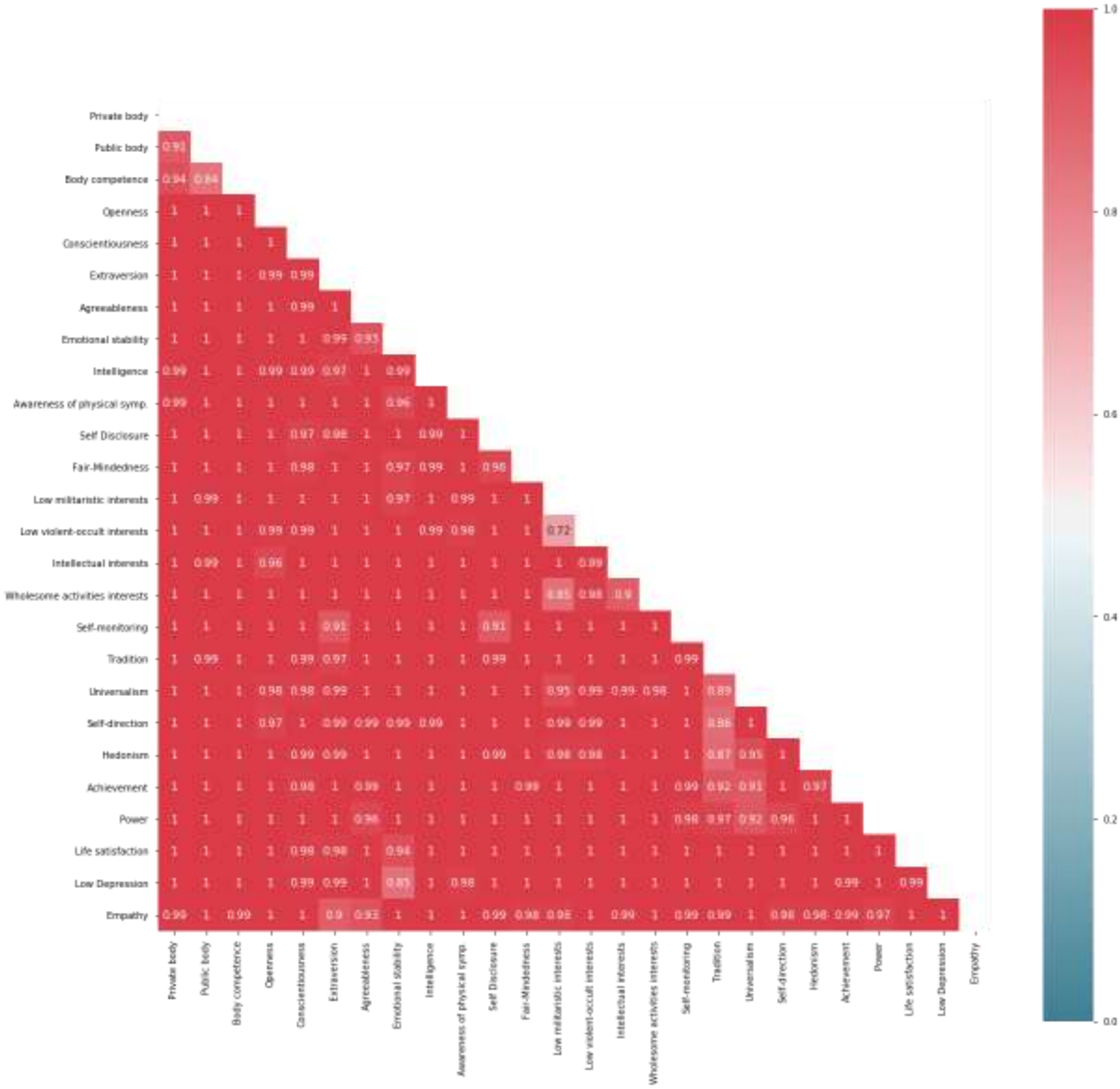


Figure 13. Distances between variables with Eq. 1

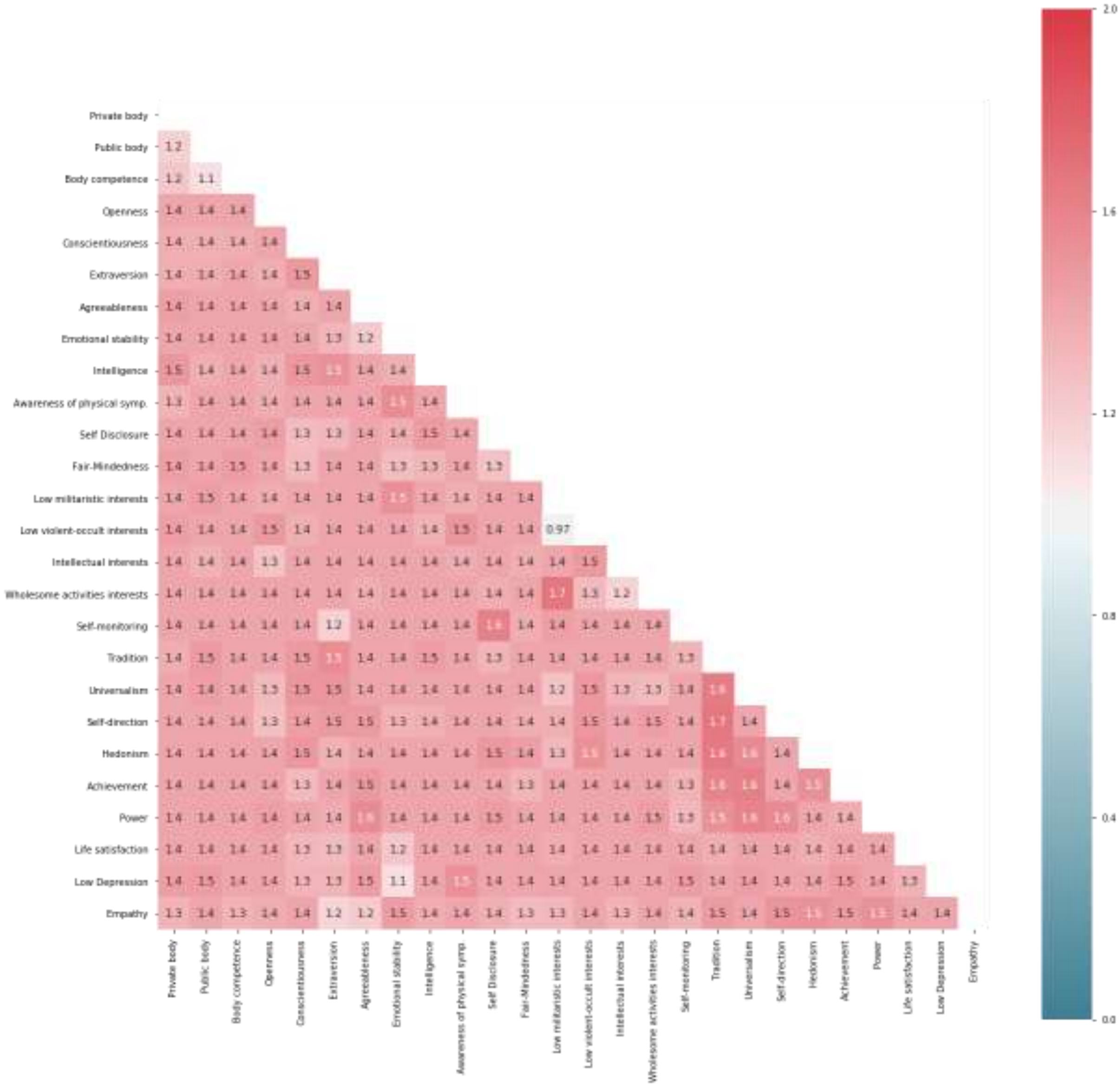


Figure 14. Distances between variables with Eq. 2

We computed the MST based on the distance measure inversely proportional to shared variance, shown in Figure 15.

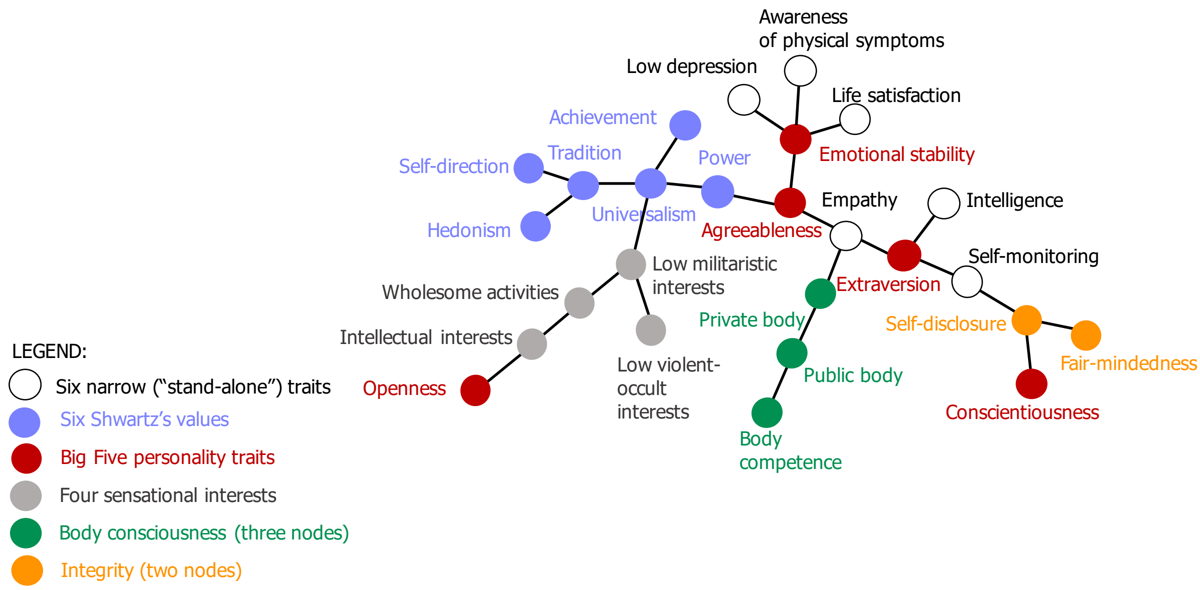


Figure 15. Minimum spanning tree of the network based on distance inversely proportional to shared variance

MST based on Eq. 1, shown in the picture above, compared with the MST based on Eq. 2, shown in the Chapter 3 (Figure 3.6), are quite different. By visual inspection it is noticeable that the average shortest path, i.e., the average number of steps between any two nodes, is smaller in this MST (disregarding the direction of the partial correlations) than in the MST based on Gower's formula (Eq.2). In other words, the differentiation between the nodes is smaller in comparison to the first MST. That is the result of the less sensitive distance measure in MST Eq.1 (see heat-maps – Figures 13 and 14). At the end, the hierarchical structure of MST Eq.1 will be less pronounced (less clear). The most central trait in the MST when not considering the direction of partial correlations is value Universalism, due to its ties to other values and Low militaristic interests. In difference with MST based on Eq. 2 where Intelligence branches out from Fair-Mindedness, here it branches out from the Extraversion.

The alignment of nodes on this MST follows more closely the pre-existing groups, except for Big five personality traits among which only Agreeableness and Emotional stability are directly connected.

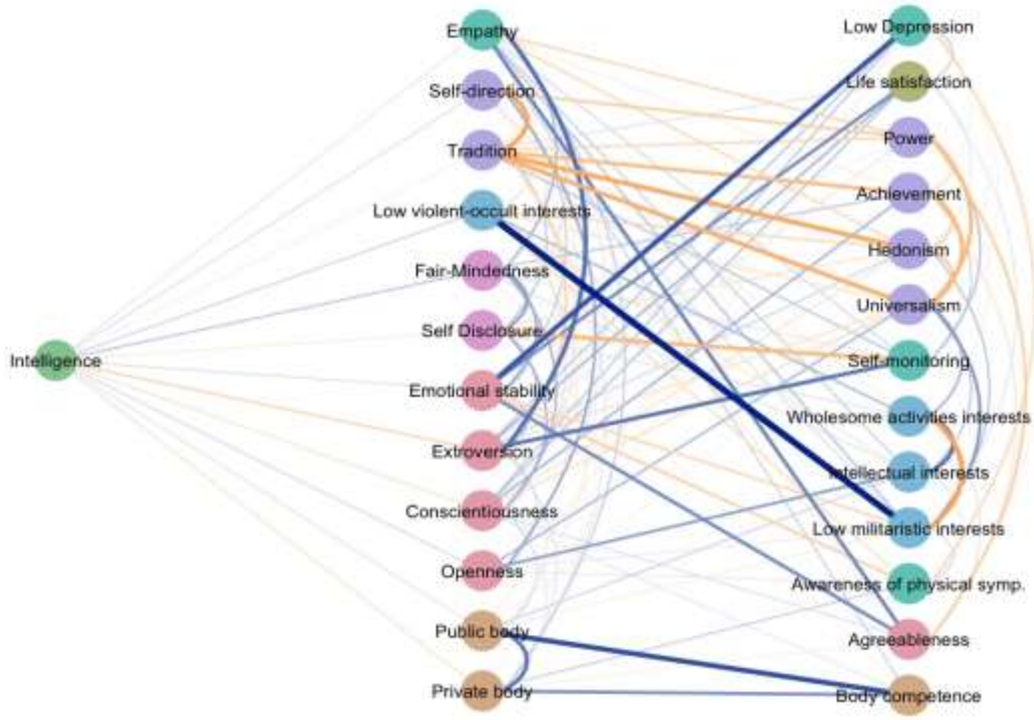


Figure 16. Intelligence and its direct ties and indirect ties in the whole network.

12 The effect of reverse coding on the analyses

To check how reverse coding affects the results of our analyses, we proceed by recoding the individual values of Emotional stability. Emotional stability is chosen because it often coded negatively as Neuroticism in the literature.

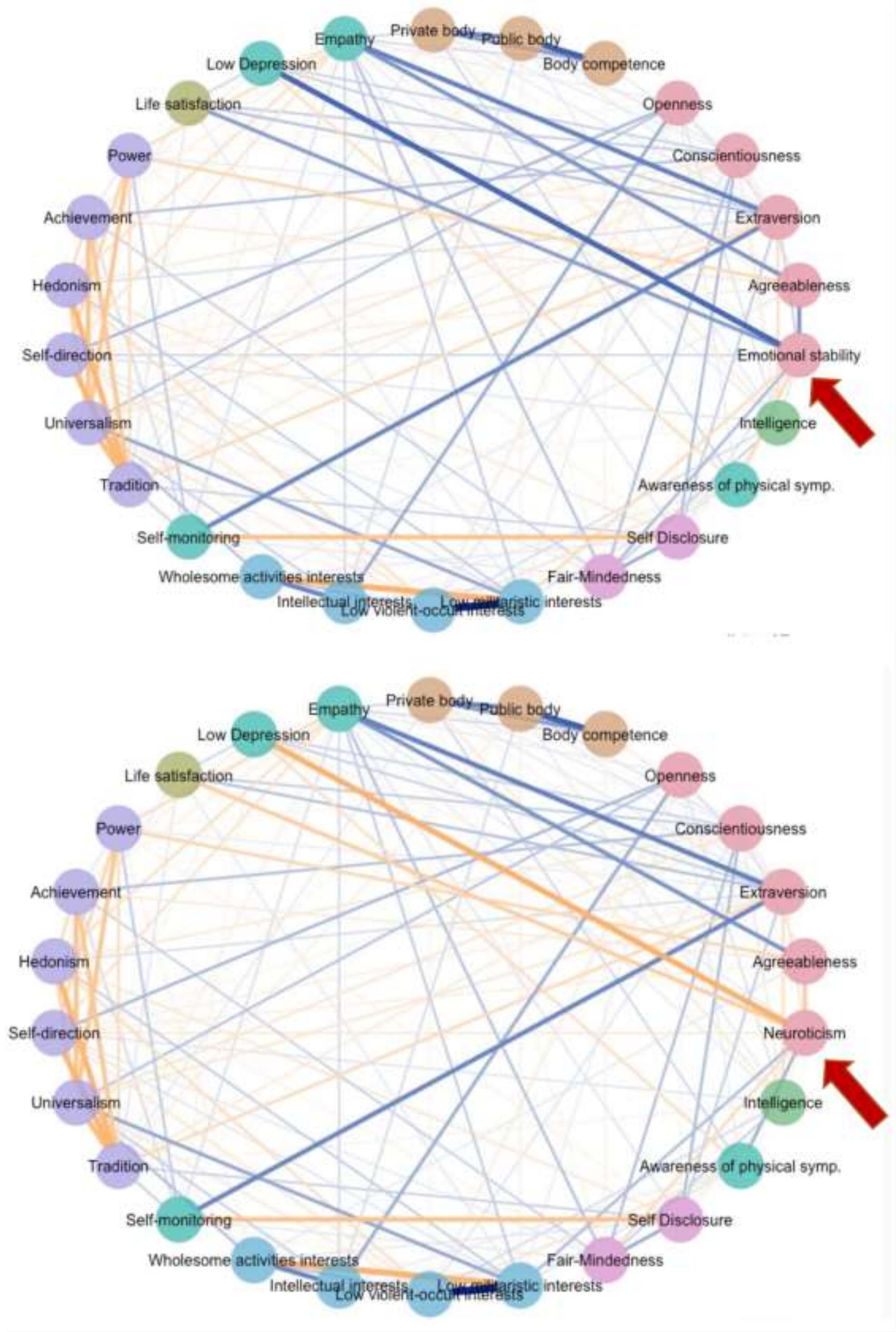


Figure 17. Emotional Stability, and after reversing the scores – Neuroticism in otherwise the same network (layout: circle). Red arrow points to the node before and after transformation.

Figure 17 shows two networks that are the same with the only difference being that in the first network node Emotional stability is reversed to Neuroticism in the second network. The circle layout is used for both networks to facilitate visual comparison. As it can be seen from the Figure, recoding resulted in change of the sign of all direct ties of the node Neuroticism. However, the absolute weights of all the ties and the sign of indirect ties in the network remained the same. An alternative way of showing the extent of difference is presented in Figure 18, where the same network is shown with the flow chart which clearly separates the node’s direct links and indirect links, showing the sign change in the first, and no change in the latter. (It also shows that Emotional Stability/Neuroticism has maximal distance of two to all nodes in the network).

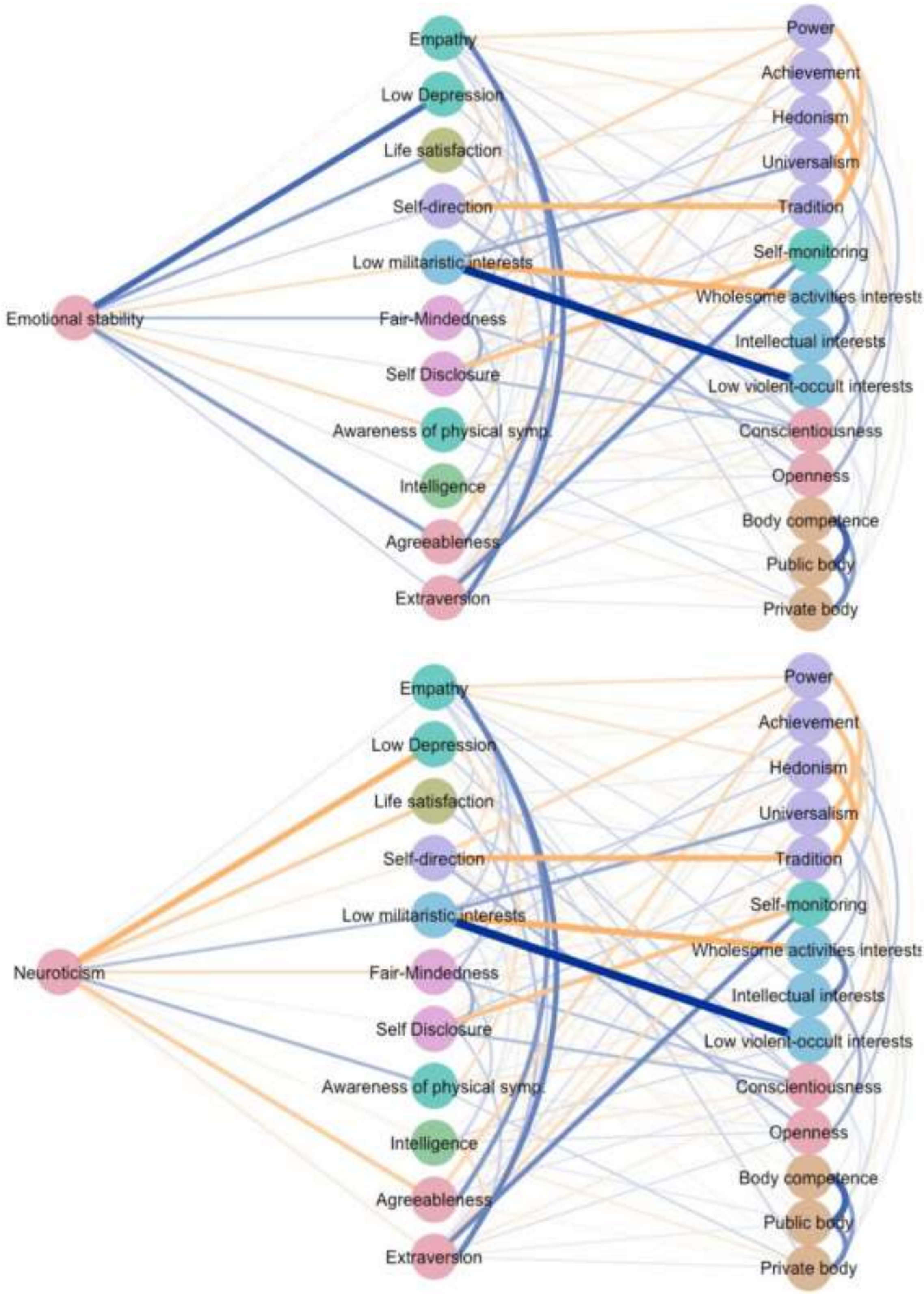


Figure 18. Flow chart of Emotional stability (up) and Neuroticism (down) in the same network

12.1 The effect of reverse scoring on MST

MST Eq.2 is sensitive to reverse coding, while MST Eq.1 is not. For example, if we reverse node Emotional stability to Neuroticism, and obtain MST with Eq. 2 for both networks, the resulting tree will differ from MST obtained for the network with Emotional stability, because all direct ties of the node Neuroticism will have the opposite sign (see Figure 19 in comparison with Figure 3.6 in Chapter 3).

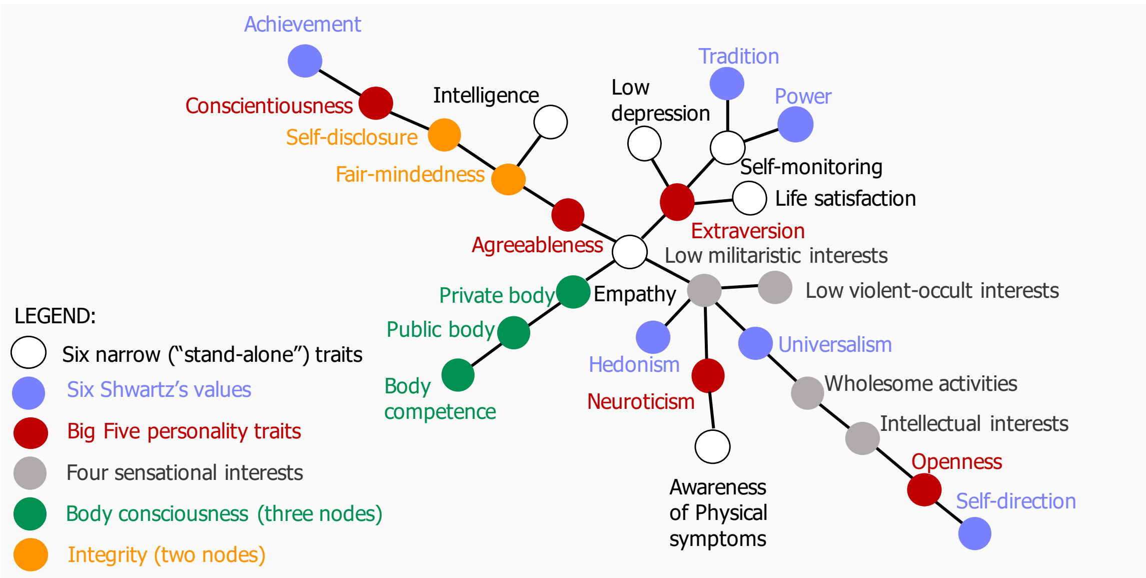


Figure 19. Minimum spanning tree of network with Neuroticism (reversed Emotional stability) based on distance that considers the sign of ties (directions of *pr*)

The placing of the node Emotional stability (ES)/Neuroticism (N) is different, and due to its associations with nodes Life satisfaction, Low depression, and Awareness of physical symptoms, the change affected their positions in the MST also. While in the first MST, ES was placed among socially desirable nodes, when transformed to N, it moved to more "problematic" branch and connected with Awareness of Physical symptoms. The distance measure used has property to consider direction of association and in that way, provide more refined placing of nodes on the MST. However, in that case the interpretation is constrained only to coding of variables used in the study.

When MST Eq.1 is used, the network stays the same. Figure 20 is identical to Figure 15, only the name of the node is different.

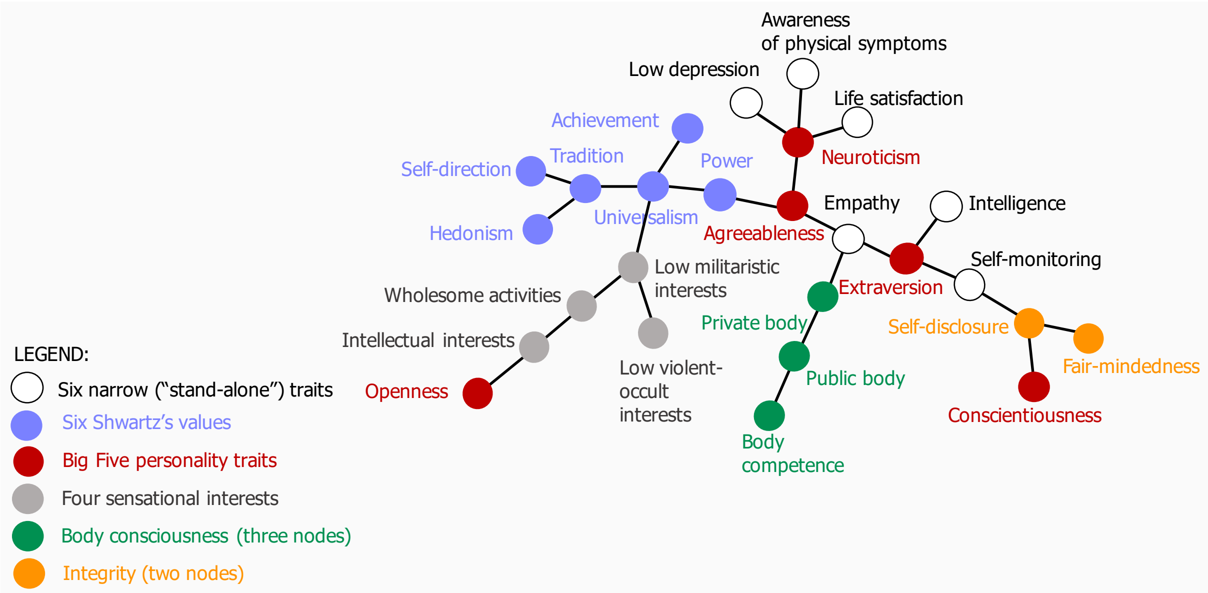
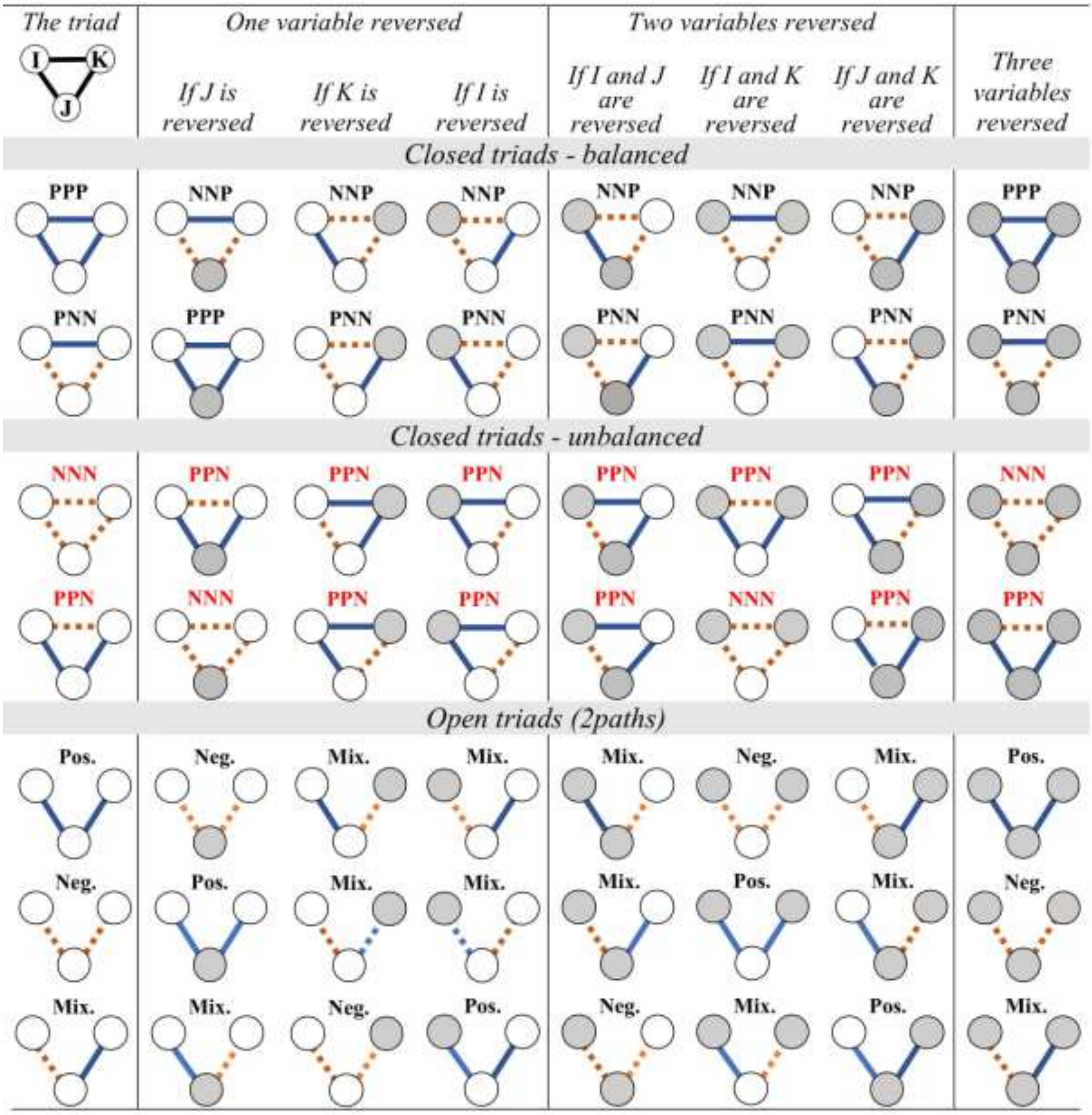


Figure 20. Minimum spanning tree of network with Neuroticism (reversed Emotional stability) based on distance inversely proportional to shared variance

12.2 The effect of reverse scoring on motif analysis

In Figure 21 we show what change in edge sign(s) will happen within each triadic motif when different number and combination of nodes is reversed.



LEGEND
Three-letter-code in black font – Balanced triads: PPP – a triad with three positive edges; PNN – a triad with one positive and two negative edges
Three-letter-code in red font – Unbalanced triads: NNN – a triad with three negative edges; PPN – a triad with two positive and one negative edge
Pos. – a 2-path (open triad) with two positive edges
Neg. – a 2-path (open triad) with two negative edges
Mix. – a 2-path (open triad) with one positive and one negative edge
variable (node)
reversed variable (node)
positive edge
negative edge

Figure 21. Changes in edge signs on triadic level with one, two, or all three nodes reversed

Reversing one or more nodes in any combination will lead to the change of a specific motif, but a closed triad will stay closed, and open triad will stay open. Within closed triads, balanced motif will always stay balanced, and an unbalanced motif will stay unbalanced. Specifically, PPN can become NNN (and vice versa), while PPP can become NNP (and vice versa). In the case of 2-path motifs, where no balanced and unbalanced motif exist, the motif can change in any of two other types of 2-paths, depending on which node(s) has (have) been reversed (see Figure 21). When all the nodes are reversed, each motif stays the same. Therefore, this transformation of the variable (here we are referring only to reversing the score of a variable, not to other kinds of transformations), will in almost all cases lead to changes in the frequency of motifs in which that node is involved. However, the presence or absence of edges and absolute values of their weights will not be affected. Additionally, the total number of balanced and unbalanced closed triads will stay identical. On a network level, the number of positive and negative ties will *likely* change[61]. For example, after reversing Emotional Stability (to Neuroticism), the distribution of weights has changed. Specifically, all node's direct ties have changed their sign (shown in Figure 22.)

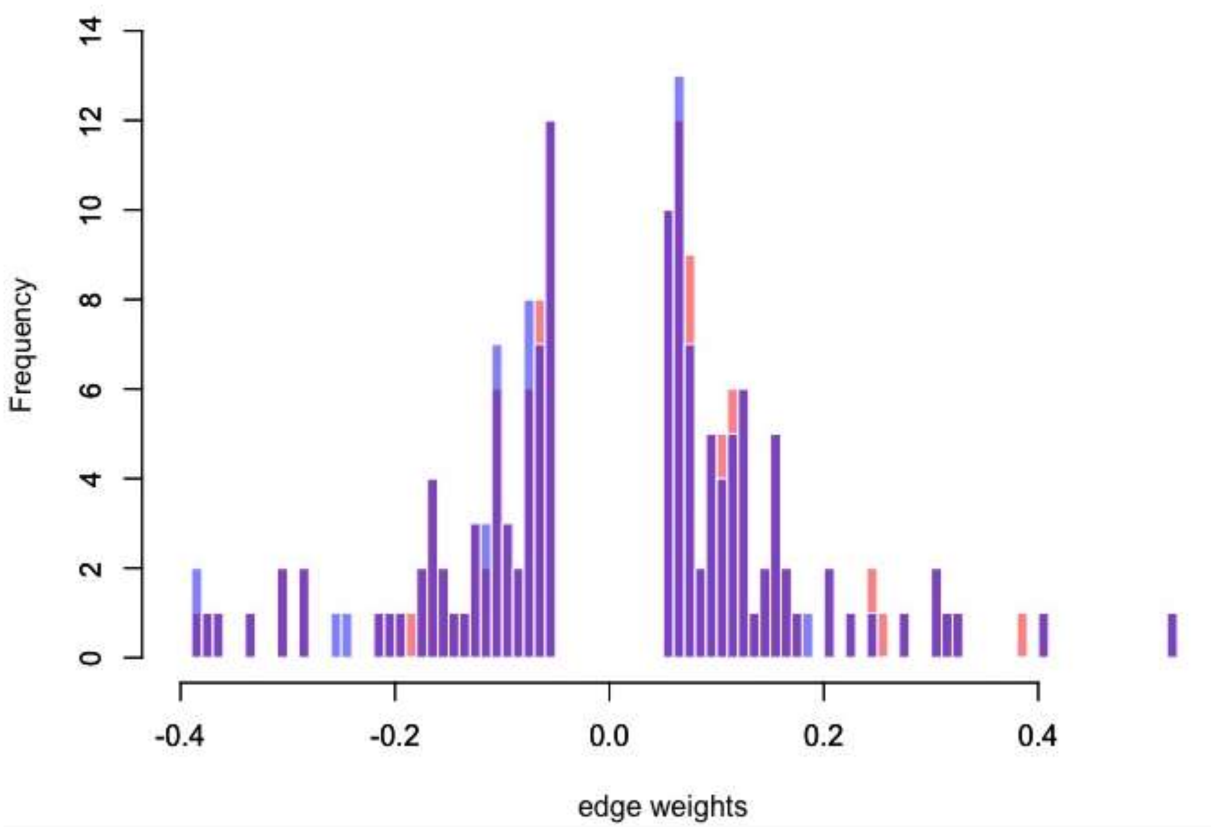


Figure 22. Distributions of weights of two networks: the network with Emotional stability ('original' network, in red) and network where Emotional stability is reversed to Neuroticism (in blue). In purple is the overlap between distributions.

Following from this, reversing a variable will affect results of measures which take the sign of edges into account. Namely, in addition to motif frequency, expected influence centrality and MST will produce different results.

While the frequency of motifs will be affected directly, their significance should not be affected in a greater extent. The reason for this expectation comes from the procedure of hypothesis testing of motif's cardinality. Each motif's frequency is compared against the distribution of 1000 random networks with the same structure and degree distribution. That means that change

[61] "Likely", because unless, for example, three variables which are being reversed are connected only to each other or the reversed variable(s) had the same number of negative and positive ties.

that happened due to reversing is controlled for – the degree distribution of all random networks changed to the degree distribution of the "new" network accordingly. Resulting *p*-value (or probability of the motif frequency) should converge to similar conclusions regarding the underrepresentation or overrepresentation of a given motif. However, some disparity should be expected due to random process included in producing the distribution of values according to the null model.

To check if our expectations were correct, we preformed the motif analysis on several versions of networks with reversed variables.

Firstly, we constructed five networks with reversed variables, three of them with just one variable reversed: Emotional Stability, Empathy, and Extraversion. These variables were selected because they had high number of ties, ensuring that their transformation will bring change to many triads in network. In the fourth network half of nodes (n=13) have been reversed without any selection criteria. Finally, in the fifth network all variables have been reversed. We proceeded with the identification of motifs, counting their frequency, calculating their intensity and coherence, and then compared those values against random distributions of networks generated for each network according to the null model which preserves the structure and weight distributions.

We present the results in Tables 16 and 17, together with results for "original" network presented in Chapter 3.

Table 16. *Motif frequency for five networks*

Motif	*"original" network*	*Em.st. R*	*Emp. R*	*Ext. R*	*13* variables R*	*All 26R*
Triangles	245	245	245	245	245	245
2Paths	818	818	818	818	818	818
Positive triads (PPP)	42	36	32	32	28	42
Negative triads (NNN)	33	38	36	37	45	33
Triangles (2 neg. - NNP)	77	83	87	87	91	77
Triangles (1 neg. - PPN)	93	88	90	89	81	93
2Paths pos.	265	240	218	225	181	265
2Paths neg.	156	188	180	198	240	156
2Paths mix.	397	390	420	395	397	397
Strong pos. triads	2	2	2	2	2	2
Strong neg. triads	6	6	6	6	6	6
Strong imb. triads I	1	1	1	1	1	1
Strong 2paths pos.	3	2	2	2	2	3
Strong 2paths neg.	5	6	6	5	7	5
Strong 2paths mix.	4	3	3	4	2	4
Imb. triads II T.	8	4	5	6	5	8
Sum of balanced triads**	119	119	119	119	119	119
Sum of imbalanced triads***	126	126	126	126	126	126

Abbreviations: Em.st. R – Emotional Stability reversed ("Neuroticism"); Emp. R – Empathy reversed ("Lack of empathy"); Ext. R – Extraversion reversed ("Introversion"); Pos. – positive; Neg. – negative; Imb. – imbalanced
Bold letters – structural motifs
Grey cells – signed and weighted motifs
* 13 reversed variables/nodes are: Emotional stability, Self-disclosure, Militaristic interests, Low Violent-occult interests, Self-monitoring, Tradition, Universalism, Self-direction, Hedonism, Achievement, Power, Low Depression, and Empathy.
** Sum of PPP and NNP motifs frequencies
*** Sum of PPN and NNN motifs frequencies

Table 16 shows that the frequency of structural motifs (all triangles and 2-paths) – which look only at presence or absence of ties, while disregarding their sign and weights – is the same in all networks. This was expected – reversing any node(s) will not affect the presence of ties in the network or its structure.

The frequency of signed motifs – which take the sign of weights into consideration – is different for each network. Transforming variable(s) led to change of signs in the motifs which they are part of, resulting in a different number of their occurrence. Reversing more than one node (Table 16, see the column with frequency of motifs of network after half of the nodes are reversed) leads to bigger changes in the number of motifs than in networks with only one node reversed (third, fourth, and fifth column in Table 16). However, the network with all 26 variables reversed gives back the same frequency of all motifs, since as shown in Figure 21, when all variables in a triad are reversed, that will not affect its edge signs.

When zooming in on the "strong" motifs only – with a cut-off for tie weights and considering their signs as well – it is noticeable that frequency is low in all the networks and it shows relatively small variations. This is because they are rare in this network of many weak ties, and transforming the nodes will not affect their number in a higher degree. However, the fact that strong positive triad, strong negative triad, and strong imbalanced triad I (with one negative tie) have the same frequency in all networks is coincidental. In the four networks with these specific nodes reversed (Emotional stability, Empathy, Extraversion, or 13 nodes), it does not affect the frequency of those motifs, but this does not mean they include the same nodes. That would be unlikely (but not impossible) and it depends on which nodes are involved in these strong motifs, and whether they have been transformed. Furthermore, the same frequency for these networks does not imply the same probability for those motifs. With the change of weight distribution in each of the networks, the probability of motifs occurrence changes accordingly.

Table 17. *Percentile values of motif frequency in 1000 random networks for five networks*

Motif	*"original" network*	*Em.St. R*	*Emp. R*	*Ext. R*	*13* variables R*	*All 26R*
Triangles	62.49	62.04	61.74	62.34	59.34	61.94
2Paths	71.08	71.48	72.18	70.78	72.03	72.08
Positive triads (PPP)	58.14	66.43	36.71	45.75	64.79	57.54
Negative triads (NNN)	**99.65**	**99.1**	97.05	96.6	**97.65**	**99.5**
Triangles (2 neg. - NNP)	26.92	22.53	41.91	36.26	23.63	28.72
Triangles (1 neg. - PPN)	12.39	13.24	20.68	21.08	17.48	12.54
2Paths pos.	91.41	96.2	41.91	84.37	29.67	91.11
2Paths neg.	34.82	56.39	24.48	72.68	96.6	34.72
2Paths mix.	21.13	7.89	74.18	12.09	13.94	20.68
Strong pos. triads	90.16	92.36	93.26	92.26	**98.85**	89.16
Strong neg. triads	**100.0**	**100.0**	**100.0**	**100.0**	**99.85**	**100.0**
Strong imb. triads I	20.68	24.98	24.43	23.28	41.76	19.03
Strong 2paths pos.	3.35	11.24	5.14	5.04	30.62	3.55
Strong 2paths neg.	79.22	45.95	67.03	48.15	32.17	78.82
Strong 2paths mix.	25.47	12.79	10.99	25.42	6.09	26.47
Imb. triads II T.	5.54	4.85	4.4	11.49	49.9	6.29

Abbreviations: Em.st. R – Emotional Stability reversed ("Neuroticism"); Emp. R – Empathy reversed ("Lack of empathy"); Ext. R – Extraversion reversed ("Introversion"); Pos. – positive; Neg. – negative; Imb. – imbalanced
Bold letters – structural motifs
Bold numbers – significant motifs
Grey cells – signed and weighted motifs
* 13 reversed variables/nodes are: Emotional stability, Self-disclosure, Militaristic interests, Low Violent-occult interests, Self-monitoring, Tradition, Universalism, Self-direction, Hedonism, Achievement, Power, Low Depression, and Empathy.

The percentile value is calculated by taking the value obtained from the empirical network and then determining its position against the distribution of those valued generated by 1000 random networks. It can be interpreted as probability of the motif occurrence in a random network. If the probability is lower than 2.5, or higher than 97.5 (two-tailed), it is interpreted as statistically significant occurrence under the used null model.

By inspection of the Table 17, several patterns can be seen. Firstly, triangles and 2-paths have similar percentile values for all networks. This is expected due to their same frequency and null model which controls for the structure. The small differences in their values are due to random process of creating 1000 random networks for each network separately.

Positive triads show similar, non-significant probabilities in all networks. Negative triads have less variation in percentile values, but since they are in the proximity of the upper cut-off value 97.5 for significance, they are not significant in two out of five networks. Similarly, strong positive triads, although with similar probabilities in all networks, they are shown to be significant in one of five. On the other hand, the frequency of strong negative ties is significant in all five networks. For all other motifs, probability of their occurrence varies more than for motifs previously discussed, but the conclusion about their significance is the same – they are not significant.

We can see from the results that the conclusions about the motif significance will tend to be the same (to converge) for all networks, regardless of whether some of nodes are reversed. However, we also can see that the results are not completely robust – they do lead sometimes to different conclusions about the motif significance. In those cases, however, other probabilities tend to be in the neighbourhood of the significance level. For not significant motifs, especially those that have one absent tie or not only positive or negative ties, probabilities vary more. Higher variability of estimated probabilities for several motifs may be explained by very constrained null model we have used – allowing only random swamping of weights among present edges. The consequence of such restrictions are smaller variations between randomly generated network, where even small differences in the frequency can lead to relatively big differences in *p*-values due to narrow distribution. The variability was further enhanced for those motifs that appear in very low frequency (e.g., one to six occurrences). Rather high agreement in probabilities of strong positive and strong negative motifs, despite their extremely low frequency is the result of their very skewed distributions (see Figure 3.11 in Chapter 3). In conclusion, although results converge across networks with different number of nodes reversed, the consistence in estimated probability is not perfect, suggesting that future research will benefit from more refined null models.

Table 18. *Results of motif intensity and coherence analysis*

Motif intensity - I	*Average value in the network*						*Percentile value in the random networks*					
	"original" network	*Em.st. R*	*Emp. R*	*Ext. R*	*13* variables R*	*All 26R*	*"original" network*	*Em.st. R*	*Emp. R*	*Ext. R*	*13* variables R*	*All 26R*
All triangles	0,119	0,119	0,119	0,119	0,119	0,119	92.91	91.51	91.91	91.31	90.61	91.51
2Paths	0,115	0,115	0,115	0,115	0,115	0,115	**0.3**	**0.3**	**0.2**	**0.1**	**0.4**	**0.4**
1 neg. (PPN)	0,115	0,115	0,119	0,117	0,115	0,115	47.8	58.34	83.72	63.84	38.61	41.86
2 neg. (NNP)	0,11	0,112	0,111	0,113	0,117	0,11	11.89	13.99	12.09	29.57	11.69	11.29
3 neg. (NNN)	0,148	0,144	0,136	0,141	0,141	0,148	**99.9**	**99.6**	**97.8**	**99.8**	**99.6**	85.56
All pos. (PPP)	0,122	0,118	0,122	0,117	0,104	0,122	84.82	81.52	86.41	58.44	87.41	97.2
2Path mix.	0,114	0,114	0,115	0,116	0,113	0,114	**1.8**	**0.9**	3.9	10.09	**1.5**	**1.0**
2Path neg.	0,121	0,125	0,122	0,117	0,126	0,121	75.82	74.18	70.73	32.97	88.51	76.02
2Path pos.	0,114	0,11	0,11	0,112	0,106	0,114	4.0	4.1	**0.3**	**1.6**	**0.9**	3.5
Motif coherence- Q	*Average value in the network*						*Percentile value in 1000 random networks*					
	"original" network	*Em.st. R*	*Emp. R*	*Ext. R*	*13* variables R*	*All 26R*	*"original" network*	*Em.st. R*	*Emp. R*	*Ext. R*	*13* variables R*	*All 26R*
All triangles	0,913	0,913	0,913	0,913	0,913	0,913	**98.8**	**99.1**	**98.5**	**99.5**	**99.2**	**99.1**
2Paths	0,925	0,925	0,925	0,925	0,925	0,925	4.0	2.8	3.6	3.6	3.9	3.8
1 neg. (PPN)	0,918	0,917	0,917	0,921	0,92	0,918	**97.5**	95.4	95.2	**98.5**	96.4	**98.0**
2 neg. (NNP)	0,914	0,915	0,909	0,906	0,915	0,914	92.41	**97.7**	84.82	80.62	87.71	93.61
3 neg. (NNN)	0,915	0,915	0,917	0,907	0,911	0,915	82.02	89.36	91.01	83.02	79.62	84.92
All pos. (PPP)	0,898	0,893	0,906	0,914	0,887	0,898	36.76	17.78	51.45	70.33	55.34	37.56
2Path mix.	0,927	0,929	0,927	0,924	0,927	0,927	22.38	42.16	23.58	7.39	43.86	23.08
2Path neg.	0,921	0,914	0,921	0,921	0,927	0,921	15.58	3.1	21.98	27.77	21.88	15.68
2Path pos.	0,925	0,927	0,924	0,93	0,919	0,925	12.99	9.39	4.9	19.18	3.9	13.69

Abbreviations: Em.st. R – Emotional Stability reversed ("Neuroticism"); Emp. R – Empathy reversed ("Lack of empathy"); Ext. R – Extraversion reversed ("Introversion"); Pos. – positive; Neg. – negative; Imb. – imbalanced
Bold letters – structural motifs
Bold numbers – significant motifs
*13 reversed variables/nodes are: Emotional stability, Self-disclosure, Militaristic interests, Low Violent-occult interests, Self-monitoring, Tradition, Universalism, Self-direction, Hedonism, Achievement, Power, Low Depression, and Empathy.

Table 18 shows the results for Intensity and Coherence of motifs across the same sample of networks (with some nodes reversed). The pattern of results is similar to the results of the analysis of motif frequency – overall, estimations converge between networks, but the consistency is not perfect.

As a final note on presented networks with reversed nodes; it should be noted that we have presented only four of many possible networks with different number and combinations of nodes reversed. Although the consistency is not perfect, our results suggest that reversing nodes does not affect the estimation of their significance to a higher extent.

13 Participation Coefficient based on empirical (data-driven) communities

Louvian community detection algorithm based on modularity optimization and a hierarchical approach (for more details see Blondel et al., 2008) detected five communities (Figure 23), and those affiliations have been used for the calculation of PCs, shown in Figures 24 and 25 (note the same issue with Empathy and Extraversion having higher geometric mean than PC and PR as in Chapter 3).

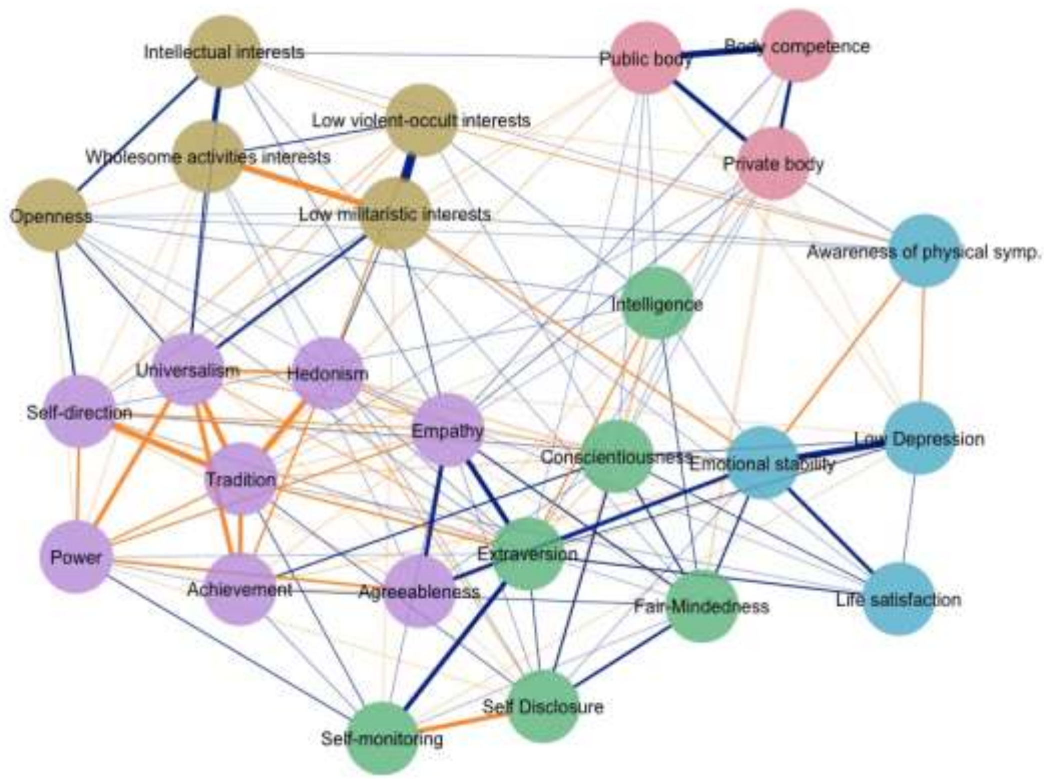


Figure 23. Five communities found with Louvian community detection algorithm

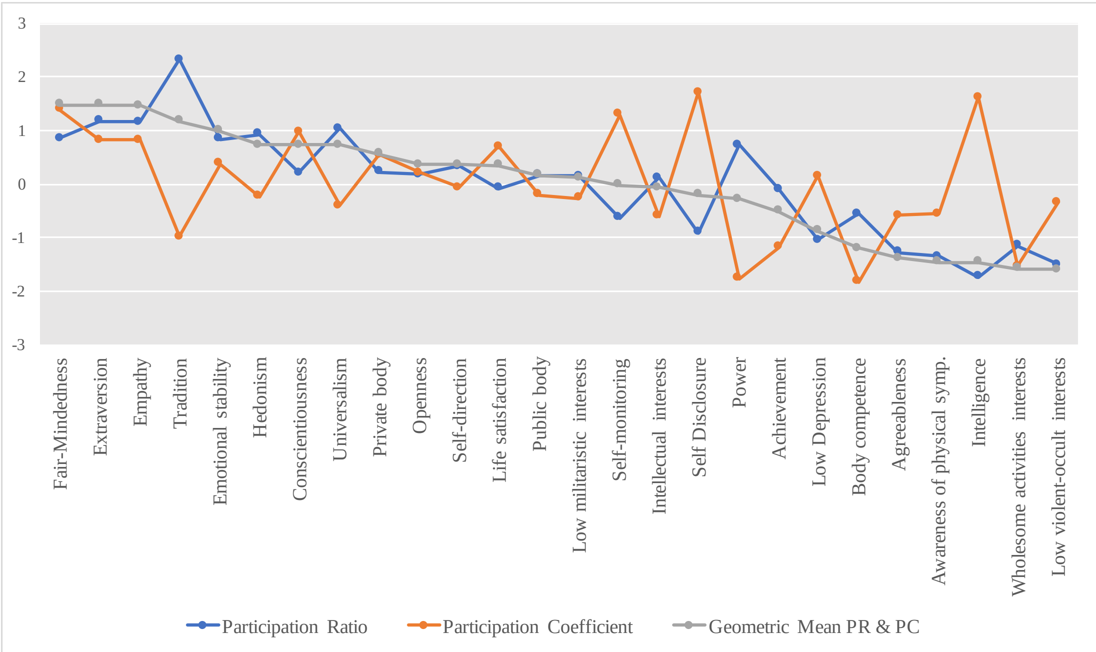


Figure 24. Participation Ratio (∝= 0.5), Participation Coefficient, and their geometric mean (standardized values) where Participation Coefficient is based on communities found by Louvian community detection algorithm

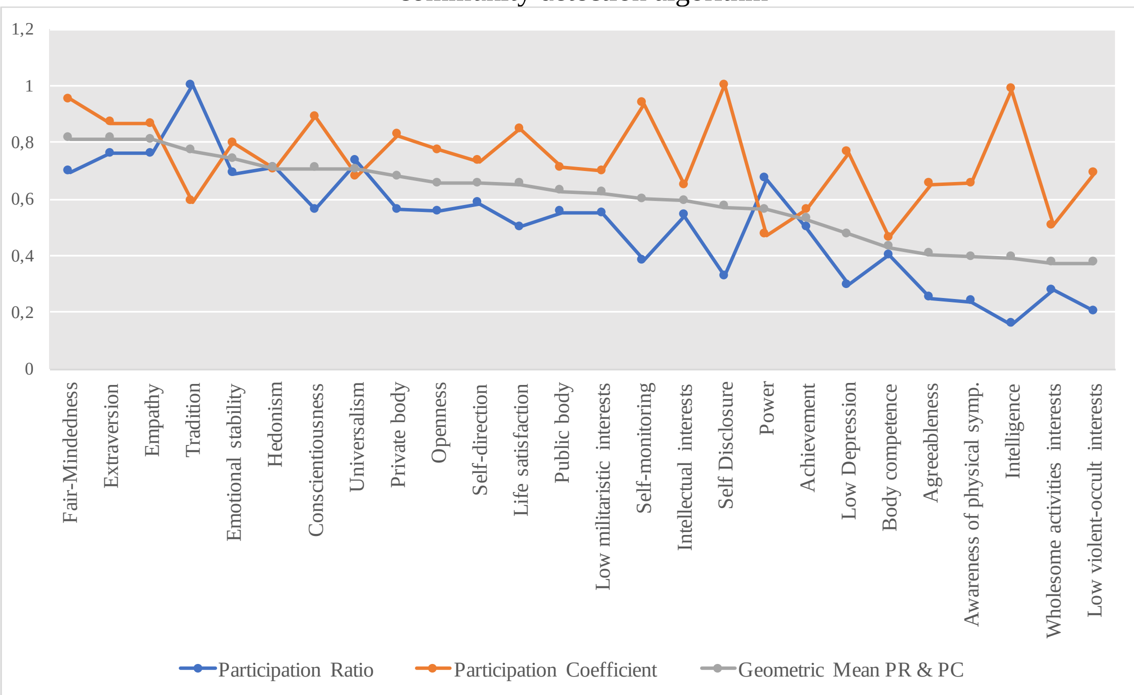


Figure 25. Participation Ratio (∝= 0.5), Participation Coefficient, and their geometric mean (unstandardized values) where Participation Coefficient is based on communities found by Louvian community detection algorithm

In this case, the nodes with highest PC values are Self-Disclosure and Intelligence, followed by Self-monitoring and Fair-Mindedness. The aforementioned is the most central node when both PR and PC are considered (with geometric mean), and was not found to be the most central according to other centrality measures and MST preformed in this study. Extraversion, Empathy, Tradition, and Emotional stability – already identified by other analyses in this study to be among the most central nodes – are in top five nodes when considering both PR and PC. This analysis additionally supports the finding reported in Chapter 3 about the important and specific role of Intelligence in this network, even though it is among the most peripheral nodes.

However, many different algorithms (for review see Fortunato, 2010; Fortunato & Hric, 2016) exist for community detection, and they usually yield different community structure (which will lead to different PC values). For example, see detected communities when other algorithms have been used in figure 26. Additionally, many algorithms are stochastic, which results in different results based on random process that generates the best partition. Although community detection algorithms have been used in the network application to psychological concepts, the guidance on which algorithm to use when analysing typically small, weighted, and signed psychological networks is yet to be established.

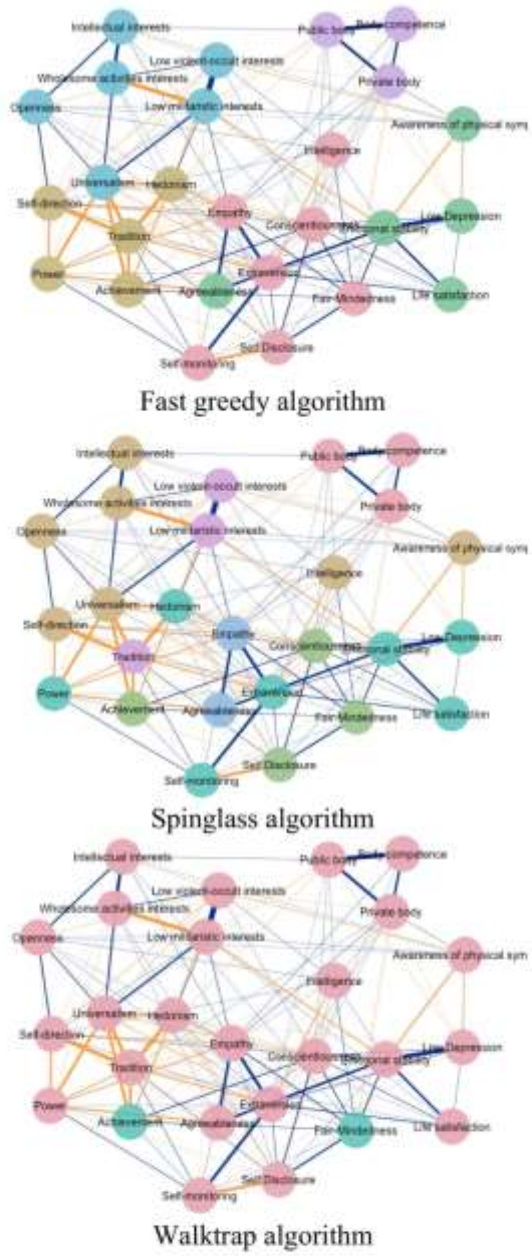


Figure 26. Different communities detected with three different algorithms

14 References

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Appendix 4

Supplementary materials for Chapter 4

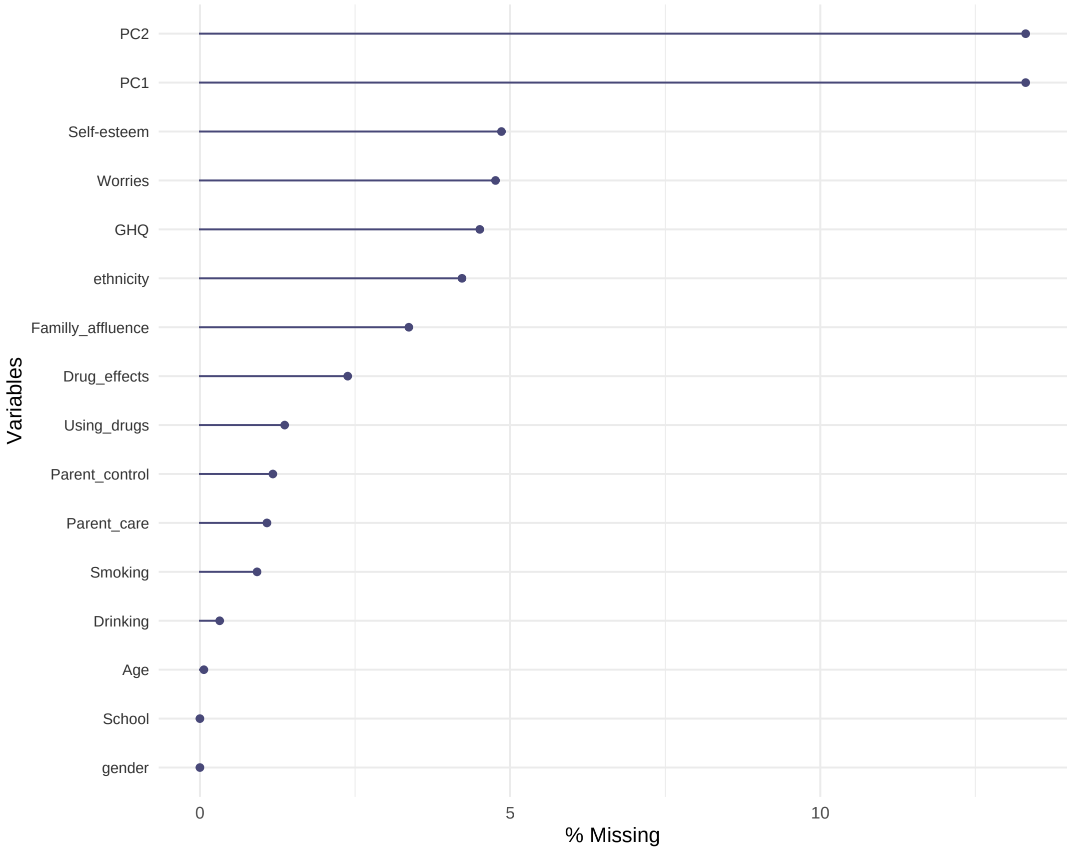
1 Dataset

Table 1. Matrix showing number of students having data about friendships within school year (network data) and some attribute data (3194 students participated in the study)

	Network data	Attributes data*
Attributes data*	**3148**	3194
Network data	3649	**3148**

501 students who did not participate in the study had network data about their in-going ties from other students who participated in the study. 46 of 3194 students that participated in the study did not nominate anyone in their school year as a friend and were not nominated by anyone. They are isolates and are not included in the further analyses.

Not all students participating in the survey had all attribute data used in the main analyses (see figure 1).



PC2, PC1 – principal component scores for the second and first component, respectively; GHQ – score on General Health Questionnaire

Figure 1. Percentage of missing data for single attributes (variables) for students participating in the study (*N*=3 194; x-axis: percentage of missing data; y-axis: attributes/variables used in the study)

Data imputation

We imputed values for students who missed some of the data on attributes although they participated in the study. To impute the data, we used all other attributes included in figure 1, but we did not include any network data (R package mice (Van Buuren, & Groothuis-Oudshoorn, 2011), 40 iterations).

3 Principal component analysis

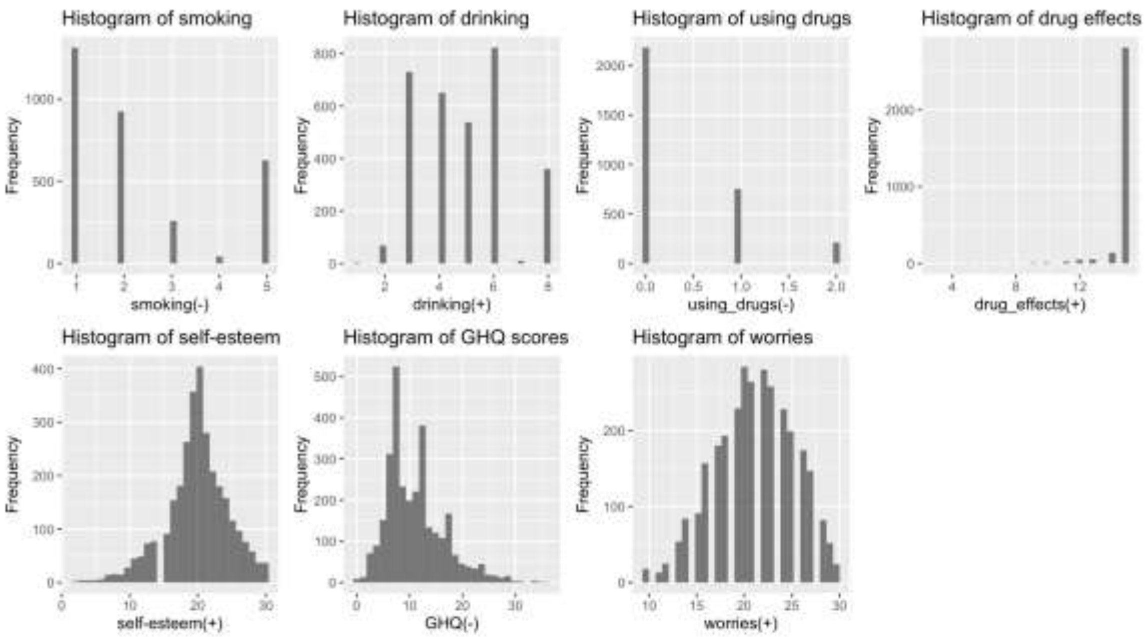


Figure 2. Distributions of seven variables used as input for principal component analysis

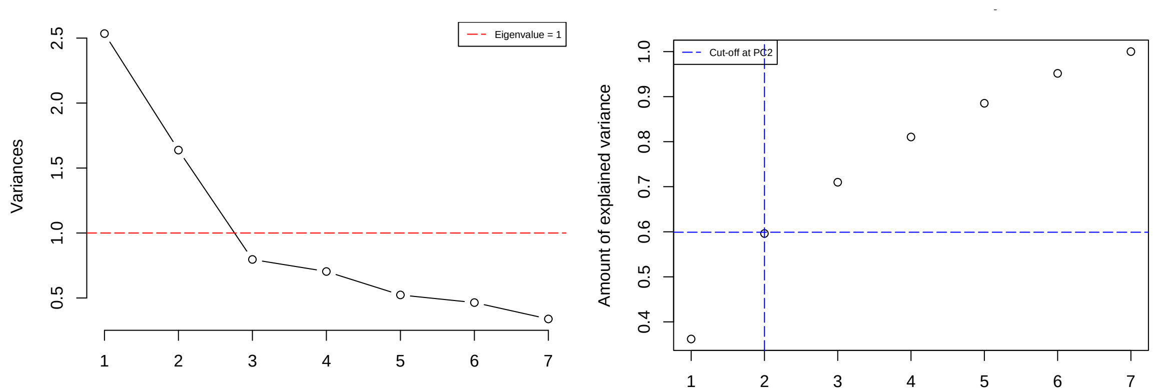


Figure 3. Screenplot of Eigen values for principal components of seven health-related variables (left) and cumulative variance plot (right)

Loadings of two components on seven health variables

All variables are recoded for the purpose of making more easily interpretable visualizations. High values in all variables signify worse health outcome.

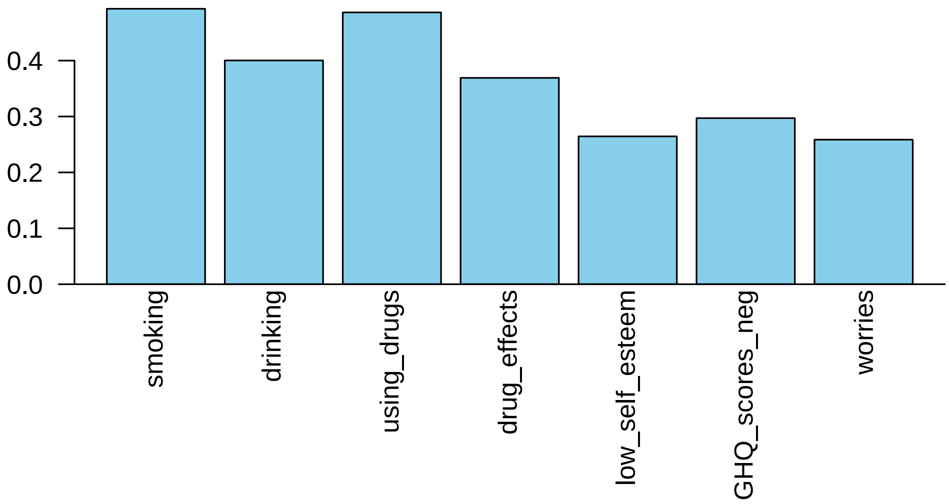


Figure 4. Loadings of the first component on seven variables

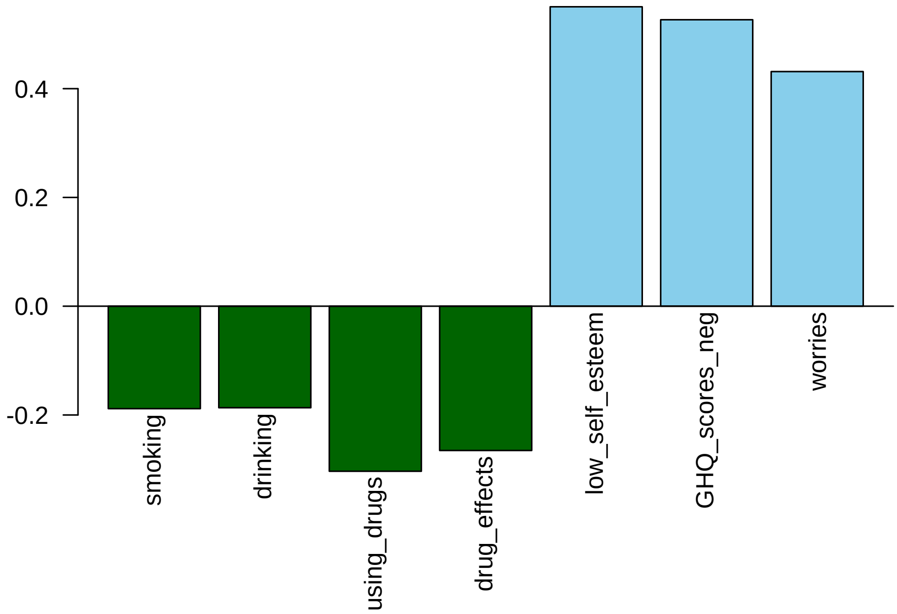


Figure 5. Loadings of the second component on seven variables

Table 2. Weights of seven health related variables for two principal components (N = 2758, cases with complete data)

Variable	*PC1 weights Substance use*	*PC2 weights Mental wellbeing*
Smoking (-)	0.31	-0.15
Drinking (-)	0.25	-0.16
Using drugs (-)	0.31	-0.23
Drug effects (-)	0.23	-0.20
Low self-esteem (-)	0.17	0.43
GHQ (-)	0.19	0.41
Worries (-)	0.16	0.34

Raw scores and factor scores

Raw scores are calculated by summing standardized values[62] for everyone as follows:

$SU =$ Smoking + Drinking + Drug use + Drug effects

$MW =$ Self-esteem + General mental health (GHQ) + Worries

The rationale is that, in contrast with principal component and factor scores, only behaviours and outcomes on which the highest loadings are found for the two identified components are used for the calculations.

Factor scores were based on factor analysis (orthogonal, factors with oblique rotation were correlated below 0.3). Since the two factors together explained 46% of variance and had scores with higher skewness, we chose to use principal component scores. However, factors had similar pattern of loadings as principal components and they are highly correlated (see correlations in figure 8).

[62] Technically, the values are not “raw” since we standardized them. We used the adjective “raw” to highlight that they are based on simpler calculations.

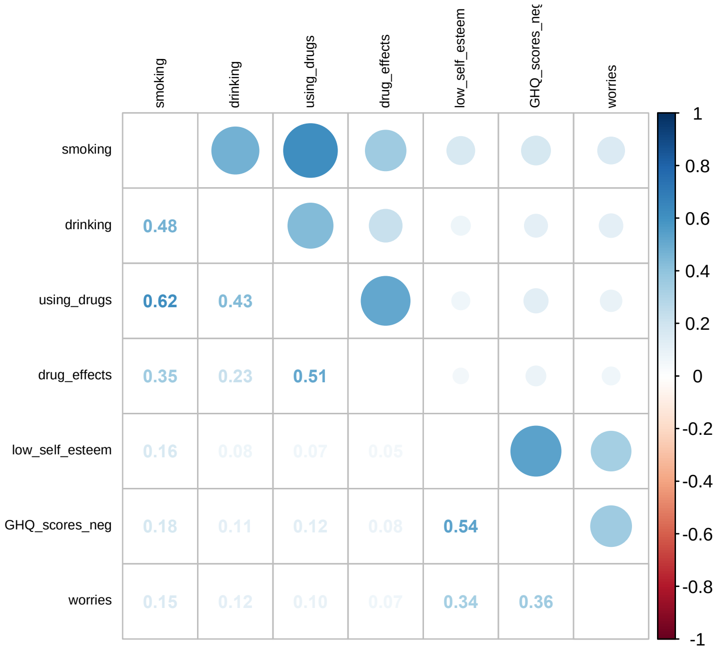


Figure 6. Pearson's correlations between seven health outcomes (*N* = 3148, non-imputed data, pair-wise complete observations; all variables are coded so higher values signify a more negative outcome)

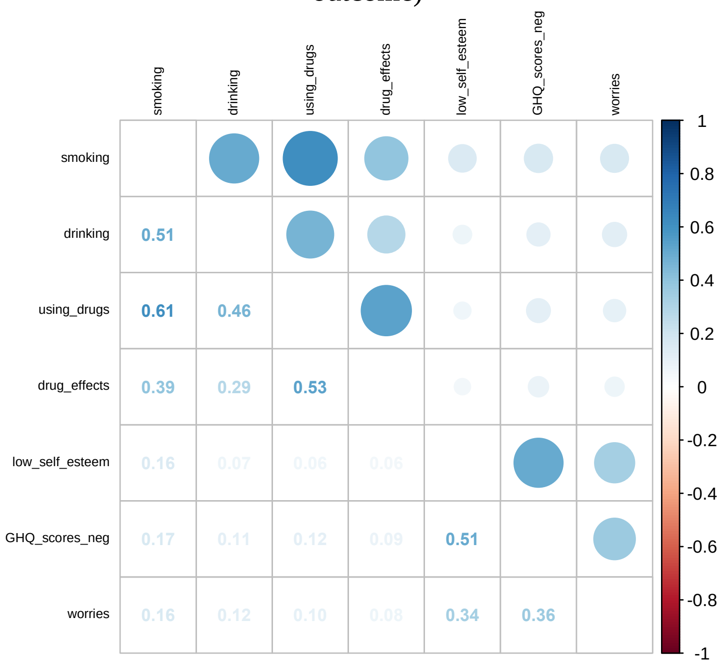
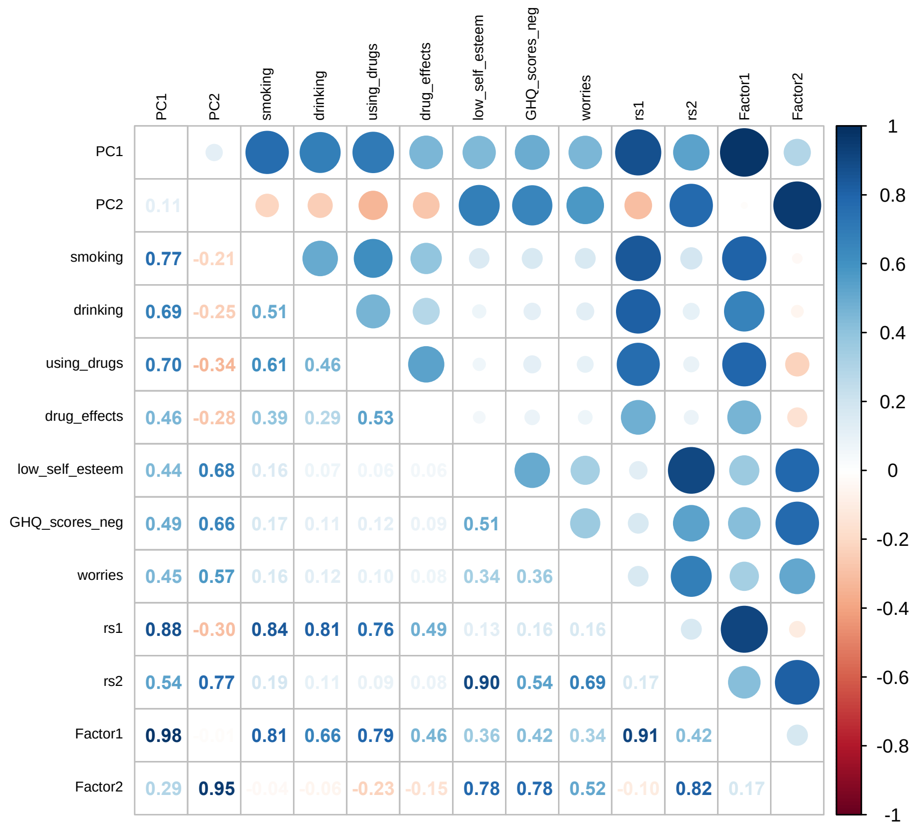


Figure 7. Spearman's correlations between seven health outcomes (*N* = 3148; non-imputed data, pair-wise complete observations; all variables are coded so higher values signify a more negative outcome)



PC1, PC2 – principal components score for first and second component, respectively; rs1, rs2 – "raw" scores for first and second component (factor); Factor1, Factor2 – factor scores for two factors extracted with factor analysis

Figure 8. Spearman's correlations between seven health outcomes and different types of composite scores (*N* = 3148; non-imputed data; pair-wise complete observations; all variables are coded so that higher value represents negative outcome)

4 Difference between isolates and non-isolates

46 out of 3194 participants in the study had no network data because they were not nominated by anyone as friends and did not nominate anyone from their school and year, as a friend. They are mostly boys (31) and white (33). Regarding age, 27 were 16 or 17 years old. Regarding family affluence, 14 isolates are in the low category, 13 in the high, and the rest in the medium (16). 17 out of 46 had missing data on PC1 and PC2, and remaining 29 was compared with the rest of the sample that are not isolates (*N*=3148, but 419 had missing data for PC1 and PC2). The comparison between non-isolates and isolates regarding two health outcomes is done with original PC scores on non-imputed dataset. Figure 9 shows the distributions (boxplots) of scores for two groups.

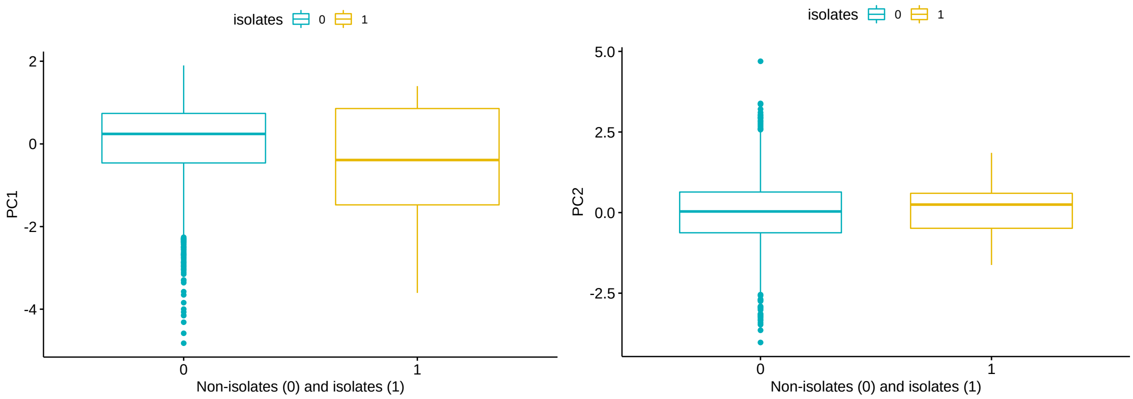


Figure 9. Boxplots of PC1 (left) and PC2 (right) scores

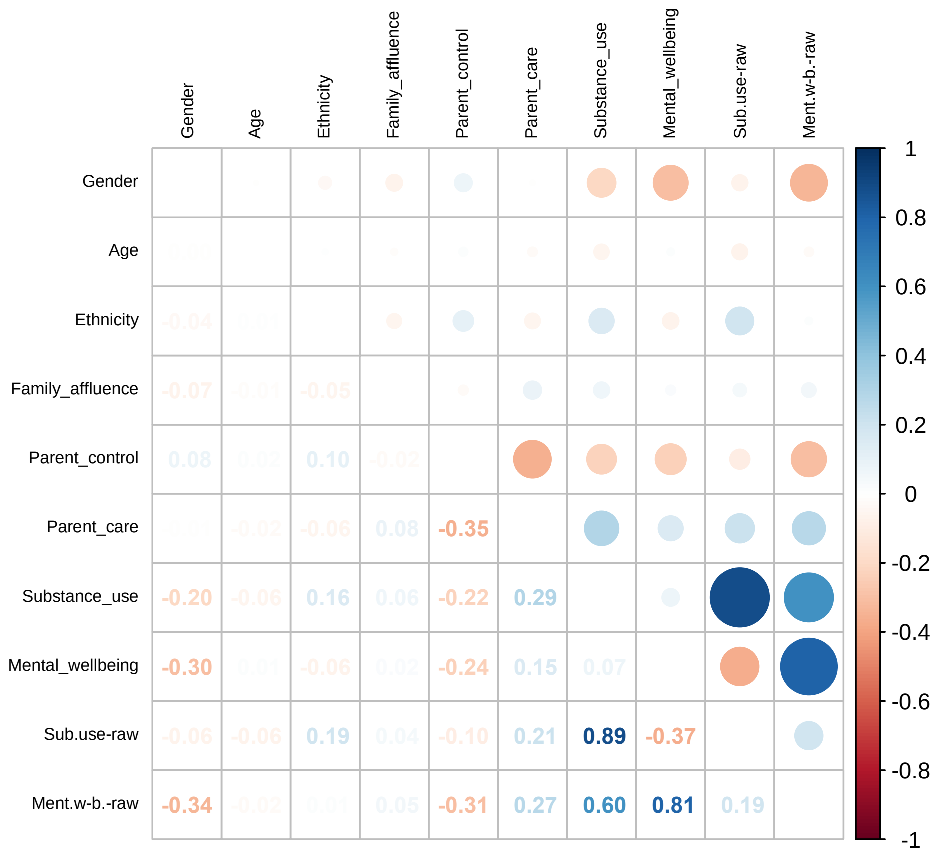
Isolates had lower average score on PC1 (*M* = -0.51) than non-isolates, (*M* = 0.04), suggesting higher tendency for substance use. The difference was not significant. Due to non-normality of distributions, non-parametric Kruskal-Wallis test is used (3.259, *df* = 1, *p*-value = 0.071); while t-test showed almost significant difference (t = 2.017, df = 28.271, *p*-value= 0.053).

Isolates had higher average score on PC2 (M = 0.18) than non-isolates (M = -0.01), but the difference is not statistically significant (Kruskal-Wallis test, 0.800, df = 1, *p*-value = 0.371; t-test, t = -1.036, df = 2756, *p*-value = 0.301).

Table 3. Descriptive statistics of dependent variables (raw scores and component scores) after transformations and imputations (*N*=3148)

Dependent variable	*Mean*	*SD*	*Median*	*Min.*	*Max.*	*Skewness*	*Kurtosis*
Substance use – component score. transformed	-0.04	0.996	0.01	-2.15	2.84	0.01	-0.63
Mental wellbeing – component score*	0.00	0.975	0.03	-4.03	4.69	-0.15	0.61
Substance use – raw scores. transformed	0.00	1.000	0.14	-2.66	1.56	-0.47	-0.53
Mental wellbeing – raw score. transformed	0.00	1.000	-0.03	-2.42	3.22	0.18	-0.26

* No transformation was performed for Mental wellbeing component score; SD – standard deviation; Min. – minimum score; Max. – maximum score



Substance use. Sub.use-raw, Ment.w-b.-raw – raw composite score of substance use and mental wellbeing, respectively, after transformations to reduce skewness (cube transformation, and square transformation, respectively); Gender: 0 – male; 2 – female; Ethnicity: 0 – white; 1 – non-white.

Figure 10. Pearson correlation coefficients between dependent variables and covariates at level 1 (imputed dataset. *N* = 3 148. after transformations)

Principal components and gender differences

Table 4. Gender differences in two components (and raw) scores (imputed data)

	Total N = 2 729	Boys N = 1 344	Girls N = 1 385	p-value
Substance use component score	0.04 (0.98)	0.22 (0.96)	-0.14 (0.96)	<.001
Substance use component score - transformed	0.00 (1.00)	0.21 (1.00)	-0.21 (0.9f)	<.001
Mental wellbeing component score	-0.01 (0.99)	0.31 (0.90)	-0.31 (0.98)	<.001
Substance use raw composite	-0.03 (0.74)	-0.06 (0.77)	0.00 (0.71)	0.026
Mental wellbeing raw composite	-0.01 (0.77)	-0.28 (0.66)	0.25 (0.78)	<.001

5 Community properties

The details about how we calculated six community properties of each peer group in the networks are provided in the text below.

Community size. The number of all students belonging to the community.

Community gender composition. Due to high gender homophily many communities will have only girls or boys as members. Therefore, each community is described as female, male, or mixed – if it had at least one member of the opposite gender.

Ratio of ties outside the community. Each member of a community can have ties with other members of the same community (inside community ties) and/or with members from other communities in the school (ties outside community). The ratio of ties outside communities is calculated by summing all outside community ties of all members and dividing it by the sum of all their (inside and outside community), expressed by formula: $\frac{\Sigma\ external\ community's\ ties}{\Sigma\ all\ (internal+external)\ community's\ ties}$. It is analogous to measure often used on whole network and all communities, known as mixing parameter (μ), but in our case it is applied to each community separately. Value of the ratio for communities with just one member is 1.

Transitivity. Transitivity measures the tendency of nodes to cluster together. There are several different versions of the measure. and we use so-called global transitivity. More specifically, it is based on triads – network subgraphs formed by three nodes. Transitivity means that if there is a tie between i and j and between j and k, there is also a tie between i and k, ignoring the direction of ties. It measures the relative frequency of triangles in the community. expressed by formula: $\frac{3*N\ of\ connected\ triads}{N\ of\ all\ connected\ triplets}$. where triplets are any two ties that share a node. Transitivity can theoretically vary from 0 to 1. and higher score means higher transitivity.

Centralization. This measure quantifies variation in centrality scores among nodes in the network. We apply the measure to nodes' total number of ties (in-going and out-going). regardless of their direction and measure it at community level. The formula for centralization (Freeman, 1979) is:

$$C_D = \frac{\sum_{i=1}^{g}[C_D(m) - C_D(n_i\ )]}{[(g-1)(g-2)]}$$

where g is the number of nodes in a community *i* represents each node, m is the centrality value of the node with highest centrality in the community. This value is normalised by dividing by the theoretical maximum centralization score for a graph with the same number of nodes. In that way, centralization is the ratio of the actual sum of differences to the maximum possible sum of differences and it ranges from 0 to 1.

Hierarchy. We use Tau statistics constructed by McFarland et al. (2019) to capture hierarchical, vertical differentiation in the network. As transitivity, this measure is based on triads. but in difference with both transitivity and centralization it considers the direction of ties. Hierarchy exists when two individuals in the network nominate the same third individual, implying an over-representation of "up" pointing triads. In directed networks 16 types of triads are possible to occur. Their labels use the number of mutual, asymmetric, and null ties, followed by an abbreviation for direction (D – down; U – up; T – transitive; and C – cycle). This measure is based on the count of five of them that show some "status ordering" (021D, 021U, 030T, 120D, 120U), subtracted by the count of one so-called antithetical case (021C) that shows inconsistency in status ordering (see figure 11). The ranked-clustering weighting scheme is built by Davis and Leinhardt (1972). The total score is compared with the total score of the sample of 250 corresponding random networks with the same degree distribution and expressed as z-value with mean 0 and variance 1. If occurrence of these specific types of directed triads (and lack of 021C) is greater than random (positive z-value) it suggests a tendency toward hierarchy in the overall network (community in our case). We added an additional step in the calculation due to high positive correlation between the community size and normalised Tau score for most GDAs (above 0.6 for Walktrap communities). The score is divided by community size to prevent collinearity issues.

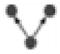
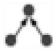
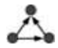
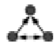
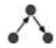
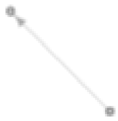
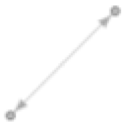
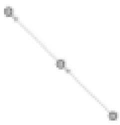
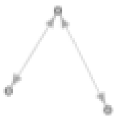
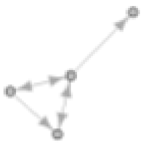
Triad label	*021D*	*021U*	*030T*	*120D*	*120U*	*021C*
Triad						
Weights	1	1	1	1	1	-1

Figure 11. Triads weighted for Tau (hierarchy) score

The centralization and hierarchy scores cannot be calculated for communities that have less than three members (to see examples on networks (communities) with two to five nodes (members), see table 5).

Table 5. Examples of transitivity. centralization related and hierarchy values for small communities

Example		Transitivity	Centralization	Theoretical maximum score	Normalised centralization	Hierarchy (simple score. not normalised)
1		0	0	0	NA	NA*
2		0	0	0	NA	NA*
3		0	2	4	0.5	-1
4		0	4	4	1	0
5		0.6	8	12	0.67	0
6		0.86	6	24	0.25	9

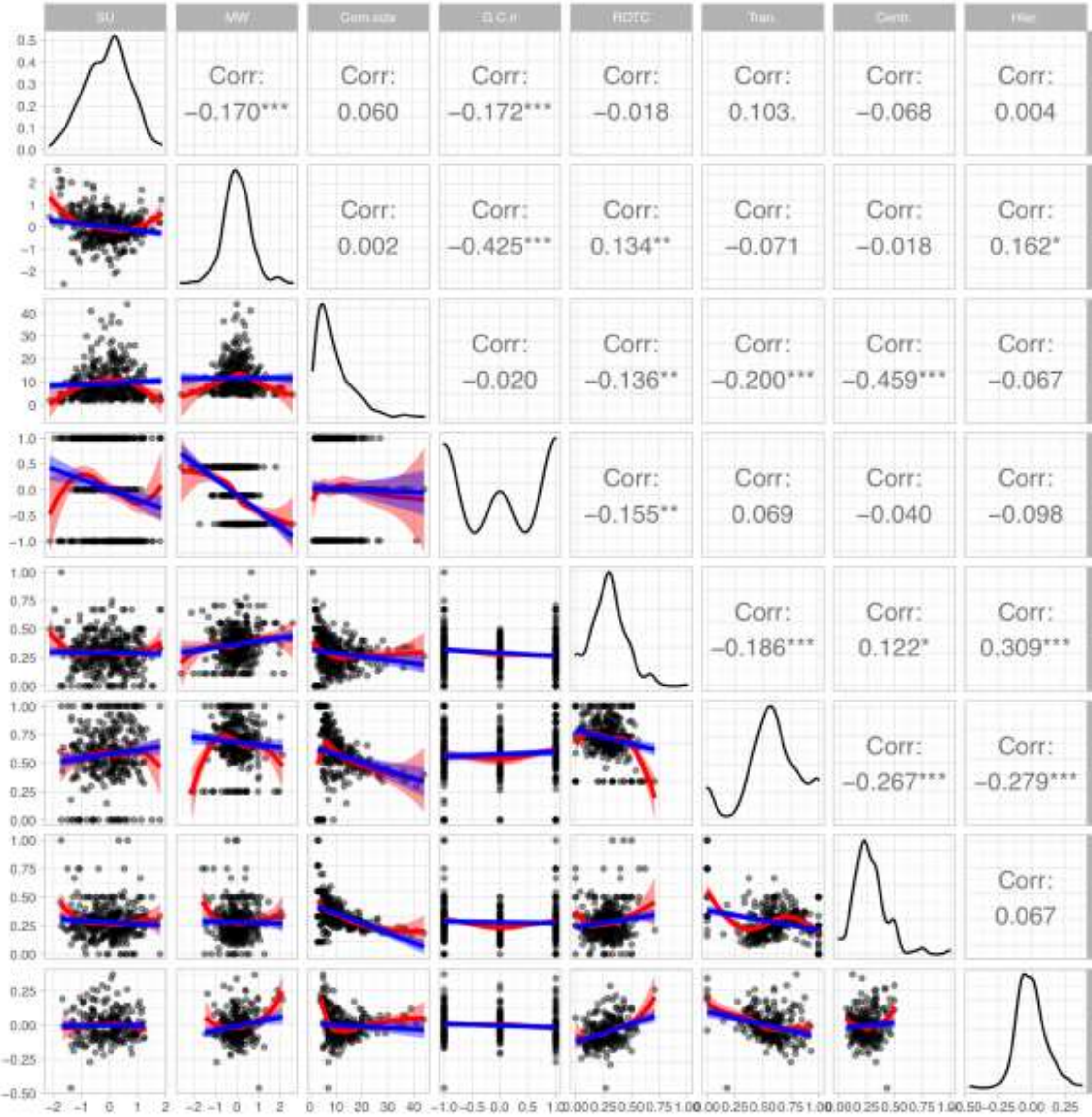
*Technically, values are zero because there are no triads. However. since values of this measure are possible to be zero even when there are triads. to distinguish between such cases. when no triad is present. no value is assigned (“NA”).

Descriptives of community properties for Walktrap algorithm are shown in table 6, and the scatterplot showing correlations between community properties and two health outcomes (mean of the group), and their distributions is shown in figure 12. Since Gender composition is a nominal property, the proportion of female students in the network (Prop. F) is used instead, and a variable called G.N.c in which mixed groups were assigned with value 0, females and males with 1 and -1, respectively. The correlation values are Pearson's correlations.

Table 6. Descriptives of community properties for Walktrap algorithm

GDA	Community property	N	Mean	SD	Median	Min.	Max.	Range	Skew.	Kurtosis
WT	Community size	387	9.43	7.216	7	1	44	43	1.679	3.546
	Prop. F	387	0.53	0.463	0.71	0	1	1	-0.128	-1.865
	Ratio of outside community ties	387	0.29	0.158	0.29	0	1	1	0.4	0.772
	Transitivity	387	0.6	0.243	0.6	0	1	1	-0.451	0.397
	Centralization	339	0.28	0.153	0.25	0	1	1	1.348	4.039
	Hierarchy	236	0	0.11	-0.01	-0.46	0.37	0.83	0.328	1.416

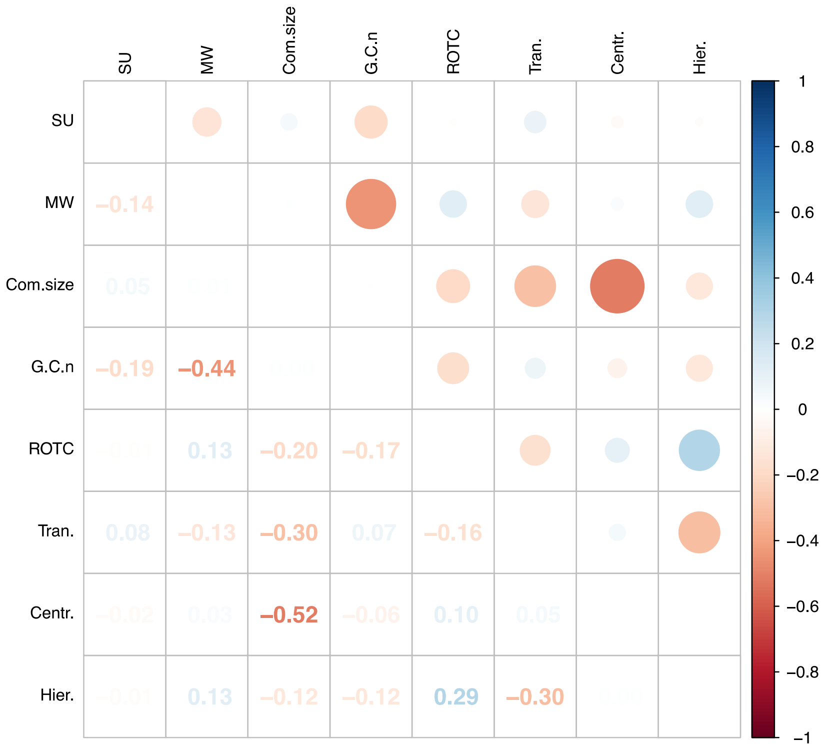
GDA – community detection algorithm; N – non-missing data; SD – standard deviation; Skew. – skewness; Prop. F – proportion of females in community



SU – substance use (higher score – better outcome); MW – mental wellbeing (higher score – better outcome); Com.size – community size; G.c.n. – gender composition as numeric variable where 1 is assigned to female, 0 to mixed and -1 to male; ROTC – ratio of ties outside the community; Tran. – transitivity; Centr. – centralization; Hier. - hierarchy

Figure 12. Scatterplots. distributions. and Pearson correlation coefficients of Walktrap's community properties and dependent variables (mean of community's members; total *N* communities = 387, pair-wise complete observations). In scatterplots: blue – linear trend based on linear regression; red – non-linear trend based on local polynomial regression fitting.

Since the distributions of properties are skewed, we used Spearman's correlation as well. The correlation plot in figure 13 shows Spearman's correlations between community properties and health outcomes for the complete sample of communities.



SU – substance use; MW – mental wellbeing; Com.size – community size; G.c.n. – gender composition as numeric variable where 1 is assigned to female, 0 to mixed and -1 to male; ROTC – ratio of ties outside the community; Tran. – transitivity; Centr. – centralization; Hier. - hierarchy

Figure 13. Spearman's correlations between community properties and two health outcomes (total *N*=387, pair-wise complete observations)

Average values and standard deviations of community properties and two health outcomes for mixed, male and female communities are shown in figures 14, 15 and 16.

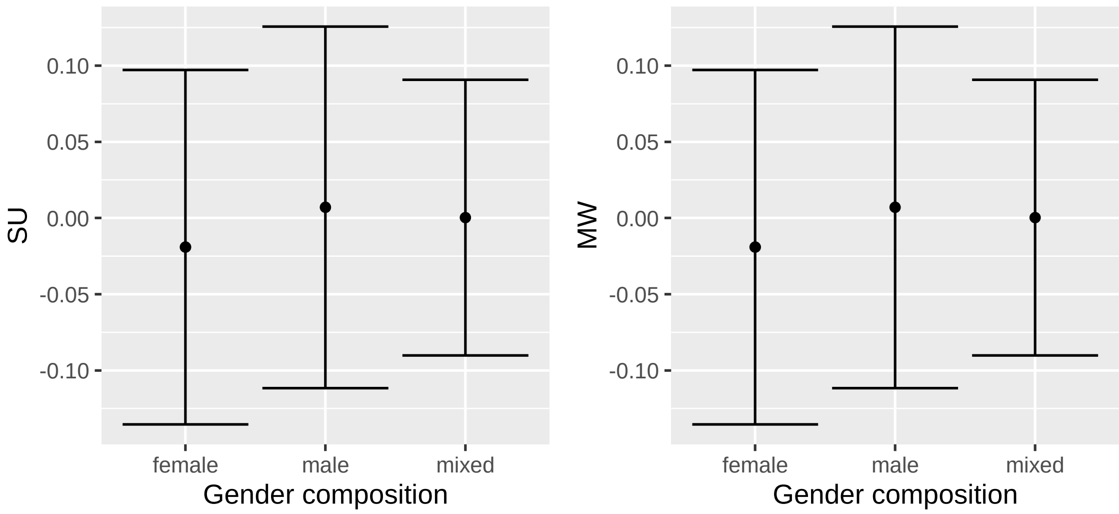


Figure 14. Average Substance use (SU) and Mental wellbeing (MW) and their standard deviations for three types of communities regarding gender composition.

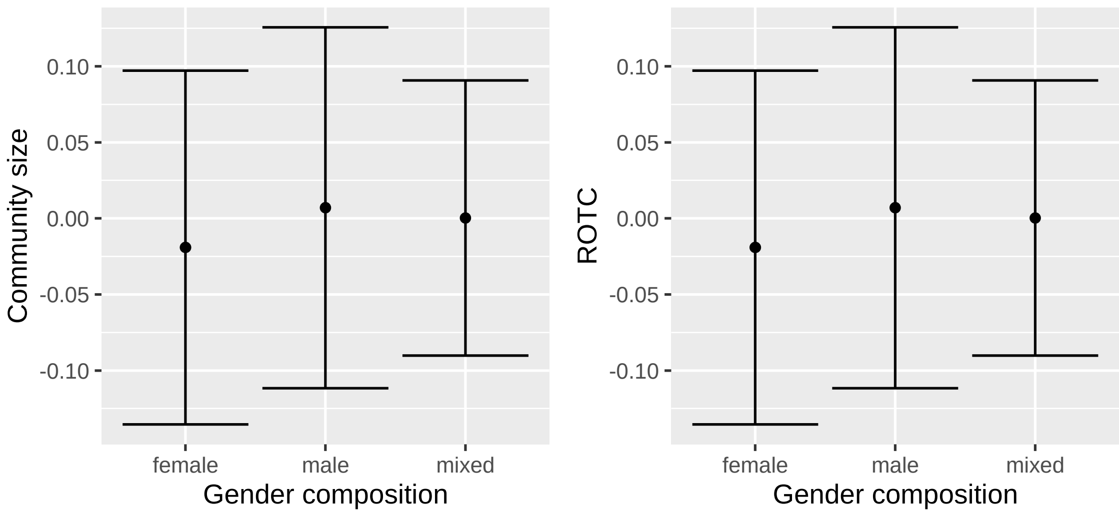


Figure 15. Average Community size and Ratio of outside community ties (ROTC) and their standard deviations for three types of communities regarding gender composition.

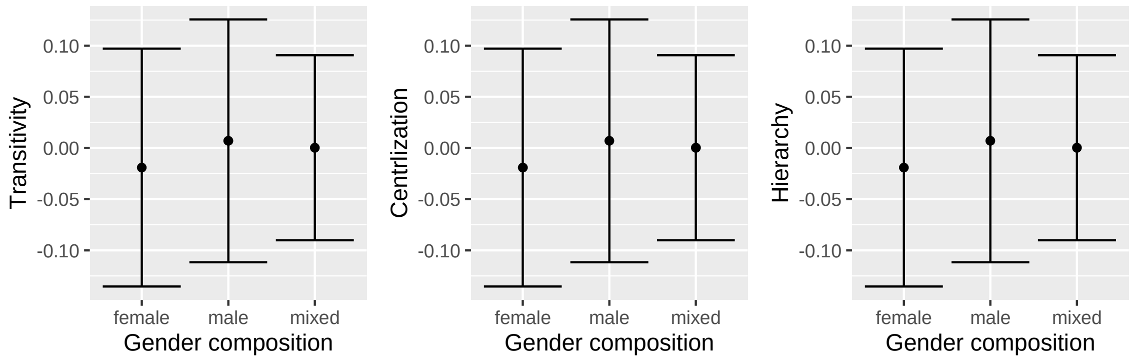


Figure 16. Average Transitivity, Centralization and Hierarchy and their standard deviations for three types of communities regarding gender composition.

1.1. Descriptive analyses of relationships between community properties and groups with different scores in two outcomes

We standardized values of community properties and categorized all communities (groups) in four categories based on their scores in SU and MW. For each outcome we assigned 25% of communities in each group, based on the quartile they belong to. We calculated average values and standard deviations for all community properties for each category of communities. Heatmaps in figure 17 show the relationship between values and variations in community properties and average substance use in communities.

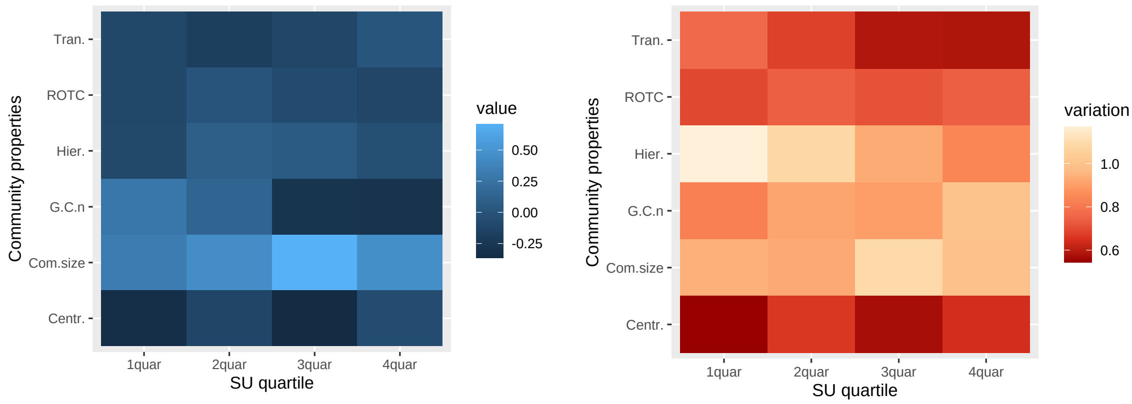


Figure 17. Average values (right) and variations (left) of community properties (x-axis) per four categories (y-axis) of communities based on their average substance use. Axis y shows four categories of communities: "1quar" – 25% with the highest average substance use; "4quar" – 25% with the lowest average substance use and two groups in between ("2quar" and "3quar")

Heatmaps in figure 18 show the relationship between values and variations in community properties and average mental wellbeing in communities.

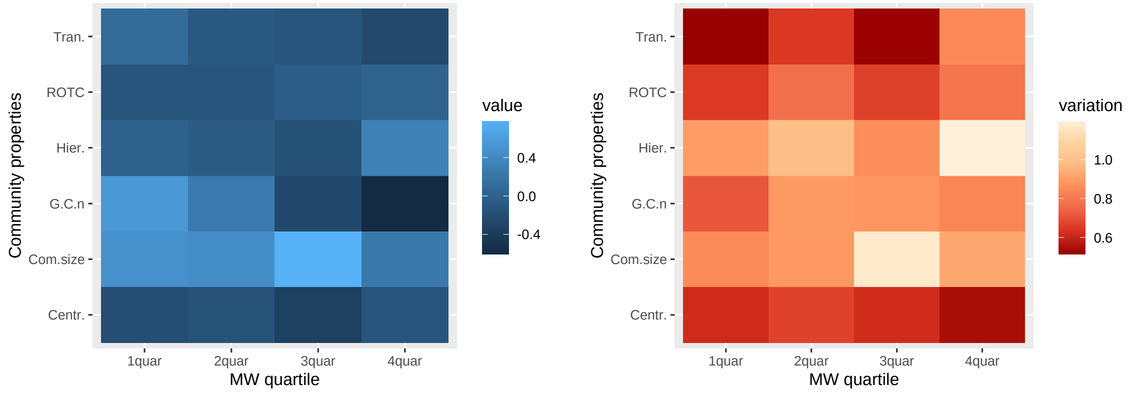
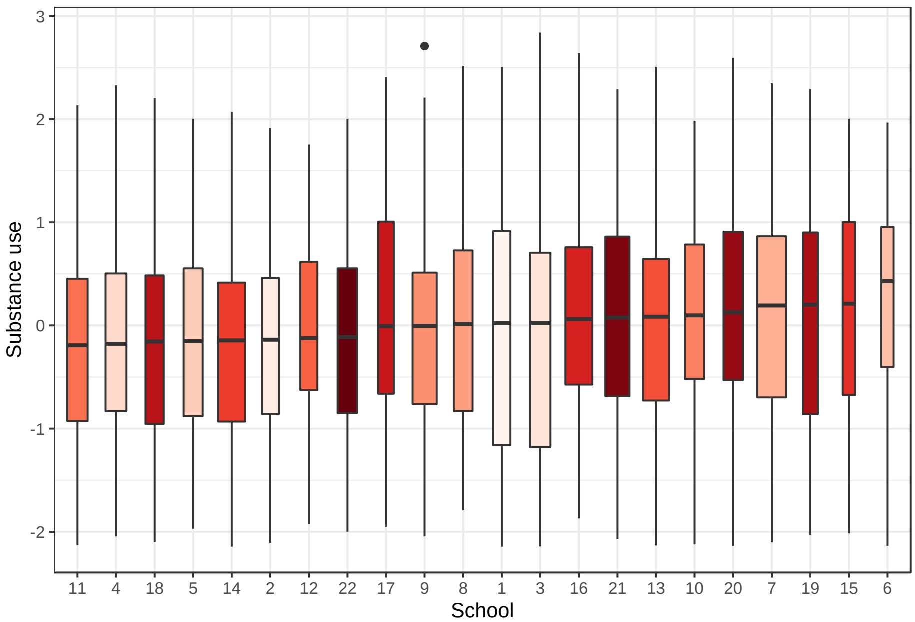


Figure 18. Average values (right) and variations (left) of community properties (x-axis) per four categories (y-axis) of communities based on their average mental wellbeing. Axis y shows four categories of communities: “1quar” – 25% with the lowest average mental wellbeing; “4quar” – 25% with the highest average mental wellbeing and two groups in between (“2quar” and “3quar”)

6 Multi-level models



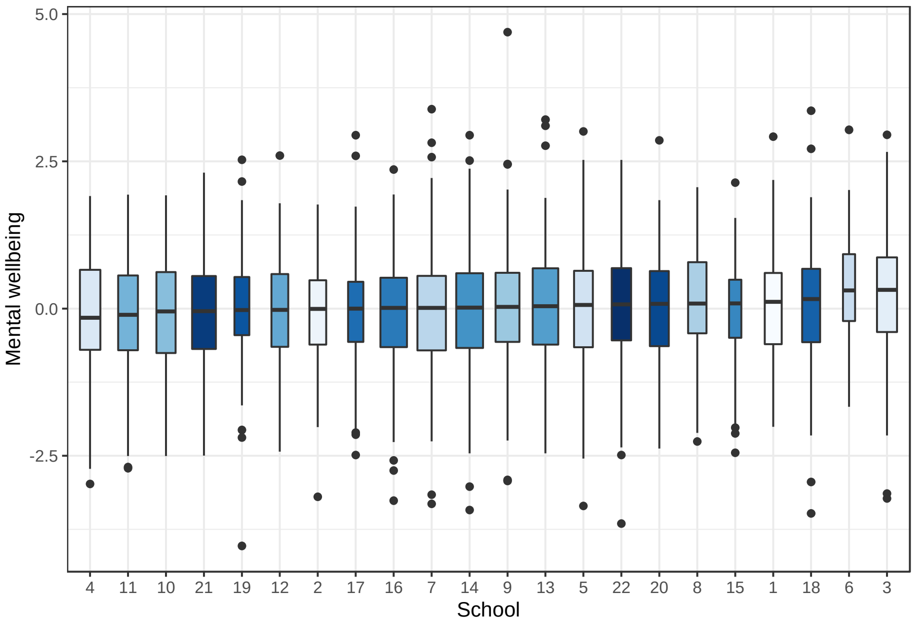
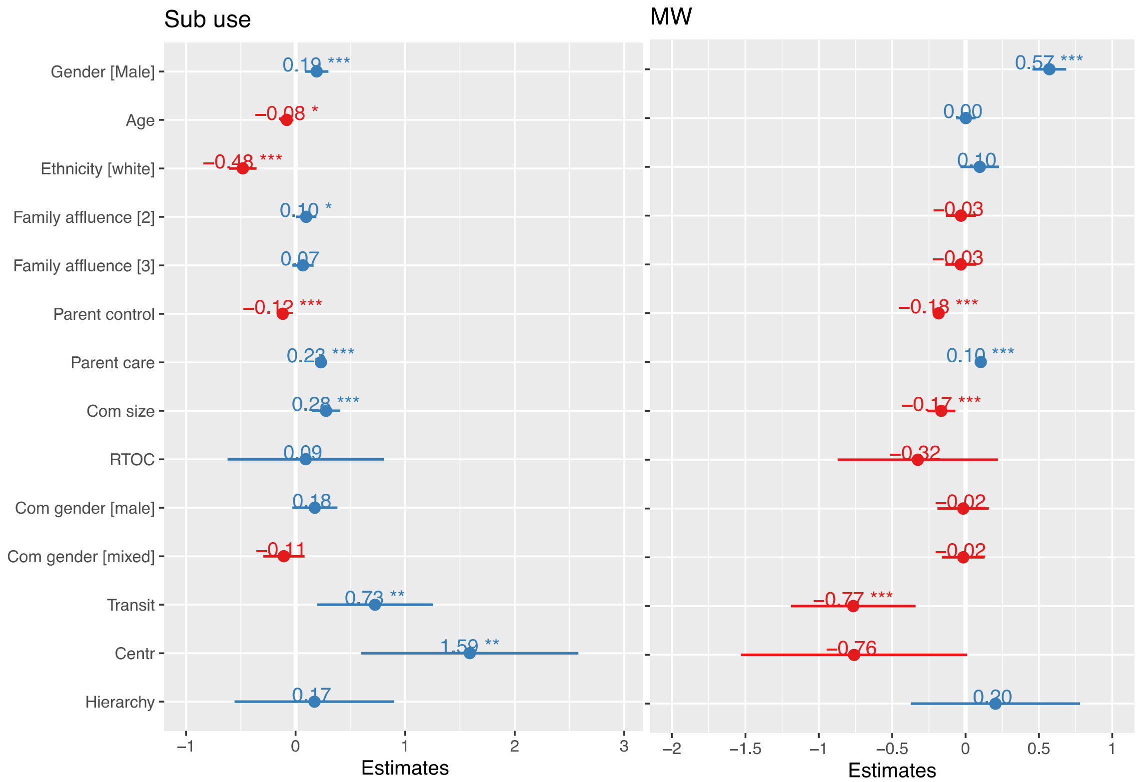


Figure 19. Boxplots for Substance use (top) and Mental wellbeing (bottom) by 22 schools (*N*= 3148, imputed dataset)



Sub use – substance use; MW – mental wellbeing; Reference group for Gender is female; Reference group for Ethnicity is non-white; Family affluence [2] – medium family affluence; Family affluence [3] – high family affluence; reference group is low family affluence; Com size – community size; RTOC – ratio of ties that are outside community; Com gender – gender composition of the community; Reference group for gender composition is female; Transit – transitivity, Centr – centralization

Figure. 20. Estimates of fixed effects for Model 5 for Substance use (left) and Mental wellbeing (right) (N=2698, communities identified by Walktrap).

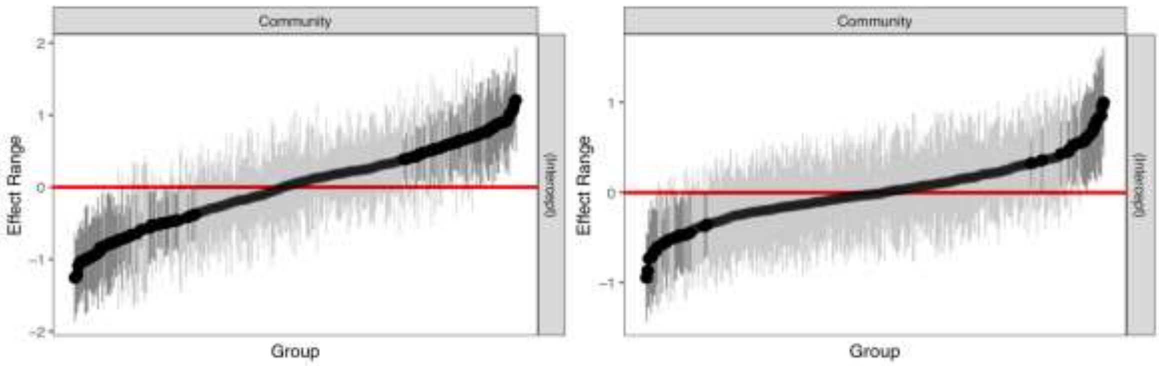


Figure. 21. Caterpillar plots of random effects for Substance use (left) and Mental wellbeing (right), Model 1

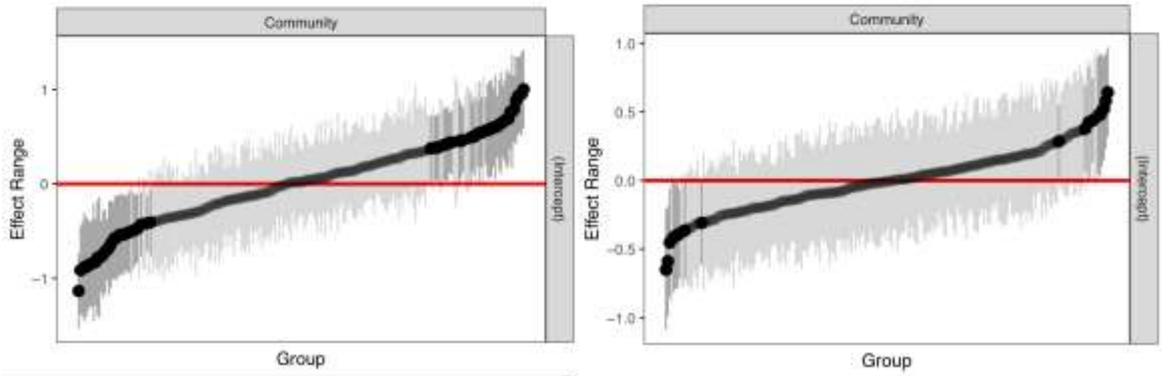


Figure. 22. Caterpillar plots of random effects for Substance use (left) and Mental wellbeing (right), Model 5

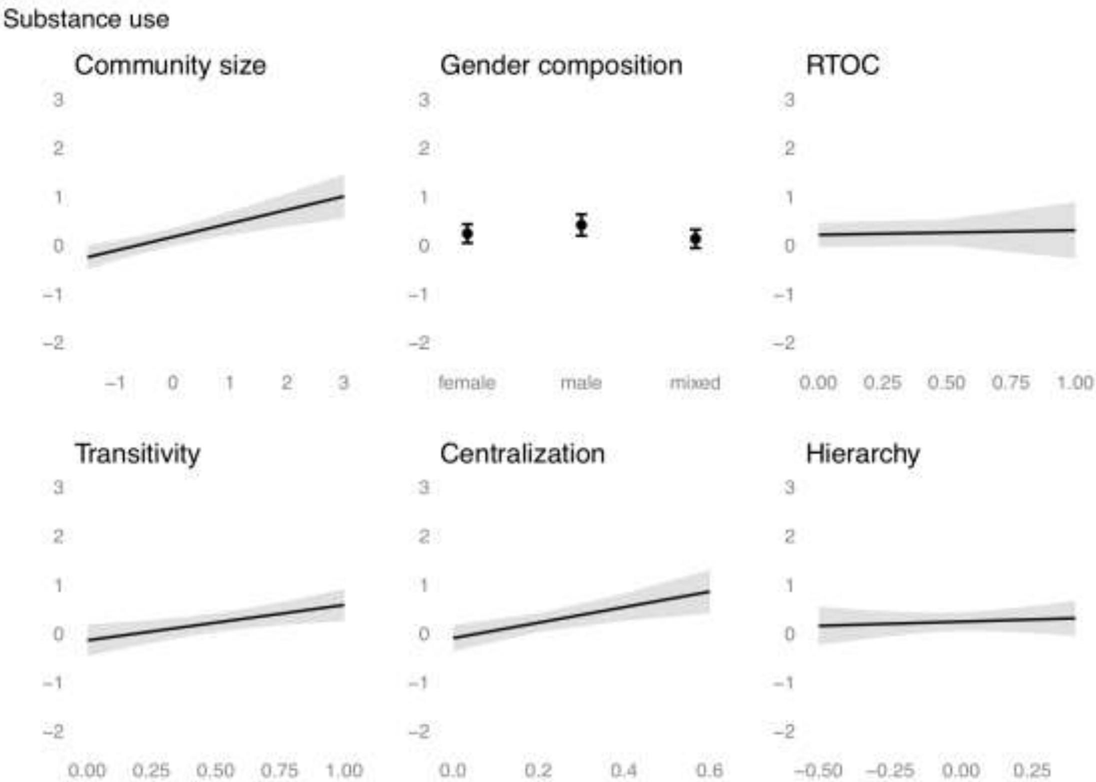


Figure 23. Predictions of Substance use (x-axis) based on Model 5 by varying the community property (y-axis, the focal variable) and holding all other community properties and level 1 covariates (the non-focal variables)

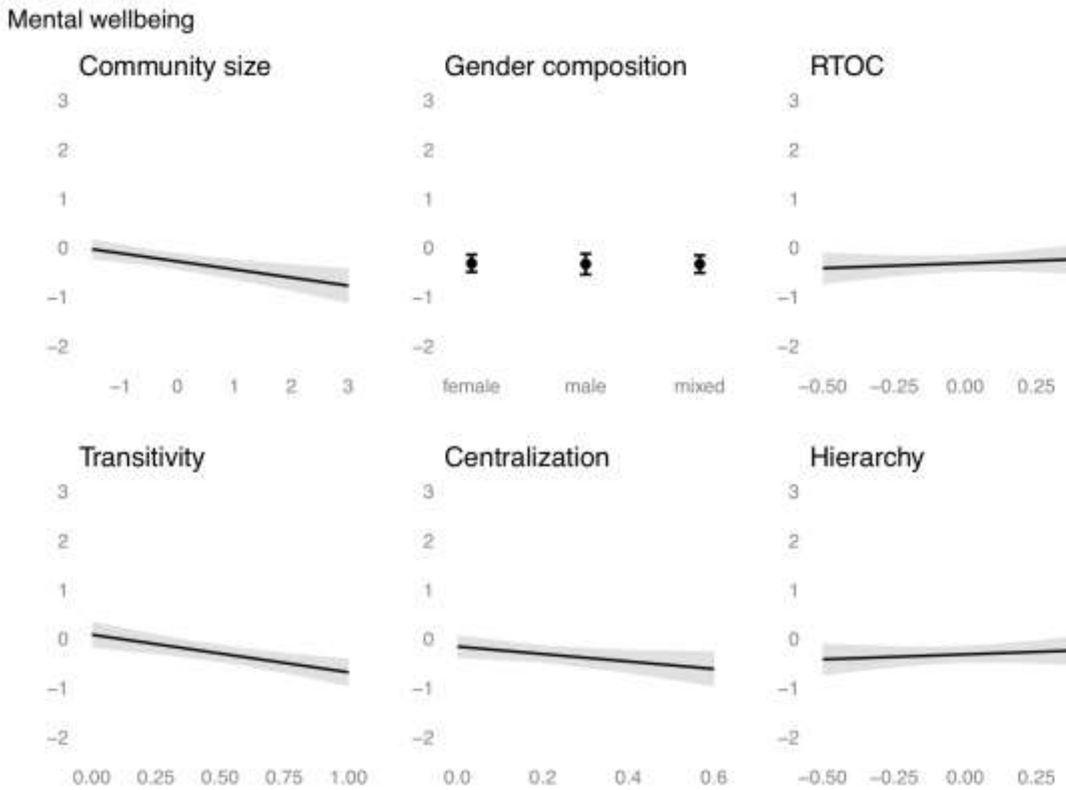


Figure 24. Predictions of Mental wellbeing (x-axis) of Model5 by varying the community property (y-axis, the focal variable) and holding all other community properties and level 1 covariates (the non-focal variables)

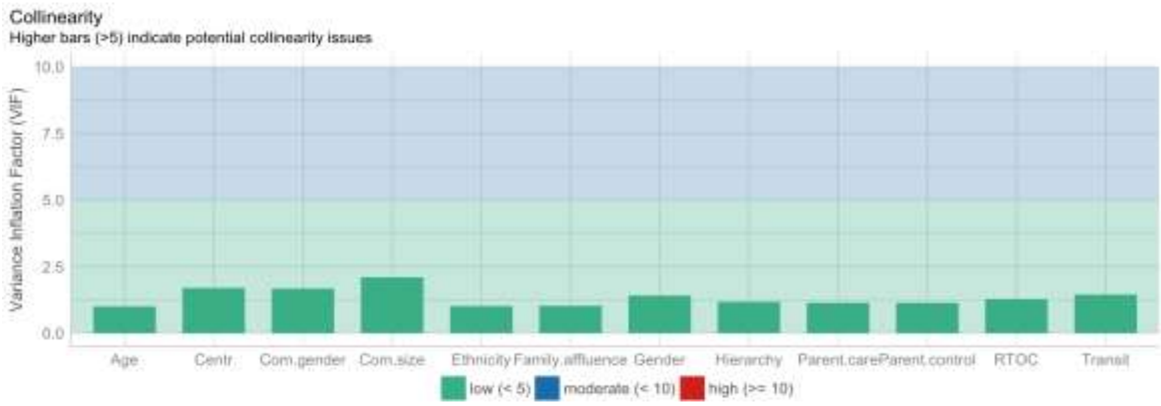


Figure 25. Variation inflation factors (Model 5, Dependent variable: Substance use)

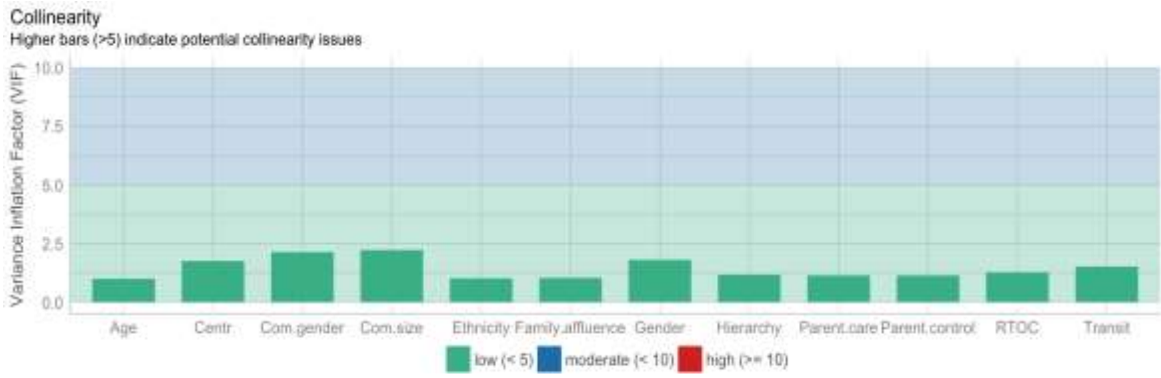


Figure 26. Variation inflation factors (Model 5, Dependent variable: Mental wellbeing)

5.1 Pair-wise model comparisons

Each progressively more complex model was compared with the previous model to gauge whether the fit is significantly better (ANOVA F test).

Results demonstrate (table 7) that for both outcomes, Model 1.1 that included schools as a level within which communities are nested and Model 1 which included only community level, did not differ in how they fit the data. When ROTC, transitivity, and centralization are added models show a significantly better fit for both outcomes.

Table 7. *P*-values of comparisons between different pairs of models

Dependent variable	Substance use	Mental wellbeing
Compared models	χ^2 p	χ^2 p
M1.1 & M1	1	1
M2 & M1	<0.001***	0
M3 & M2	1	1
M4 & M3	0.04*	0.01*
M5 & M4	0.79	1
M6 & M5	0.8	1

****p*<0.001
***p*<0.01
**p*<0.05

5.2 Comparison of all models

We compared all six models, for each outcome separately, using performance R package (Lüdecke et al., 2021). Using *compare_performance* function allowed us to assess model fit and rank them from the best to the worst based on five indices: R^2 (adjusted R squared), ICC (adjusted intraclass correlation coefficient), RMSE (root-mean-square error), AIC (Akaike information criterion), Sigma (residual standard error) and BIC (Bayesian information criterion). Based on those indices, Performance Score is calculated for both health outcomes M5 is ranked as the best model (for more details on the exact procedure see Lüdecke et al., 2021).

Table 8. Ranked models – Substance use

Model	R^2 conditional	R^2 marginal	ICC	RMSE	Sigma	AIC	BIC	Performance Score
M5	0.41	0.17	0.29	0.73	0.76	0.92	1.00	0.82
M3	0.41	0.13	0.33	0.73	0.76	0.00	0.00	0.60
M4	0.41	0.14	0.32	0.73	0.76	0.00	0.00	0.59
M2	0.41	0.12	0.33	0.73	0.76	0.00	0.00	0.58
M6	0.41	0.17	0.29	0.73	0.76	0.08	0.00	0.56
M1	0.37	0.00	0.37	0.77	0.81	0.00	0.00	0.14

Abbreviations: For the meaning of the acronyms in the first row, see the text above table 8.

Table 9. Ranked models – Mental wellbeing

Model	R^2 conditional	R^2 marginal	ICC	RMSE	Sigma	AIC	BIC	Performance Score
M5	0,26	0,16	0,12	0,82	0,84	0,97	1,00	0,84
M6	0,26	0,16	0,12	0,82	0,84	0,03	0,00	0,57
M3	0,26	0,15	0,14	0,82	0,85	0,00	0,00	0,57
M2	0,26	0,15	0,14	0,82	0,85	0,00	0,00	0,56
M4	0,26	0,15	0,13	0,82	0,84	0,00	0,00	0,55
M1	0,19	0,00	0,19	0,86	0,89	0,00	0,00	0,14

. Abbreviations: For the meaning of the acronyms in the first row, see the text above table 8.

6.1 Diagnostics of Model 5 (Walktrap)

We performed model diagnostics for Model 5 (GDA: Walktrap) for both dependent variables to check if assumptions required for multilevel modelling are violated. We tested normality of residuals at level 1 and 2, heteroscedasticity, existence of outliers, and autocorrelation (*check_model* function in performance R package: Ludecke at al., 2021).

The assumption of homoscedascity is met, residuals appear to be independent, and no outliers are detected for both outcomes.

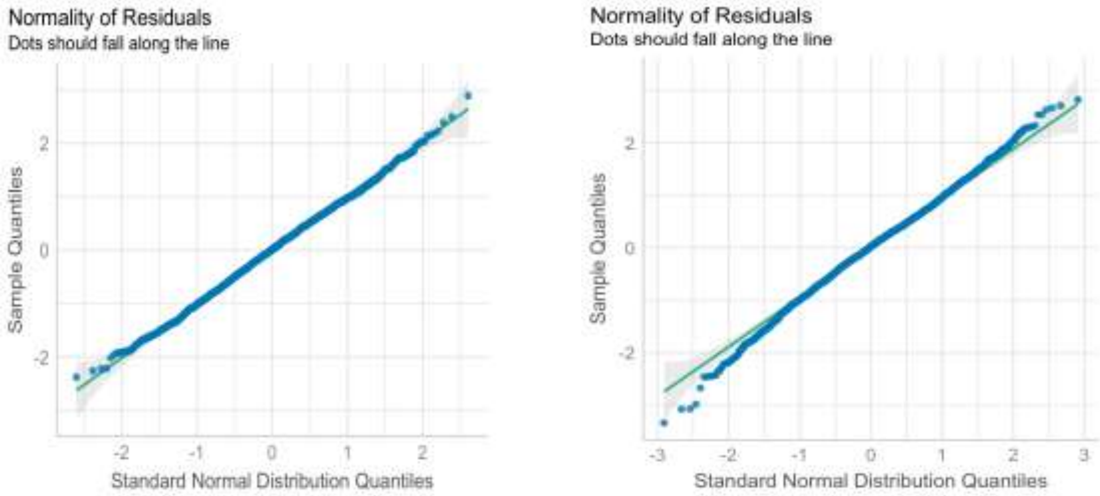


Figure 27. Normality of residuals for Substance use (p = 0.196) and Mental Wellbeing (p< .001, non-normality detected)

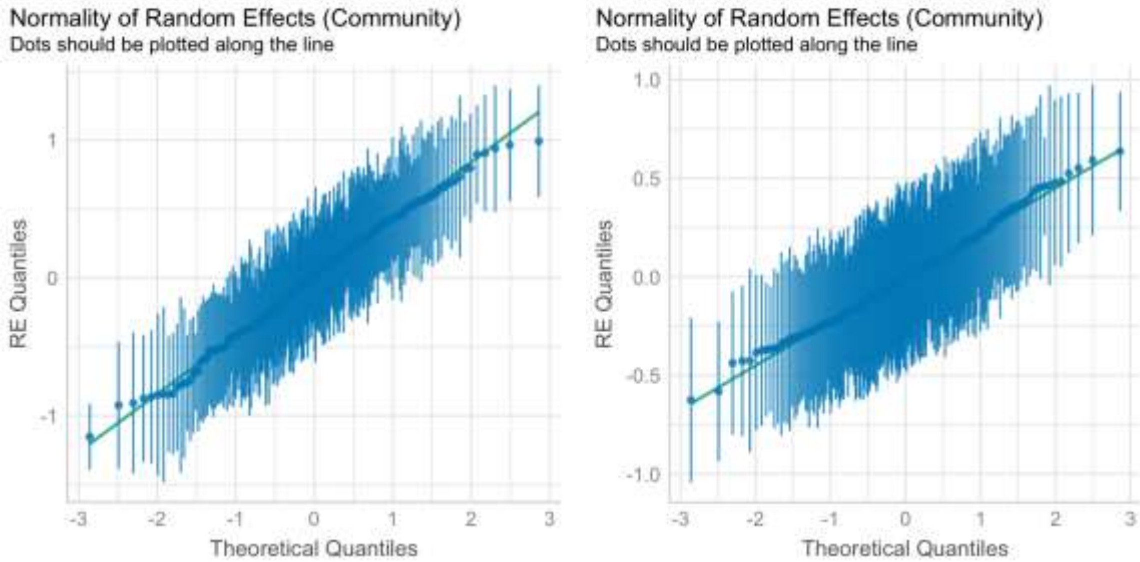


Figure 28. Normality of random effects for Substance use (p = 0. 443) and Mental Wellbeing (p = 0. 378, non-normality detected)

6.2 Effect sizes

Effects sizes for all significant predictors in Model 5 (for both outcomes) are calculated and interpreted using Hopkins' and Cohen's interpretations, shown in tables 10 and 11.

Table 10. Effect sizes for Substance use (Model 5)

Variables	t	df	Effect Size (Cohen's *d*)	Hopkins' interpretation	Cohen's interpretation
Gender (male vs female)	3,51	2666,69	0,14	Trivial	Small
Age (dich)	-2,57	2582,37	-0,10	Trivial	Small
Ethnicity (white vs non-white)	-7,47	2669,18	-0,29	Small	Small
Family affluence (medium vs low)	2,03	2594,24	0,08	Trivial	Small
Family affluence (high vs low)	1,35	2641,14	/	/	/
Parental control	-6,95	2561,18	-0,27	Small	Small
Parental care	13,72	2562,02	0,54	Small	Medium
Community size	4,24	205,69	0,59	Small	Medium
Community gender comp.(male vs female)	1,67	398,83	/	/	/
Community gender comp.(mixed vs female)	-1,11	234,29	/	/	/
Ratio of ties outside community	0,26	231,59	/	/	/
Transitivity	2,69	280,48	0,32	Small	Small
Centralization	3,14	245,41	0,40	Small	Small
Hierarchy	0,47	263,13	/	/	/

/ - Statistically not significant effects.

Table 11. Effect sizes for Mental wellbeing (Model 5)

Variables	t	df	Effect Size (Cohen's *d*)	Hopkins' interpretation	Cohen's interpretation
Gender (male vs female)	9,75	2548,40	0,39	Small	Small
Age (dich)	0,05	2662,63	/	/	/
Ethnicity (white vs non-white)	1,43	2355,03	/	/	/
Family affluence (medium vs low)	-0,60	2668,07	/	/	/
Family affluence (high vs low)	-0,59	2675,78	/	/	/
Parental control	-10,02	2639,51	-0,39	Small	Small
Parental care	5,62	2644,96	0,22	Small	Small
Community size	-3,41	176,64	-0,51	Small	Medium
Community gender comp.(male vs female)	-0,18	510,29	/	/	/
Community gender comp.(mixed vs female)	-0,21	237,84	/	/	/
Ratio of ties outside community	-1,17	227,89	/	/	/
Transitivity	-3,54	324,72	-0,39	Small	Small
Centralization	-1,93	254,84	/	/	/
Hierarchy	0,69	294,11	/	/	/

/ - Statistically not significant effects.

7 Community detection algorithms

We applied ten GDAs to friendship networks of 22 schools. Figures 29, 30 and 31 illustrate different partitions of the friendship network for one school. We chose schools with relatively smaller number of students, so that partitions are easier to see in visualizations. Note that all GDAs find exclusive communities (where nobody is a member of two or more groups). CP originally gives overlapping communities, but all students that were assigned to more than one groups are placed in the community with which they had the most ties. Overlap between colours of different communities is result of the node placement in the plots. Isolates are not shown in figures 29, 30 and 31.

A short description of ten GDAs is provided in table 12.

Table 12. Short description of all GDAs used in Chapter 4

Algorithm (abbreviation)	**Directed**	**Basic logic**	Tuning parameters	Possible use
Block-modelling – indirect approach (BIA)	Yes	Identifies groups of nodes with similar position and profile of ties to others. Based on the notion of structural equivalence (Batagelj et al., 1992).	Similarity measure based on profile of in and out going ties; partition is done with hierarchical clustering (average method); number of clusters for each school/network is based on combination of indices: average Jaccard similarity and Instability (1000 bootstrap samples), and R^2.	When not interested in the social influence within a community, but rather in different social positions and roles in the network.
Clique Percolation (CP)	No	Starts with identifying k-cliques, which are fully connected networks with k nodes. A community is defined as a set of adjacent k-cliques that share exactly k−1 nodes. With k=3, two 3-cliques are adjacent if they share exactly two nodes (equivalent to an edge). A node can belong to more than one community (Palla et al., 2005)	Cliques of size 3 are considered (González et al., 2007).	When interested in social influence for which tight, small communities with possibly structurally strong ties are supposed to be relevant and there is no emphasis on minimising outside community ties.
Edge-betweenness (EB)	Yes*	Gradually removes the edges with the highest edge betweenness score (Newman & Girvan, 2004).	For directed networks. Directed paths are considered when determining the shortest paths.	When the interest is in identifying edges that are the most crucial for transmission – the ones that have the highest edge-betweenness score and are between communities
Fast-greedy (FG)	No	Tries to find dense subgraphs in graphs via directly optimising the modularity score (Clauset et al., 2005).	None/default settings	
Infomap (IM)	Yes	Finds community structure by simulating the flow of information through a network that minimises the expected description length of a random walker trajectory (Rosvall & Bergstrom, 2007).	The number of attempts to partition the network is set to 10.	Questions about transmission of information, behaviours as simple contagion because it defines communities on basis of flow
Leiden (LE)	No	Similar approach to Louvian method, but with the goal of identifying well-connected communities (Traag et al., 2019).	Objective function is set to "modularity"; resolution parameter = 1; beta = 0.01; number of iterations = 2; initial membership is not provided.	When interested in processes within communities and not between them, LO and LE are good choices because they minimise the outside community connections and maximise inside community connections
Louvain (LO)	No	Based on the modularity measure and a hierarchical approach. In every step, vertices are re-assigned to communities in a local, greedy way: each vertex is moved to the community with which it achieves the highest contribution to modularity (Blondel et al., 2008).	None/default settings	
Label propagation (LP)	No	Starts with random assignment of labels to vertices, and keeps reassigning the labels iteratively based on the labels of nearest neighbours until reaching convergence (Raghavan et al., 2007).	None/default settings	Questions about adoption of social norms because it is based on the processes of iterative adoption

Stochastic block modelling (SBM)	Yes	Identifies groups of nodes with similar position. Based on the notion of regular equivalence (Kolaczyk & Csárdi, 2014).	Performs estimation of blockmodels for bernoulli probability distribution, verbosity = 3; exploration factor = 5.	When not interested in the social influence within a community, but rather in different social positions and roles in the network.
Walktrap (WT)	Yes	Finds densely connected communities in a graph by simulating the path of a random walker over time. The idea is that short random walks tend to be trapped in the same community (Pons & Latapy, 2005).	The length of random walk to perform is set to 4.	Research questions about transmission of information, behaviours as simple contagion because it defines communities on basis of flow

***** The function *cluster_edge_betweenness* in igraph R package calculates directed edge betweenness for directed graphs.

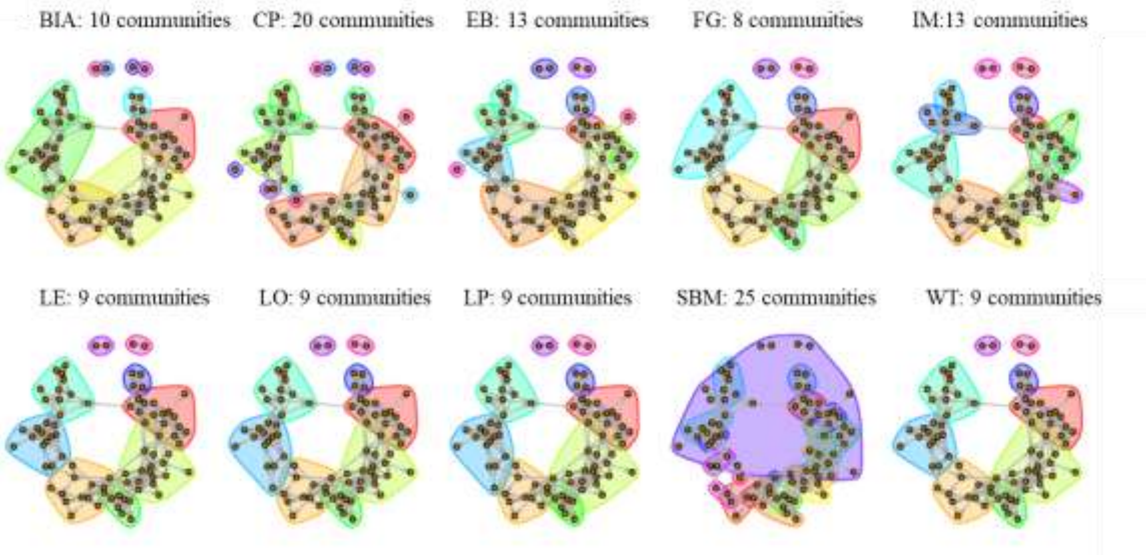


Figure 29. Partitions of ten GDAs for school 3 *(N* = 73; Non-responders = 18%)

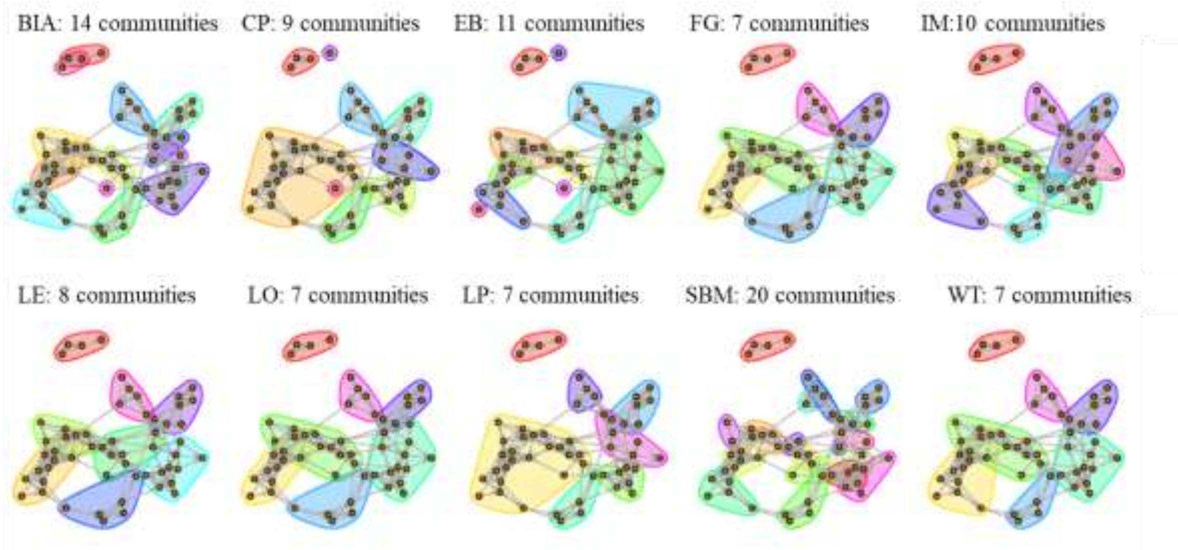


Figure 30. Partitions of ten GDAs for school 15 (*N* = 57; Non-responders = 7%)

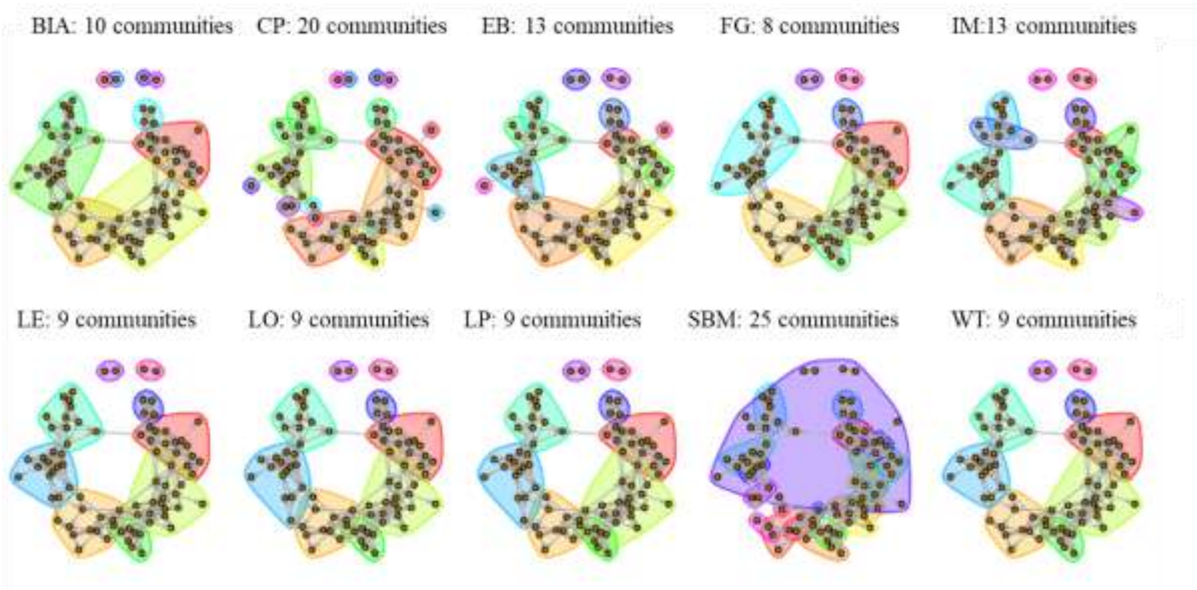


Figure 31. Partitions of ten GDAs for school 19 (N = 86; Non-responders = 11%)

7.1 Similarity between ten GDAs – Adjusted Rand index

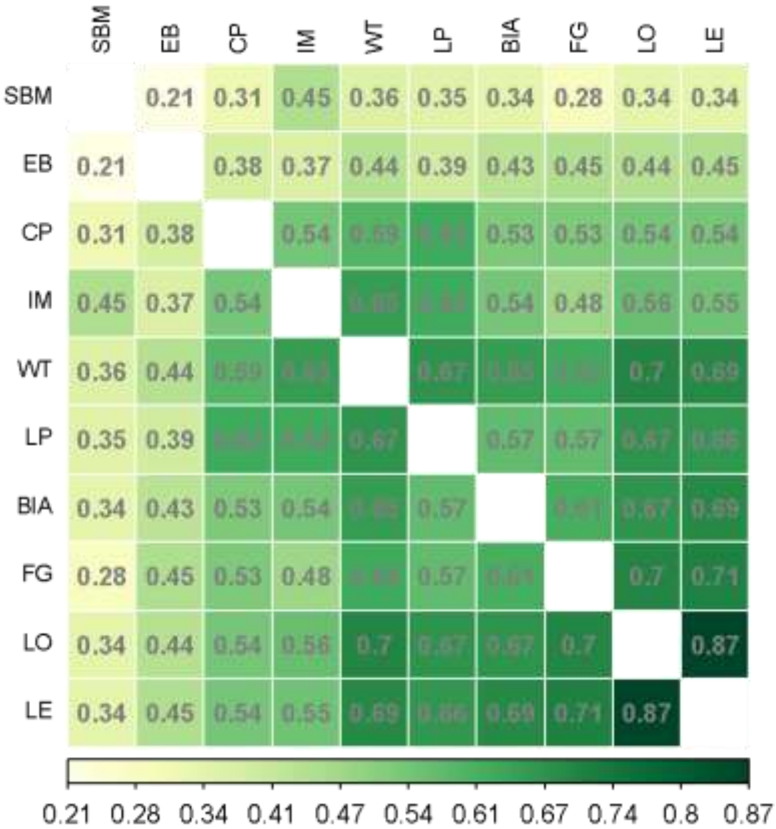


Figure 32. Average similarity based on adjusted Rand measure of 22 schools between ten GDAs (ordering by hierarchical clustering, method "average")

Figure 32 shows adjusted Rand (AR) indices for each pair of GDAs. AR can range from 0 (no overlap) to 1 (completely the same partition). The ordering of GDAs in the plot was done by hierarchical clustering (method average). SBM has the smallest overlap, followed by EB and CP, while LE and LO have the highest overlap with other methods (the highest being between the two).

Table 13. Descriptives of community properties for each GDA

GDA	Community property	N	Mean	SD	Median	Min.	Max.	Range	Skew.	Kurtosis
BIA	Community size	300	12.16	9.592	11	1	62	61	1.237	2.462
	Prop. F	287	0.53	0.447	0.67	0	1	1	-0.122	-1.824
	Ratio of outside community ties	300	0.42	0.317	0.31	0	1	1	0.943	-0.513
	Transitivity	300	0.58	0.194	0.56	0	1	1	0.092	0.8
	Centralization	237	0.24	0.111	0.22	0	0.708	0.708	1.116	1.917
	Hierarchy	199	0	0.08	0	-0.22	0.19	0.41	-0.033	-0.397
CP	Community size	895	4.08	6.715	1	1	98	97	5.653	54.515
	Prop. F	667	0.48	0.481	0.42	0	1	1	0.057	-1.936
	Ratio of outside community ties	895	0.76	0.308	1	0	1	1	-0.799	-0.961
	Transitivity	895	0.81	0.204	0.8	0	1	1	-0.859	0.585
	Centralization	341	0.26	0.145	0.25	0	0.75	0.75	0.285	0.646
	Hierarchy	188	-0.03	0.107	-0.05	-0.27	0.36	0.63	0.601	0.89
EB	Community size	546	6.68	12.476	3	1	106	105	4.295	22.153
	Prop. F	465	0.55	0.466	0.75	0	1	1	-0.219	-1.842
	Ratio of outside community ties	546	0.63	0.349	0.67	0	1	1	-0.248	-1.471
	Transitivity	546	0.78	0.259	0.89	0	1	1	-1.046	0.457
	Centralization	268	0.22	0.17	0.2	0	1	1	1.144	2.076
	Hierarchy	137	0.02	0.112	0.02	-0.22	0.37	0.59	0.05	-0.234
FG	Community size	235	15.53	12.296	13	2	81	79	1.931	5.335
	Prop. F	235	0.54	0.428	0.65	0	1	1	-0.18	-1.717
	Ratio of outside community ties	235	0.23	0.134	0.24	0	0.62	0.62	0.16	-0.132
	Transitivity	235	0.56	0.187	0.54	0	1	1	0.255	0.859
	Centralization	215	0.22	0.124	0.2	0	1	1	2.092	8.26
	Hierarchy	191	0.01	0.08	0.01	-0.22	0.26	0.48	0.276	0.924
IM	Community size	525	6.95	3.951	6	1	28	27	1.185	2.25
	Prop. F	522	0.52	0.469	0.68	0	1	1	-0.104	-1.894
	Ratio of outside community ties	525	0.38	0.194	0.38	0	1	1	0.254	0.27
	Transitivity	525	0.64	0.247	0.64	0	1	1	-0.749	0.744
	Centralization	460	0.32	0.163	0.3	0	1	1	1.205	3.253
	Hierarchy	294	-0.02	0.11	-0.03	-0.27	0.36	0.63	0.494	0.101

LE	Community size	252	14.48	8.496	14	2	45	43	0.76	0.543
	Prop. F	252	0.54	0.437	0.66	0	1	1	-0.183	-1.761
	Ratio of outside community ties	252	0.23	0.124	0.24	0	0.56	0.56	-0.148	-0.297
	Transitivity	252	0.56	0.172	0.54	0	1	1	0.529	1.01
	Centralization	234	0.21	0.103	0.2	0	0.75	0.75	1.483	4.28
	Hierarchy	212	0	0.084	0	-0.22	0.37	0.59	0.607	2.134
LO	Community size	253	14.42	8.286	13	2	41	39	0.681	0.167
	Prop. F	253	0.54	0.435	0.64	0	1	1	-0.177	-1.75
	Ratio of outside community ties	253	0.23	0.124	0.25	0	0.55	0.55	-0.322	-0.483
	Transitivity	253	0.56	0.167	0.54	0	1	1	0.507	1.224
	Centralization	235	0.22	0.103	0.2	0	0.75	0.75	1.52	4.233
	Hierarchy	214	0	0.085	0	-0.22	0.37	0.59	0.505	1.635
LP	Community size	401	9.1	6.08	7	1	40	39	1.704	4.143
	Prop. F	401	0.54	0.465	0.75	0	1	1	-0.173	-1.869
	Ratio of outside community ties	401	0.34	0.17	0.35	0	1	1	0.064	0.266
	Transitivity	401	0.64	0.221	0.6	0	1	1	-0.21	0.195
	Centralization	374	0.27	0.129	0.26	0	1	1	0.895	3.233
	Hierarchy	253	-0.01	0.109	-0.02	-0.46	0.37	0.83	0.282	1.819
SBM	Community size	680	5.37	4.642	4	1	43	42	3.362	18.606
	Prop. F	666	0.51	0.468	0.54	0	1	1	-0.057	-1.886
	Ratio of outside community ties	680	0.67	0.274	0.68	0	1	1	-0.296	-1.115
	Transitivity	663	0.75	0.279	0.8	0	1	1	-1.256	1.087
	Centralization	446	0.24	0.18	0.23	0	1	1	0.994	2.114
	Hierarchy	228	0.03	0.143	0.02	-0.3	0.37	0.67	-0.043	-0.875
WT	Community size	387	9.43	7.216	7	1	44	43	1.679	3.546
	Prop. F	387	0.53	0.463	0.71	0	1	1	-0.128	-1.865
	Ratio of outside community ties	387	0.29	0.158	0.29	0	1	1	0.4	0.772
	Transitivity	387	0.6	0.243	0.6	0	1	1	-0.451	0.397
	Centralization	339	0.28	0.153	0.25	0	1	1	1.348	4.039
	Hierarchy	236	0	0.11	-0.01	-0.46	0.37	0.83	0.328	1.416

Abbreviations: GDA – community detection algorithm; N – non-missing data; SD – standard deviation; Skew. – skewness; Prop. F – proportion of females in community

We started with the ensemble of methods available in R software. All methods used are available in igraph package (Csardi & Nepusz, 2006). except for CP method which is available in clique percolation package (Lange, 2021). We slightly modified the original code so that it can handle network matrices as input data and provide results for non-weighted networks. Igraph package also includes Spinglass, Fluid communities and Leading eigenvector, but we have not used them since they require the input network to be connected, which was not the case for 17 out of 22 school networks. For SBM, we used blockmodels R package (Leger, 2016). For choosing the optimal number of clusters for each network for BIA method, we used *clusterboot* function from fpc R package (Hennig & Imports, 2015).

As Table 12 shows. CP, FG, LE, LO, and LP algorithms are implemented only for undirected networks. Therefore, we used the undirected version of original networks for these algorithms. Specifically, we symmetrized networks with so-called "weak rule". Weak rule means that the information about directionality of ties is disregarded – both mutual and non-mutual ties are treated equally, as an undirected tie. In other words, if student A nominated student B as their friend, but B did not nominate A, this tie is treated equally as if A and B nominated each other.

Table 14. Community detection algorithms and female. male. and mixed communities found in 22 schools

GDA	BIA	CP	EB	FG	IM	LE	LO	LP	SBM	WT
N Com.	300	895	546	235	525	252	253	401	680	387
N F com	100	281	213	77	215	86	83	167	285	156
N M com	93	317	174	66	213	75	77	149	275	148
% F com	33.33	31.4	39.01	32.77	40.95	34.13	32.81	41.65	41.91	40.31
%students in F com	26.51	33.36	24.52	23.49	36.94	25.71	25.65	34.89	36	33.13
%students in M com	25.3	32.54	20.82	20.96	38.78	26.97	27.35	33.41	35.14	32.42
%students in Mix com	48.2	34.09	54.65	55.55	24.27	47.33	47	31.71	28.86	34.45

Abbreviations: GDA – group detection algorithm; N – number; Com. – community; F – female; M – male; Mix com – mixed communities

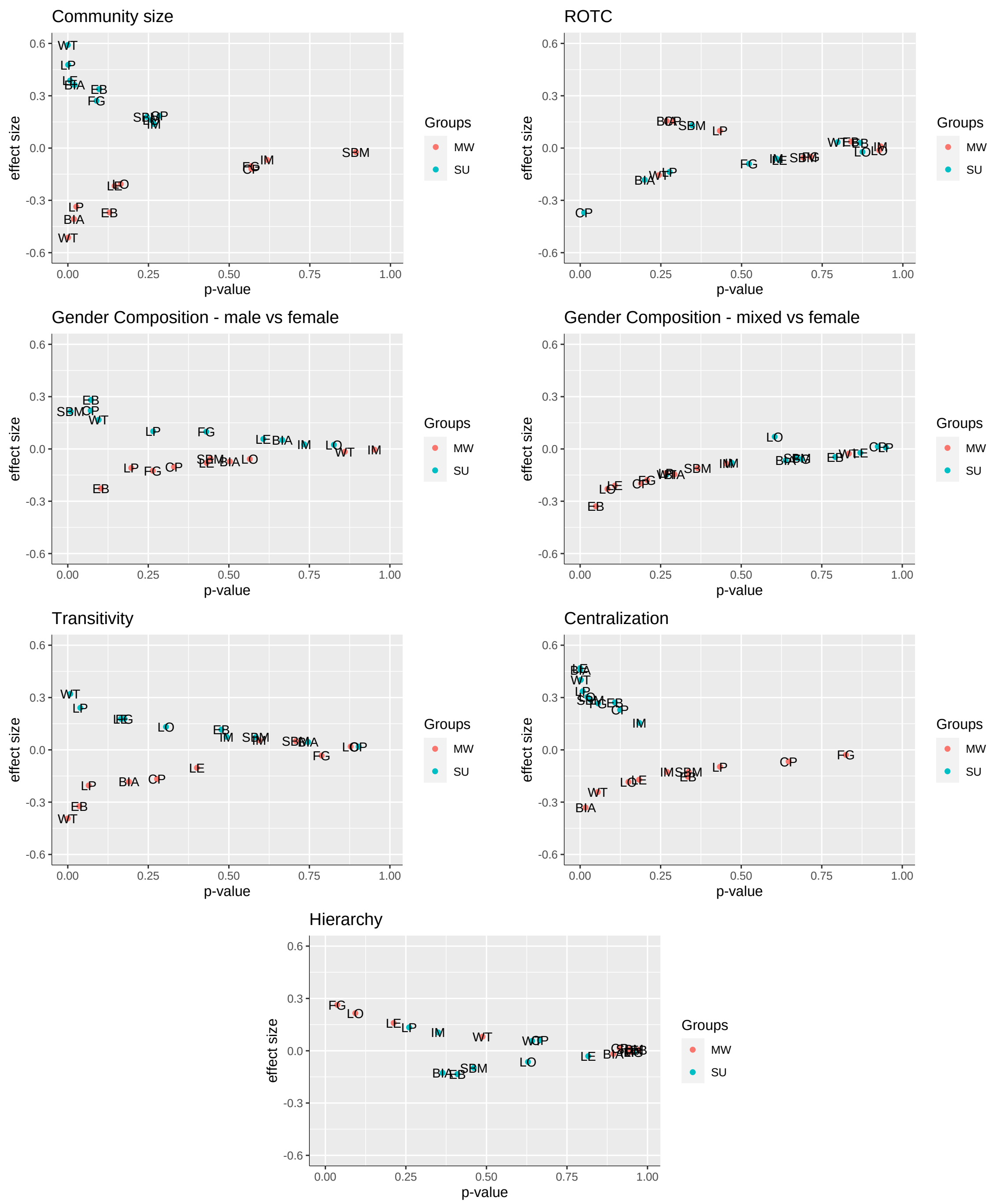


Figure 33. Effect sizes and *p* values for six community properties (Model 5), for two outcomes Substance use (SU) and Mental wellbeing (MW) and for ten GDAs.

7.2 Additional community indices: the mixing parameter and high-risk communities

Mixing parameter

The mixing parameter is a value similar to the ratio of ties outside community (ROTC), but can be calculated on all network levels. The formula is as follows:

$$\mu = \frac{\Sigma_i k_i^{ext}}{\Sigma_i k_i^{tot}}$$

$\Sigma_i k_i^{ext}$ is the sum of all outside community ties of a node i, and $\Sigma_i k_i^{tot}$is the sum of all i's ties – inside and outside the community. It is possible to calculate μ for each node, community and for the whole network.

High-risk communities

For both dependent variables. 25% of students in the whole sample with lowest scores were identified as "cases". We defined high risk communities as communities with at least four members of which 50% or more are "cases".

Table 15. Additional indices for GDAs related with mixing parameter and high risk communities

GDA	BIA	CP	EB	FG	IM	LE	LO	LP	SBM	WT
N communities	300	895	546	235	525	252	253	401	680	387
Mixing parameter	0.2	0.2	0.21	0.1	0.2	0.1	0.1	0.1	0.4	0.2
% students with all ties inside	47.1	33.13	40.81	55.9	35.2	53.1	52.8	43.1	17.1	46.3
Substance use										
N communities without DV data*	13	228	81	0	3	0	0	0	14	0
N of high risk communities	44	69	43	39	97	39	37	81	97	65
% students in high risk com.	15.1	14.7	10.8	15.5	20	17.1	16.1	18.6	18.7	16.1
% cases in high risk com.	39.6	41.8	28.3	38.8	52.2	44.1	40.7	49.4	47.6	42.8
Mental wellbeing										
N communities without DV data*	32	55	35	31	81	26	27	57	81	43
N of high risk communities	10.8	11.4	9.1	10.5	15.9	9.3	10.7	13.9	13.8	12
% students in high risk com.	113	110	74	110	142	128	110	133	120	107
% cases in high risk com.	14.3	13.9	9.3	13.9	18	16.2	13.9	16.8	15.2	13.6

Abbreviations: GDA – group detection algorithm; N – number; DV – dependent variable (outcome); high risk com. – high risk communities

8 Robustness checks

We conducted several robustness checks:

- Models on raw composite score and factor scores (models 1, 2, 5 and 6, Walktrap)
- Models with dichotomized DV, so that 25% of students with worse outcome have a score of 1(models 1, 2, 5 and 6, Walktrap)
- A simulation of having more partly-missing network data – random deletion of out-going ties school network (Model 1 and 5, Walktrap)

8.1 Raw scores for Substance use and Mental wellbeing as outcome

Models on raw composite scores (Models1, 2, 5, and 6; Walktrap, imputed data) are shown in tables 16 and 17.

Table 16. Dependent variable: Raw score for Substance use - results for Walktrap community detection algorithm; Models 1, 2, 5, and 6

Parameters/ Models	M1	M2	M5	M6
(Intercept)	-0.03 (0.04)	0.46 (0.08) ***	-0.55 (0.27) *	-0.42 (1.06)
Level 1 covariates				
Gender (male)		-0.02 (0.05)	-0.06 (0.06)	-0.07 (0.06)
Age (dich)		-0.08 (0.03) **	-0.08 (0.03) *	-0.08 (0.03) *
Ethnicity (white)		-0.53 (0.06) ***	-0.50 (0.07) ***	-0.50 (0.07) ***
Family affluence (medium)		0.08 (0.04)	0.08 (0.05)	0.08 (0.05)
Family affluence (high)		0.02 (0.05)	0.05 (0.05)	0.05 (0.05)
Parental control		-0.02 (0.02)	-0.02 (0.02)	-0.02 (0.02)
Parental care		0.17 (0.02) ***	0.17 (0.02) ***	0.17 (0.02) ***
Level 2 covariates				
Community size			0.33 (0.08) ***	0.34 (0.08) ***
Community gender comp.(male)			0.17 (0.12)	0.16 (0.12)
Community gender comp.(mixed)			-0.10 (0.11)	-0.12 (0.11)
Ratio of ties outside community			0.16 (0.42)	0.29 (0.49)
Transitivity			0.99 (0.31) **	1.09 (0.33) ***
Centralization			1.74 (0.58) **	1.67 (0.59) **
Hierarchy			0.13 (0.43)	0.12 (0.43)
Level 3 covariates				
School/network size				-0.06 (0.06)
Modularity (school)				0.64 (1.24)
Prop. F in school				-1.10 (0.90)
Num. obs.	3148	3148	2698	2698
N groups: Community	387	387	236	236
AIC	8073.20	7903.76	6696.80	6700.71
BIC	8091.37	7964.30	6797.10	6818.72
Log Likelihood	-4033.60	-3941.88	-3331.40	-3330.36
Var: Community (Intercept)	0.48	0.42	0.34	0.34
Var: Residual	0.61	0.57	0.58	0.58
ICCadj./ICCcond.	0.44/0.44	0.42/0.40	0.37/0.34	0.37/0.34
R^2mar./ R^2cond.	0/0.44	0.05/0.45	0.09/0.43	0.09/0.43

Abbreviations: Community gender comp. – community gender composition; Prop. F in school – proportion of females in the school; Num. obs. – Number of observations; AIC – Akaike information criterion; BIC – Bayesian information criterion; Var – variance; N groups – number of groups; ICCadj. – adjusted intraclass correlation coefficient; ICCcond. – conditional intraclass correlation coefficient; R^2mar. – marginal R^2; R^2cond. – conditional R^2; Age is dichotomized: 15 yrs = 0; 16 and 17 yrs = 1

Reference categories for factors: Gender – female; Ethnicity – non-white; Family affluence – low; Community gender comp. – female

Table 17. Dependent variable: Raw score for Mental wellbeing - results for Walktrap community detection algorithm; Models 1, 2, 5, and 6

Parameters/ Models	M1	M2	M5	M6
(Intercept)	-0.02 (0.03)	-0.19 (0.07) **	-0.05 (0.15)	0.02 (0.54)
Level 1 covariates				
Gender (male)		0.62 (0.04) ***	0.59 (0.06) ***	0.59 (0.06) ***
Age (dich)		-0.03 (0.03)	-0.04 (0.03)	-0.04 (0.03)
Ethnicity (white)		-0.13 (0.06) *	-0.15 (0.06) *	-0.16 (0.07) *
Family affluence (medium)		0.02 (0.05)	0.03 (0.05)	0.03 (0.05)
Family affluence (high)		0.03 (0.05)	0.02 (0.05)	0.03 (0.05)
Parental control		-0.22 (0.02) ***	-0.22 (0.02) ***	-0.22 (0.02) ***
Parental care		0.20 (0.02) ***	0.21 (0.02) ***	0.21 (0.02) ***
Level 2 covariates				
Community size			0.02 (0.04)	0.03 (0.04)
Community gender comp.(male)			0.05 (0.08)	0.06 (0.08)
Community gender comp.(mixed)			-0.06 (0.06)	-0.06 (0.06)
Ratio of ties outside community			-0.14 (0.22)	-0.15 (0.26)
Transitivity			-0.20 (0.18)	-0.20 (0.19)
Centralization			0.23 (0.31)	0.25 (0.32)
Hierarchy			0.07 (0.24)	0.09 (0.24)
Level 3 covariates				
School/network size				-0.01 (0.03)
Modularity (school)				-0.22 (0.64)
Prop. F in school				0.22 (0.44)
Num. obs.	3148	3148	2698	2698
N groups: Community	387	387	236	236
AIC	8772.16	8163.42	6977.20	6986.83
BIC	8790.32	8223.97	7077.50	7104.83
Log Likelihood	-4383.08	-4071.71	-3471.60	-3473.41
Var: Community (Intercept)	0.14	0.03	0.03	0.03
Var: Residual	0.86	0.75	0.73	0.73
ICCadj./ICCcond.	0.14/0.14	0.04/0.03	0.03/0.03	0.04/0.03
R^2mar./ R^2cond.	0/0.14	0.22/0.25	0.24/0.26	0.24/0.26

Abbreviations: Community gender comp. – community gender composition; Prop. F in school – proportion of females in the school; Num. obs. – Number of observations; AIC – Akaike information criterion; BIC – Bayesian information criterion; Var – variance; N groups – number of groups; ICCadj. – adjusted intraclass correlation coefficient; ICCcond. – conditional intraclass correlation coefficient; R^2mar. – marginal R^2; R^2cond. – conditional R^2; Age is dichotomized: 15 yrs = 0; 16 and 17 yrs = 1;
Reference categories for factors: Gender – female; Ethnicity – non-white; Family affluence – low; Community gender comp. – female

8.2 Factor scores for Substance use and Mental wellbeing as outcome

Models on factor scores (Models1, 2, 5, and 6; Walktrap, imputed data) are shown in tables 18 and 19.

Table 18. Substance use – factor scores, Walktrap, Models 1, 2, 5, and 6

	M1	M2	M5	M6
(Intercept)	-0.03 (0.04)	0.24 (0.08) **	-0.63 (0.26) *	-1.42 (0.98)
Level 1 covariates				
Gender (male)		0.26 (0.05) ***	0.23 (0.06) ***	0.23 (0.06) ***
Age (dich)		-0.07 (0.03) *	-0.07 (0.03)	-0.07 (0.03)
Ethnicity (white)		-0.50 (0.07) ***	-0.47 (0.07) ***	-0.47 (0.07) ***
Family affluence (medium)		0.15 (0.05) **	0.16 (0.05) **	0.17 (0.05) **
Family affluence (high)		0.10 (0.05) *	0.13 (0.06) *	0.14 (0.06) *
Parental control		-0.12 (0.02) ***	-0.12 (0.02) ***	-0.12 (0.02) ***
Parental care		0.23 (0.02) ***	0.23 (0.02) ***	0.23 (0.02) ***
Level 2 covariates				
Community size			0.27 (0.07) ***	0.30 (0.07) ***
Community gender comp.(male)			0.15 (0.11)	0.14 (0.11)
Community gender comp.(mixed)			-0.12 (0.10)	-0.13 (0.10)
Ratio of ties outside community			0.11 (0.39)	0.44 (0.46)
Transitivity			0.81 (0.30) **	0.96 (0.31) **
Centralization			1.48 (0.54) **	1.45 (0.55) **
Hierarchy			0.09 (0.40)	0.02 (0.41)
Level 3 covariates				
School/network size				-0.08 (0.06)
Modularity (school)				1.42 (1.15)
Prop. F in school				-0.48 (0.83)
Num. obs.	2729	2528	2197	2197
N groups: Community	7184.12	6317.40	5447.70	5451.87
AIC	7201.86	6375.75	5544.51	5565.77
BIC	-3589.06	-3148.70	-2706.85	-2705.93
Log Likelihood	380	371	236	236
Var: Community (Intercept)	0.38	0.30	0.25	0.25
Var: Residual	0.67	0.58	0.58	0.58
ICCadj./ICCcond.	0.39/0.39	0.37/0.35	0.33/0.29	0.33/0.29
R^2mar./ R^2cond.	0.0/0.39	0.07/0.42	0.11/0.40	0.12/0.41

Abbreviations: Community gender comp. – community gender composition; Prop. F in school – proportion of females in the school; Num. obs. – Number of observations; AIC – Akaike information criterion; BIC – Bayesian information criterion; Var – variance; N groups – number of groups; ICCadj. – adjusted intraclass correlation coefficient; ICCcond. – conditional intraclass correlation coefficient; R^2mar. – marginal R^2; R^2cond. – conditional R^2; Age is dichotomized: 15 yrs = 0; 16 and 17 yrs = 1; **Reference categories** for factors: Gender – female; Ethnicity – non-white; Family affluence – low; Community gender comp. – female

Table 19. Mental wellbeing – factor scores, Walktrap, Models 1, 2, 5, and 6

	M1	M2	M5	M6
(Intercept)	-0.01 (0.03)	-0.35 (0.08) ***	0.25 (0.21)	0.05 (0.75)
Level 1 covariates				
Gender (male)		0.58 (0.04) ***	0.55 (0.06) ***	0.55 (0.06) ***
Age (dich)		-0.00 (0.04)	-0.01 (0.04)	-0.01 (0.04)
Ethnicity (white)		0.10 (0.07)	0.09 (0.07)	0.08 (0.07)
Family affluence (medium)		-0.04 (0.05)	-0.05 (0.06)	-0.05 (0.06)
Family affluence (high)		-0.02 (0.06)	-0.05 (0.06)	-0.05 (0.06)
Parental control		-0.19 (0.02) ***	-0.20 (0.02) ***	-0.20 (0.02) ***
Parental care		0.10 (0.02) ***	0.10 (0.02) ***	0.10 (0.02) ***
Level 2 covariates				
Community size			-0.12 (0.05) *	-0.13 (0.06) *
Community gender comp.(male)			0.03 (0.10)	0.03 (0.10)
Community gender comp.(mixed)			-0.04 (0.08)	-0.03 (0.08)
Ratio of ties outside community			-0.30 (0.30)	-0.34 (0.36)
Transitivity			-0.58 (0.24) *	-0.62 (0.25) *
Centralization			-0.65 (0.43)	-0.62 (0.43)
Hierarchy			0.27 (0.32)	0.28 (0.33)
Level 3 covariates				
School/network size				0.02 (0.04)
Modularity (school)				-0.17 (0.89)
Prop. F in school				0.59 (0.63)
Num. obs.	2729	2528	2197	2197
N groups: Community	7510.45	6625.06	5736.29	5743.46
AIC	7528.19	6683.41	5833.10	5857.35
BIC	-3752.23	-3302.53	-2851.14	-2851.73
Log Likelihood	380	371	236	236
Var: Community (Intercept)	0.19	0.10	0.10	0.10
Var: Residual	0.81	0.72	0.71	0.71
ICCadj./ICCcond.	0.17/0.17	0.07/0.06	0.07/0.05	0.07/0.05
R^2mar./ R^2cond.	0.0/0.17	0.19/0.25	0.21/0.26	0.21/0.26

Abbreviations: see table 18.

8.3 Dichotomized scores for Substance use and Mental wellbeing as outcome

Models on dichotomized dependent variables (Models1, 2, 5, and 6; Walktrap, imputed data) are shown in tables 20 and 21. The dichotomization is done for each outcome by assigning values 1 to all students in the complete sample whose principal component score was among the lowest 25% - signifying the worse outcome (so-called “cases” – individuals who would potentially benefit from an intervention). Note that the in models shown in tables 20 and 21, a higher value is associated with a worse outcome, in difference with other presented models. Therefore, the direction of the effects should be the opposite. Note also that instead of odds ratio, regression beta coefficients for logistic multilevel models are reported. The coefficients represent the logarithmic form (using the natural base represented by “e”) of odds associated with each variable.

Table 20. Substance use – dichotomized scores, Walktrap, Models 1, 2, 5, and 6

	M1	M2	M5	M6
(Intercept)	-1.40 (0.09) ***	-2.36 (0.29) ***	-0.22 (0.69)	0.42 (2.59)
Level 1 covariates				
Gender (male)		-0.54 (0.14) ***	-0.44 (0.19) *	-0.41 (0.19) *
Age (dich)		0.24 (0.10) *	0.27 (0.11) *	0.26 (0.11) *
Ethnicity (white)		1.30 (0.26) ***	1.15 (0.27) ***	1.13 (0.27) ***
Family affluence (medium)		-0.22 (0.15)	-0.18 (0.16)	-0.17 (0.16)
Family affluence (high)		-0.24 (0.15)	-0.29 (0.17)	-0.29 (0.17)
Parental control		0.23 (0.05) ***	0.24 (0.06) ***	0.24 (0.06) ***
Parental care		-0.53 (0.05) ***	-0.53 (0.06) ***	-0.53 (0.06) ***
Level 2 covariates				
Community size			-0.68 (0.18) ***	-0.74 (0.19) ***
Community gender comp.(male)			-0.19 (0.33)	-0.22 (0.32)
Community gender comp.(mixed)			0.23 (0.27)	0.22 (0.27)
Ratio of ties outside community			-0.64 (1.03)	-1.02 (1.20)
Transitivity			-2.03 (0.77) **	-2.26 (0.80) **
Centralization			-3.60 (1.47) *	-3.61 (1.46) *
Hierarchy			0.10 (1.06)	0.04 (1.06)
Level 3 covariates				
School/network size				0.17 (0.15)
Modularity (school)				-1.31 (3.04)
Prop. F in school				0.48 (2.14)
Num. obs.	3148	3148	2698	2698
N groups: Community	387	387	236	236
AIC	3183.33	2991.19	2527.50	2532.20
BIC	3195.43	3045.68	2621.90	2644.30
Log Likelihood	-1589.66	-1486.60	-1247.75	-1247.10
Var: Community (Intercept)	2.09	1.83	1.56	1.51
ICCadj./ICCcond.	0.39/0.39	0.36/0.32	0.32/0.28	0.31/0.27
R^2mar./ R^2cond.	0.00/0.00	0.11/0.08	0.14/0.11	0.14/0.11

Abbreviations: see table 18.

Table 21. Mental wellbeing– dichotomized scores, Walktrap, Models 1, 2, 5, and 6

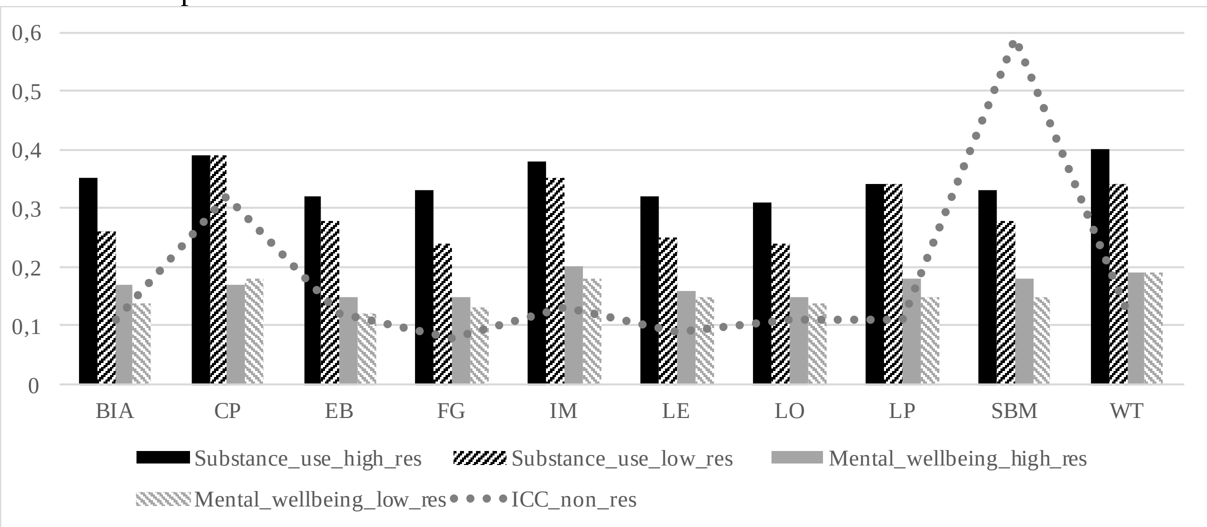
	M1	M2	M5	M6
(Intercept)	-1.21 (0.06) ***	-0.54 (0.19) **	-1.02 (0.45) *	-0.37 (1.58)
Level 1 covariates				
Gender (male)		-1.18 (0.11) ***	-1.06 (0.17) ***	-1.04 (0.17) ***
Age (dich)		0.06 (0.09)	0.07 (0.10)	0.07 (0.10)
Ethnicity (white)		-0.26 (0.16)	-0.20 (0.18)	-0.17 (0.18)
Family affluence (medium)		0.03 (0.13)	0.03 (0.15)	0.01 (0.15)
Family affluence (high)		-0.02 (0.14)	-0.00 (0.15)	-0.04 (0.15)
Parental control		0.37 (0.05) ***	0.39 (0.05) ***	0.39 (0.05) ***
Parental care		-0.30 (0.05) ***	-0.32 (0.05) ***	-0.32 (0.05) ***
Level 2 covariates				
Community size			0.17 (0.11)	0.13 (0.11)
Community gender comp.(male)			-0.33 (0.23)	-0.34 (0.23)
Community gender comp.(mixed)			-0.05 (0.15)	-0.05 (0.16)
Ratio of ties outside community			-0.11 (0.63)	-0.44 (0.76)
Transitivity			0.37 (0.56)	0.20 (0.58)
Centralization			1.30 (0.92)	1.21 (0.92)
Hierarchy			-0.06 (0.71)	-0.00 (0.73)
Level 3 covariates				
School/network size				0.12 (0.09)
Modularity (school)				-0.65 (1.87)
Prop. F in school				-0.45 (1.27)
Num. obs.	3148	3148	2698	2698
N groups: Community	387	387	236	236
AIC	3467.30	3190.57	2710.50	2714.52
BIC	3479.41	3245.06	2804.90	2826.63
Log Likelihood	-1731.65	-1586.29	-1339.25	-1338.26
Var: Community (Intercept)	0.51	0.24	0.20	0.20
ICCadj./ICCcond.	0.13/0.13	0.07/0.06	0.06/0.05	0.06/0.05
R^2mar./ R^2cond.	0.0/0.0	0.16/0.11	0.18/0.12	0.18/0.12

Abbreviations: Community gender comp. – community gender composition; Prop. F in school – proportion of females in the school; Num. obs. – Number of observations; AIC – Akaike information criterion; BIC – Bayesian information criterion; Var – variance; N groups – number of groups; ICCadj. – adjusted intraclass correlation coefficient; ICCcond. – conditional intraclass correlation coefficient; R^2mar. – marginal R^2; R^2cond. – conditional R^2; Age is dichotomized: 15 yrs = 0; 16 and 17 yrs = 1; **Reference categories** for factors: Gender – female; Ethnicity – non-white; Family affluence – low; Community gender comp. – female

8.4 Differences in ICCs between schools with high and low response rate (all GDAs)

For checking the sensitivity of findings to missing attribute data (as a specific kind of robustness) the following analyses were done:

- Separate analysis on 11 schools with lowest non-response rate and 11 schools with highest non-response rate (Model 1) – to gauge the effect of missing data on clustering (ICC).
- Models where being a non-responder as the DV and community the random effect. This is done for all GDAs to assess the tendency of GDAs to place non-responders in the same community. A high ICC by itself would not directly imply that the GDA is incorrect or sensitive to missing values, because there is a theoretical possibility that non-responders tend to belong to same communities.
- We ran separate analysis on two subsamples made of 11 schools with lowest non-response rate and 11 schools with highest non-response rate (Model 1). High-responding schools are all schools that have less than 12.5% non-responders.



Legend:
Substance use high res – ICC on sample of schools with relatively less non-responders
Mental wellbeing high res – ICC on sample of schools with relatively less non-responders
Substance use low res – ICC on sample of schools with relatively more non-responders
Mental wellbeing low res – ICC on sample of schools with relatively more non-responders
ICC_non_res – ICC for being a non-participant in the study with communities as random effect
ICC – adjusted intraclass correlation coefficient

Figure 34. Adjusted intraclass correlation coefficients (ICC) for Substance use and Mental wellbeing (Model 2) for each GDA on subsample of high responding schools (11 schools, *N*=1605) and subsample of low responding schools (11 schools, *N*=1543) and ICC for being a non-responder as dependent variable and communities as random effect (x-axis: community detection algorithm, y-axis: ICC values)

8.5 Simulations of more non-responders in the network (Walktrap)

Students who did not participate in the study could have been nominated by others as a friend and therefore included in the network data. Such nodes in the network could not have out-going ties and could not have ties with each other. Nevertheless, they were considered equally when communities where detected by group detection algorithms. We wanted to check the sensitivity of findings to having more such cases. In each of 22 school networks we randomly selected 5 to 40% nodes, limiting our selection to those who were not non-responders (they had out-going ties) and that had at least one in-going ties (to minimize the number of newly created isolated). After each random deletion, we excluded newly created isolates from the analysis, repeated community detection with Walktrap, and recalculated the properties of the found communities. This allowed us to create new datasets (that were consequently smaller than the original dataset) and rerun Model 1 and Model 5 to gauge how robust the findings are when there are more non-responders in the network. We repeated the process six times, creating 5, 10, 15, 20, 30, and 40% of new "non-responders". However, the simulation was done only once for each condition.

Similarity of the original partition with the one after some nodes are turned to non-responders (AR values) and the adjusted ICCs for Model1 for both outcomes are shown in table 22. Tables 23 and 24 show results for Model 5 for substance use and mental wellbeing, respectively.

Table 22. Adjusted Rand (AR), N, and adjusted intraclass correlations (ICCadj.)for Substance use and Mental wellbeing after 5, 10, 15, 20, 30, and 40% of nodes with deleted out-going ties

Deleting out-going ties (percentage of new "non-responders")	5%	10%	15%	20%	30%	40%
Adjusted Rand with the original network partition*	0.89	0.83	0.79	0.73	0.71	0.63
N before excluding new "isolates"	3640	3618	3611	3581	3491	3303
ICCadj. for Model 1- Substance use	0.36	0.36	0.35	0.37	0.35	0.37
ICCadj. for Model 1- Mental wellbeing	0.19	0.19	0.20	0.19	0.20	0.19

*including new "isolates" as separate communities

Table 23. Model 5 for Substance use with different percentage of randomly selected nodes with deleted out-going ties

Parameters/ Percentage of deleted	5%	10%	15%	20%	30%	40%
(Intercept)	-0.40 (0.24)	-0.58 (0.25) *	-0.27 (0.24)	-0.36 (0.24)	-0.01 (0.24)	0.08 (0.25)
Gender (male)	0.28 (0.06) ***	0.24 (0.06) ***	0.29 (0.05) ***	0.18 (0.05) ***	0.32 (0.06) ***	0.28 (0.06) ***
Age (dich)	-0.08 (0.03) **	-0.07 (0.03) *	-0.06 (0.03)	-0.09 (0.03) **	-0.06 (0.03)	-0.03 (0.04)
Ethnicity (white)	-0.50 (0.07) ***	-0.46 (0.07) ***	-0.47 (0.07) ***	-0.49 (0.07) ***	-0.44 (0.07) ***	-0.41 (0.07) ***
Family affluence (medium)	0.08 (0.05)	0.09 (0.05)	0.06 (0.05)	0.09 (0.05)	0.06 (0.05)	0.12 (0.06) *
Family affluence (high)	0.05 (0.05)	0.07 (0.05)	0.02 (0.05)	0.09 (0.05)	0.05 (0.05)	0.10 (0.06)
Parental control	-0.12 (0.02) ***	-0.12 (0.02) ***	-0.12 (0.02) ***	-0.12 (0.02) ***	-0.12 (0.02) ***	-0.12 (0.02) ***
Parental care	0.23 (0.02) ***	0.23 (0.02) ***	0.23 (0.02) ***	0.22 (0.02) ***	0.25 (0.02) ***	0.23 (0.02) ***
Community size	0.21 (0.07) **	0.25 (0.07) ***	0.17 (0.07) *	0.12 (0.07)	0.10 (0.08)	0.04 (0.08)
Community gender comp.(male)	0.03 (0.11)	0.21 (0.11)	0.11 (0.11)	0.28 (0.11) *	0.11 (0.12)	0.23 (0.13)
Community gender comp.(mixed)	-0.11 (0.10)	-0.08 (0.10)	-0.11 (0.10)	0.01 (0.10)	-0.05 (0.10)	-0.00 (0.12)
Ratio of ties outside community	0.10 (0.37)	0.05 (0.38)	-0.03 (0.39)	0.50 (0.39)	-0.38 (0.43)	-0.54 (0.40)
Transitivity	0.73 (0.28) **	0.85 (0.29) **	0.79 (0.31) *	0.58 (0.30)	0.02 (0.30)	0.35 (0.35)
Centralization	1.23 (0.54) *	1.39 (0.56) *	0.52 (0.64)	0.56 (0.59)	1.20 (0.72)	-0.03 (0.76)
Hierarchy	0.32 (0.39)	0.22 (0.42)	0.54 (0.43)	0.67 (0.49)	-0.08 (0.51)	-0.29 (0.58)
Num. obs.	2651	2613	2577	2527	2370	2020
AIC	6521.94	6452.29	6330.81	6205.58	5786.17	4907.04
BIC	6621.94	6552.05	6430.33	6304.77	5884.27	5002.43
Log Likelihood	-3243.97	-3209.14	-3148.40	-3085.79	-2876.08	-2436.52
N groups: Community	229	219	215	207	192	155
Var: Community (Intercept)	0.25	0.22	0.24	0.24	0.24	0.23
Var: Residual	0.58	0.59	0.58	0.58	0.57	0.56
ICC adjusted	0.31	0.27	0.30	0.29	0.29	0.29

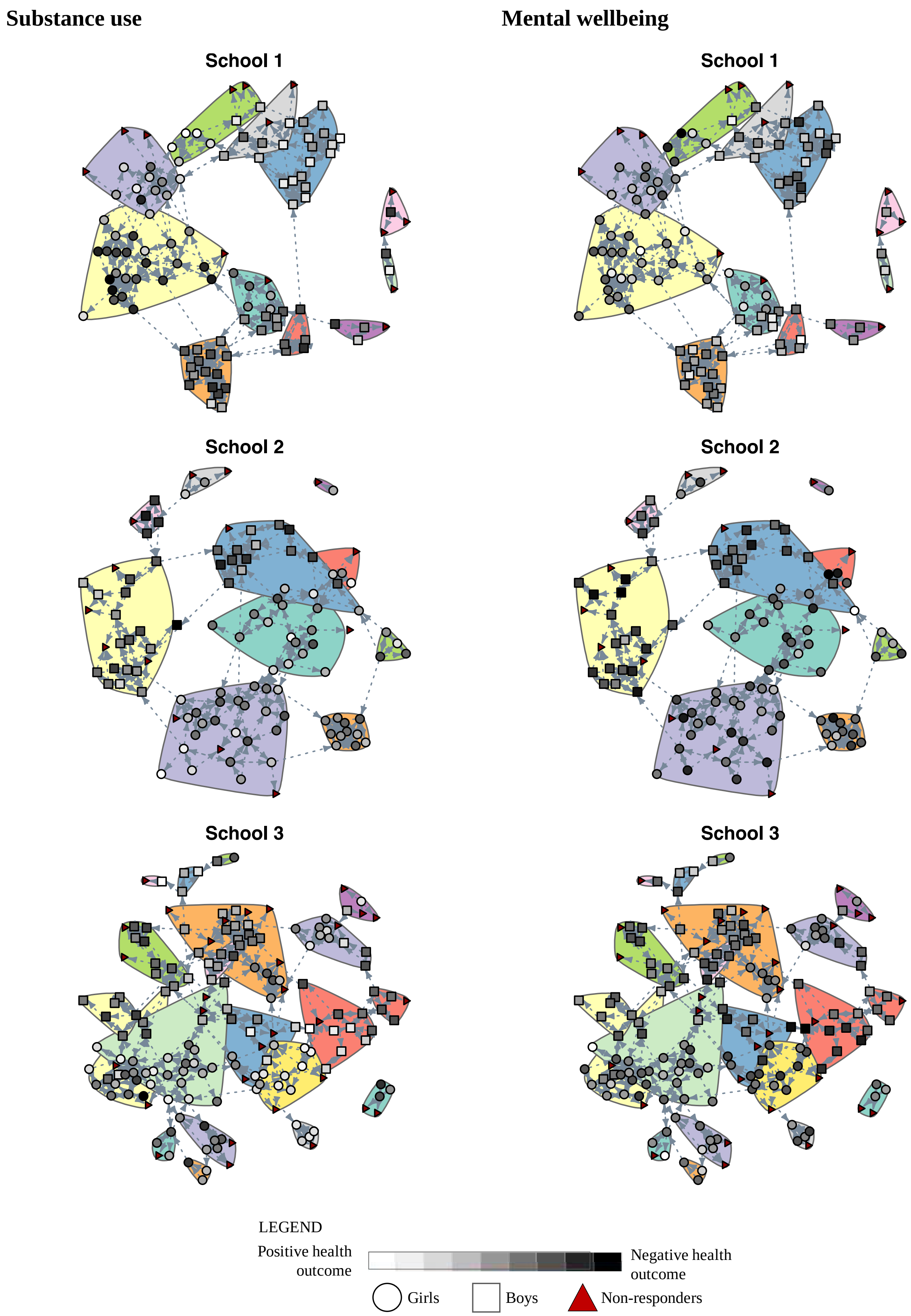
Abbreviations: see table 21.

Table 24. Model 5 for Mental Wellbeing with different percentage of randomly selected nodes with deleted out-going ties

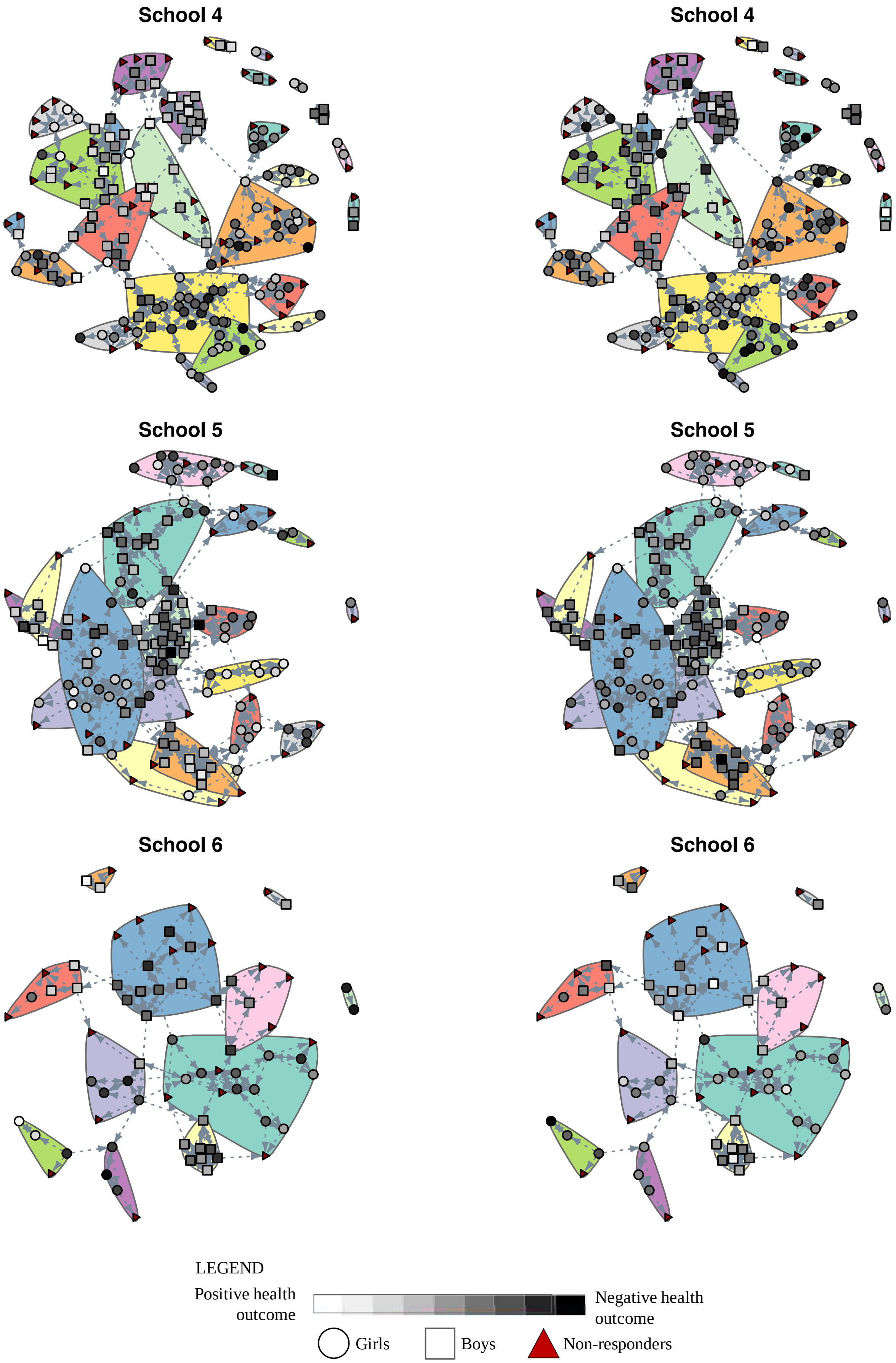
Parameters/ Percentage of deleted	5%	10%	15%	20%	30%	40%
(Intercept)	0.20 (0.18)	0.26 (0.20)	0.26 (0.19)	0.18 (0.18)	-0.26 (0.19)	-0.12 (0.18)
Gender (male)	0.57 (0.06) ***	0.62 (0.06) ***	0.53 (0.06) ***	0.60 (0.06) ***	0.50 (0.06) ***	0.57 (0.06) ***
Age (dich)	0.01 (0.03)	-0.01 (0.03)	-0.00 (0.03)	-0.00 (0.03)	0.02 (0.04)	0.01 (0.04)
Ethnicity (white)	0.10 (0.07)	0.08 (0.07)	0.07 (0.07)	0.09 (0.07)	0.07 (0.07)	0.02 (0.08)
Family affluence (medium)	-0.03 (0.05)	-0.03 (0.05)	-0.05 (0.05)	-0.06 (0.05)	-0.05 (0.06)	0.01 (0.06)
Family affluence (high)	-0.02 (0.05)	-0.02 (0.05)	-0.03 (0.06)	-0.03 (0.05)	-0.04 (0.06)	0.01 (0.06)
Parental control	-0.18 (0.02) ***	-0.18 (0.02) ***	-0.18 (0.02) ***	-0.18 (0.02) ***	-0.17 (0.02) ***	-0.21 (0.02) ***
Parental care	0.10 (0.02) ***	0.11 (0.02) ***	0.11 (0.02) ***	0.10 (0.02) ***	0.10 (0.02) ***	0.10 (0.02) ***
Community size	-0.12 (0.05) *	-0.15 (0.05) **	-0.12 (0.06) *	-0.08 (0.05)	0.02 (0.06)	0.04 (0.05)
Community gender comp.(male)	-0.04 (0.09)	-0.08 (0.09)	0.05 (0.10)	-0.11 (0.09)	0.01 (0.10)	-0.17 (0.10)
Community gender comp.(mixed)	-0.05 (0.07)	-0.01 (0.07)	0.01 (0.08)	-0.10 (0.08)	-0.01 (0.08)	-0.10 (0.08)
Ratio of ties outside community	-0.19 (0.27)	-0.37 (0.28)	-0.46 (0.30)	-0.18 (0.28)	0.09 (0.32)	0.06 (0.27)
Transitivity	-0.55 (0.22) *	-0.59 (0.23) **	-0.46 (0.25)	-0.54 (0.23) *	-0.22 (0.23)	-0.60 (0.25) *
Centralization	-0.86 (0.40) *	-0.75 (0.43)	-0.97 (0.50)	-0.67 (0.45)	0.10 (0.56)	0.67 (0.52)
Hierarchy	0.11 (0.30)	0.17 (0.33)	0.15 (0.34)	-0.24 (0.37)	0.20 (0.39)	-0.74 (0.41)
Num. obs.	2651	2613	2577	2527	2370	2020
AIC	6879.20	6768.45	6685.88	6523.44	6142.16	5216.83
BIC	6979.21	6868.21	6785.41	6622.63	6240.26	5312.21
Log Likelihood	-3422.60	-3367.23	-3325.94	-3244.72	-3054.08	-2591.41
N groups: Community	229	219	215	207	192	155
Var: Community (Intercept)	0.09	0.08	0.10	0.09	0.10	0.06
Var: Residual	0.71	0.71	0.70	0.70	0.70	0.71
ICC adjusted	0.11	0.11	0.13	0.11	0.12	0.08

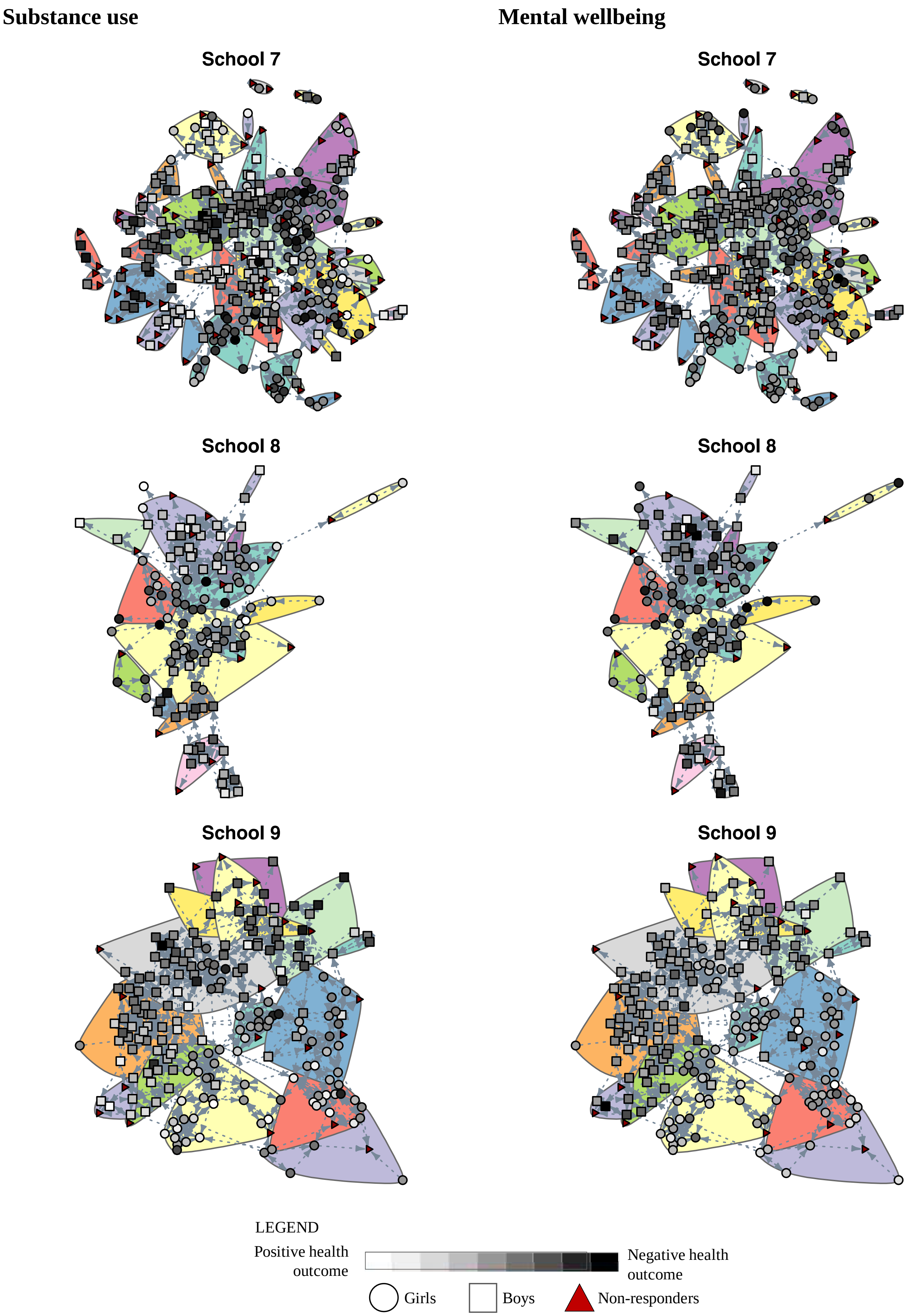
Abbreviations: Community gender comp. – community gender composition; Prop. F in school – proportion of females in the school; Num. obs. – Number of observations; AIC – Akaike information criterion; BIC – Bayesian information criterion; Var – variance; N groups – number of groups; ICCadj. – adjusted intraclass correlation coefficient; Age is dichotomized: 15 yrs = 0; 16 and 17 yrs = 1; **Reference categories** for factors: Gender – female; Ethnicity – non-white; Family affluence – low; Community gender comp. – female

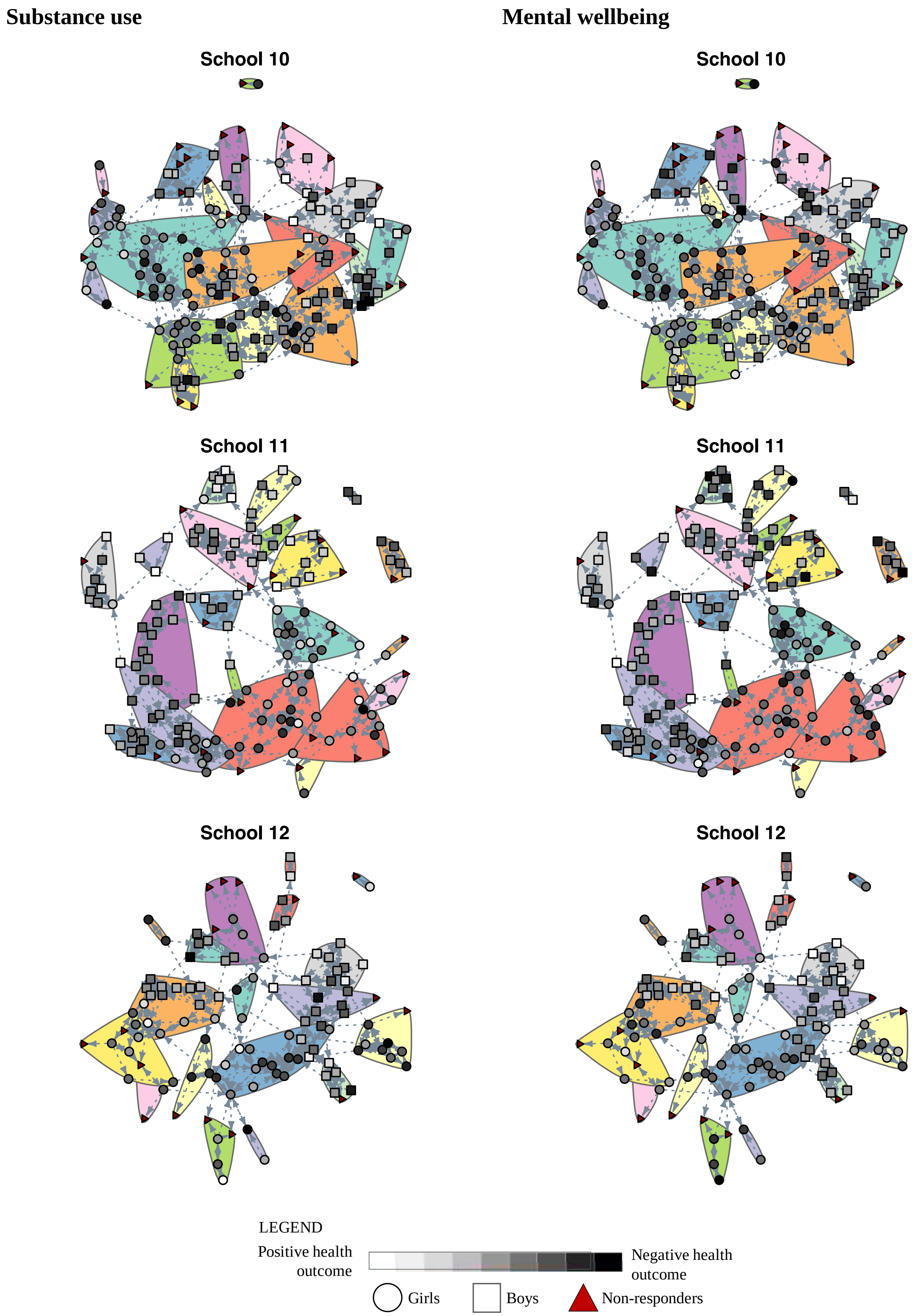
9 Two health outcomes and Walktrap communities

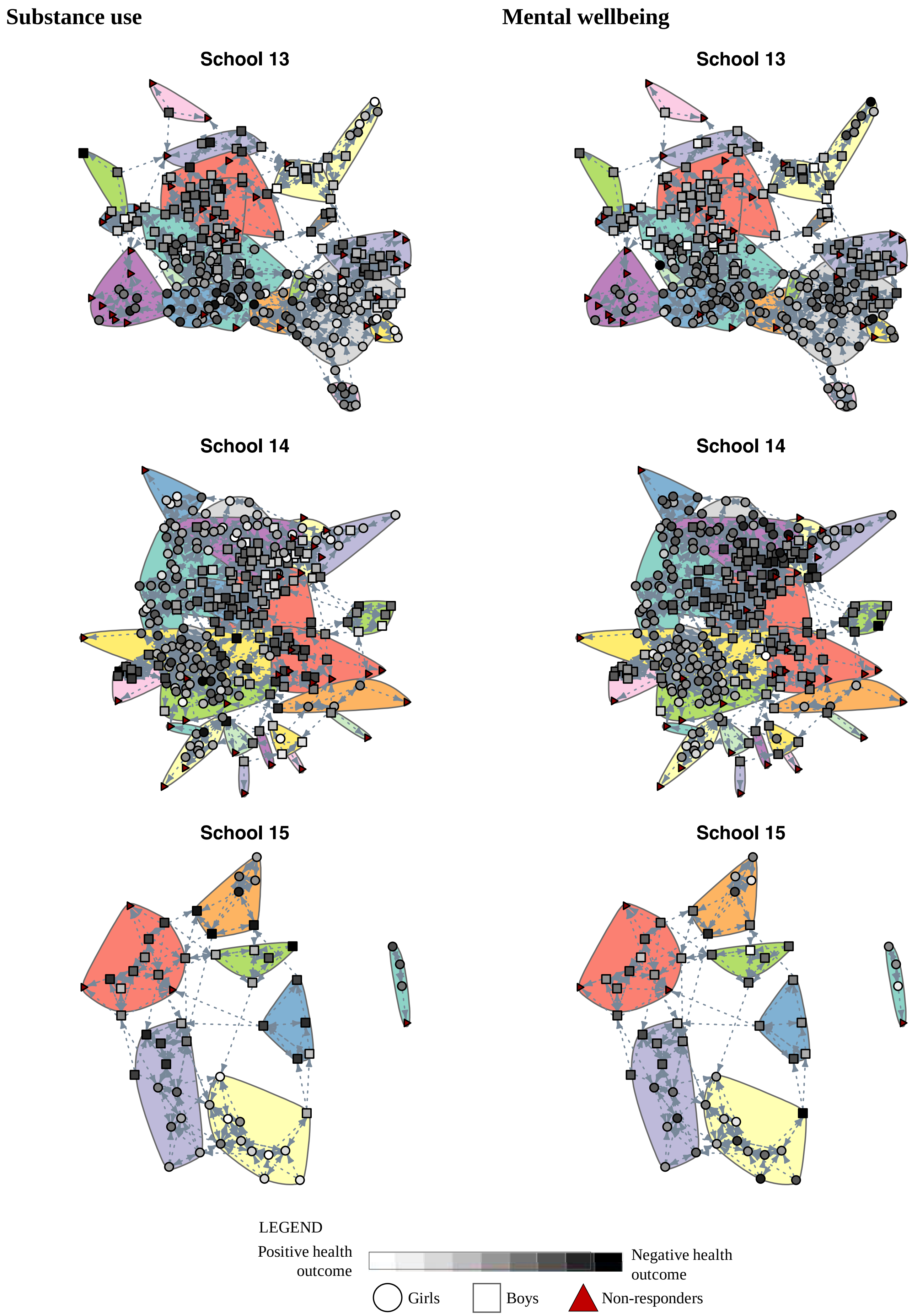

Substance use
Mental wellbeing
School 1
School 1
School 2
School 2
School 3
School 3
LEGEND
Positive health outcome
Negative health outcome
Girls
Boys
Non-responders

Substance use **Mental wellbeing**

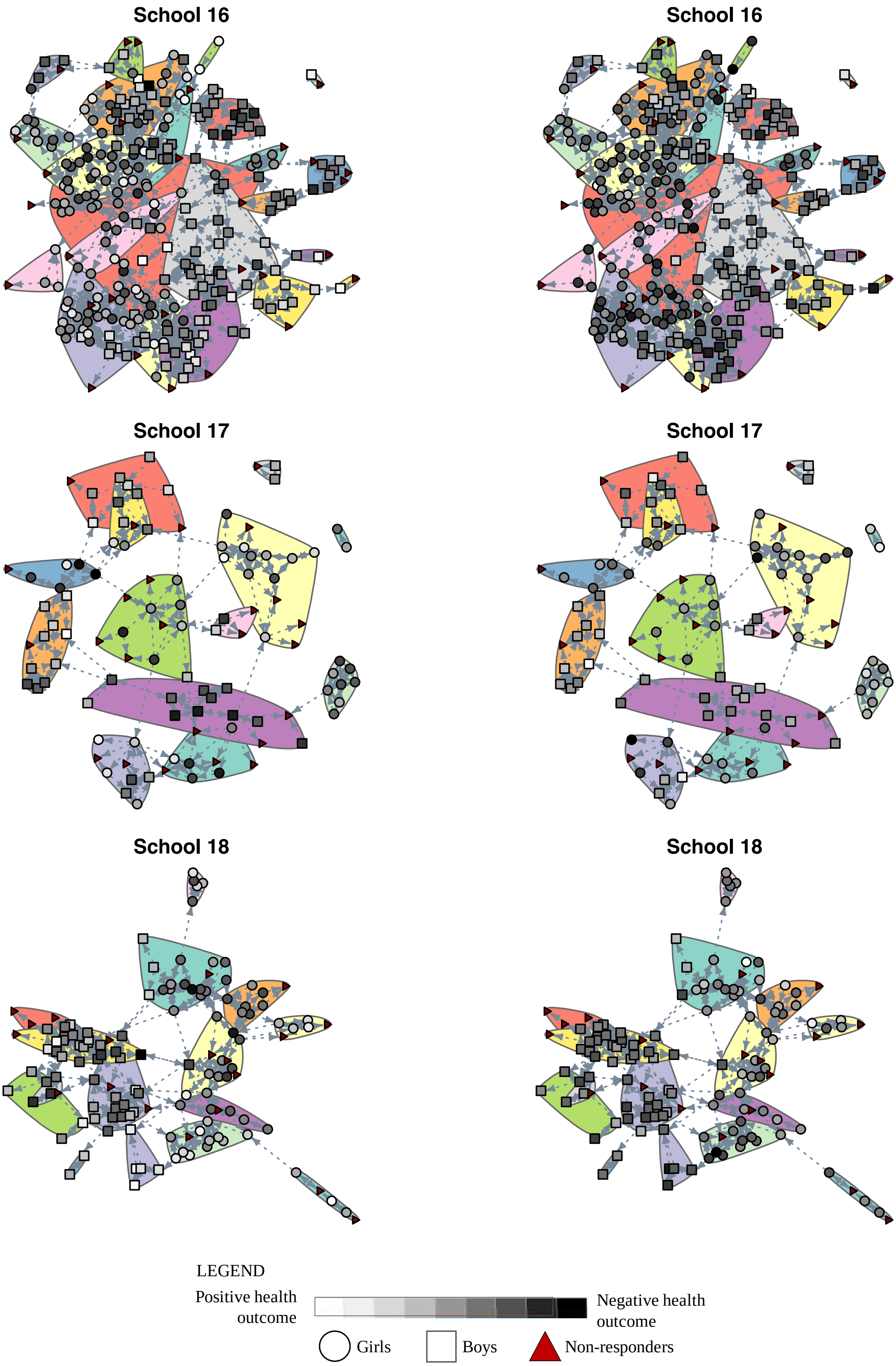



Substance use
Mental wellbeing
School 7
School 7
School 8
School 8
School 9
School 9
LEGEND
Positive health outcome
Negative health outcome
Girls
Boys
Non-responders

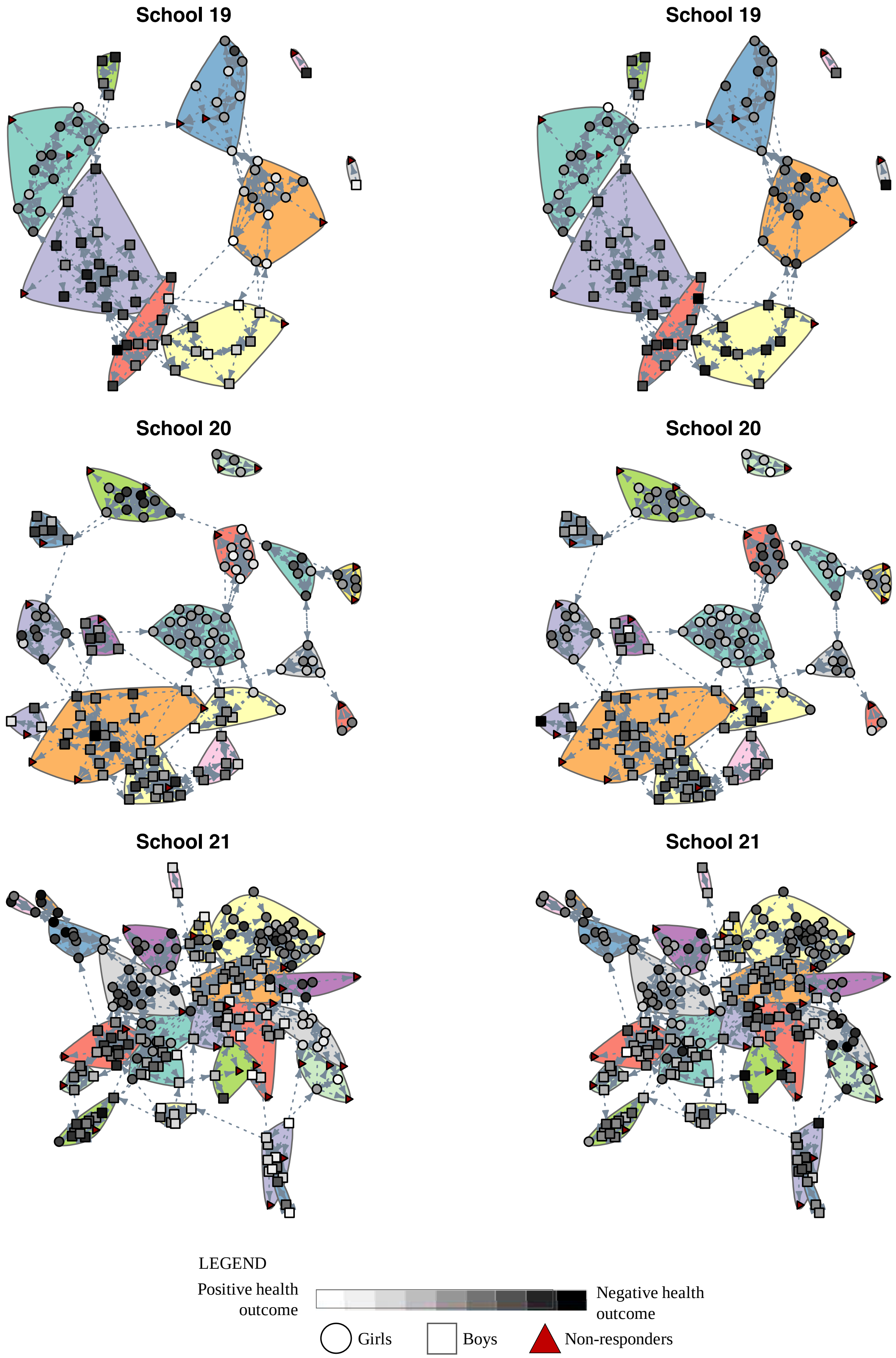

Substance use
Mental wellbeing
School 10
School 10
School 11
School 11
School 12
School 12
LEGEND
Positive health outcome
Negative health outcome
Girls
Boys
Non-responders


Substance use
Mental wellbeing
School 13
School 13
School 14
School 14
School 15
School 15
LEGEND
Positive health outcome
Negative health outcome
Girls
Boys
Non-responders

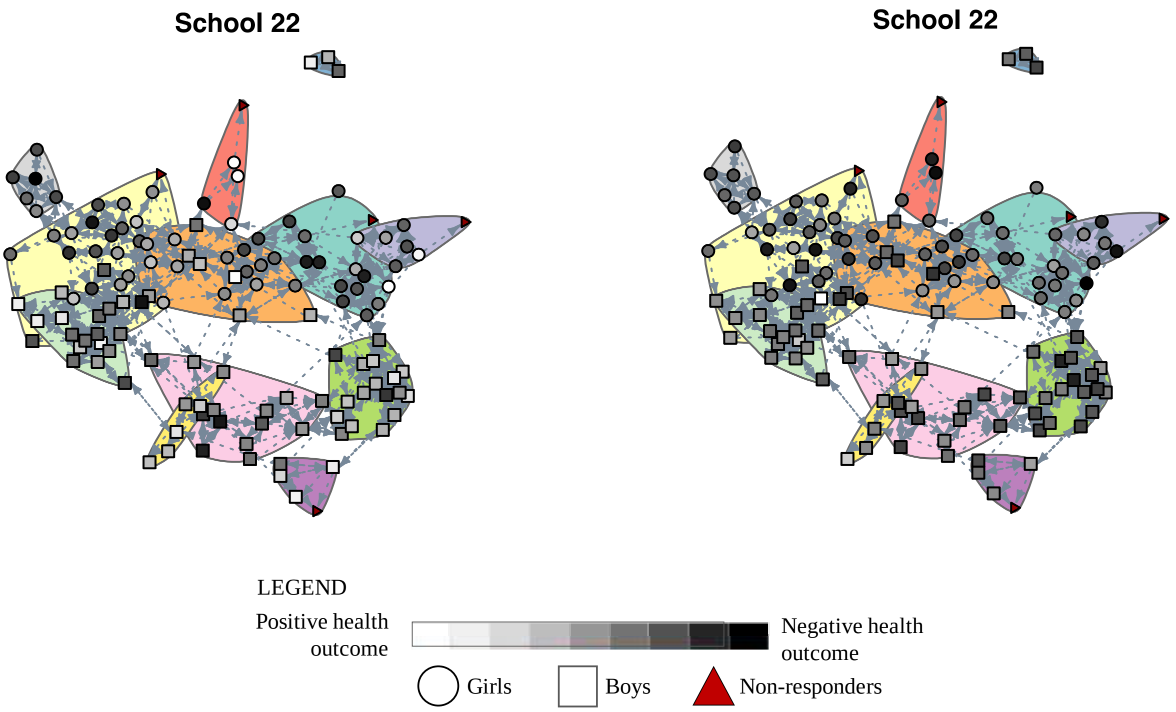
Substance use **Mental wellbeing**



Substance use **Mental wellbeing**



Substance use **Mental wellbeing**



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