The use of social network analysis (SNA) in educational psychology

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Abstract: The aim of this article is to present the possibilities offered by Social Network Analysis (SNA) in educational psychology research. The first part discusses the general principles of the network approach, with a particular focus on social networks. This is followed by a presentation of selected features of network data and a review of the most important analytical techniques, both descriptive and inferential, offered by network analysis. The final section gives examples of the use of SNA in educational psychology research published in the last few years. The discussion in the article concludes with the thesis that the contribution of SNA to the analysis of variables in the field of educational psychology seems particularly interesting. This alternative way of understanding and analysing data from the field of educational psychology, opens up new possibilities for exploring issues, as it allows a slightly different way of modelling and analysing relationships between variables, designing new strategies for psycho-educational interventions or better explaining the aetiology of certain phenomena. SNA can therefore respond to the needs of both psychologists academically involved in education as well as psychologists-practitioners.
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1. General characteristics of the network approach and Social Network Analysis (SNA)

The origins of network theory date back almost a century (see e.g. McGloin, Kirk, 2010), but it entered the social sciences, including psychology, much later. A particularly dynamic development took place in the early 1990s, when, on the one hand, important theoretical considerations for this approach were published and resonated in the scientific community (see e.g. Coleman, 1990, after: Gilman, Carboni, 2022), and, on the other hand, user-friendly analysis software was developed (Brass, 2022). Researchers point out that network theory can be extremely useful and widely used in the social sciences, such as sociology or criminology, to describe and explain various types of social phenomena, e.g. the basis of crime, analysis of social groups, the development of crime suppression interventions and tactics, social control, group efficacy, or social disintegration (see e.g. McGloin, Kirk, 2010). In recent years, network research has also been gaining popularity in psychology (see e.g. Kornienko, Rivas-Drake, 2021). However, it is important to note that this is mainly happening in two fields – social psychology, as well as clinical psychology and psychopathology. In social psychology network analyses are used to examine, for example, how prosocial and antisocial behaviour spreads in the network through connections between network participants (van den Bos et al., 2018), how neighbours influence non-violent but socially rule-breaking behaviour of adolescents (Burt et al., 2019), or how the process of "contagion" of suicide attempts among adolescents takes place in a network of interpersonal relationships (Zimmerman et al., 2016), etc. In clinical psychology and psychopathology, on the other hand, the network paradigm analyses, for example, the different symptoms of disorders, examining what the key symptoms are and how they affect each other (see, e.g. Fried, Cramer, 2017; Isvoranu et al., 2017). However, in general, modelling psychological phenomena based on network theories is not yet very popular. A significant shortage of this type of research can be seen, for example, in Polish educational psychology. Meanwhile, the potential contribution of the network model to the analysis of psychological variables seems particularly interesting. According to network science researchers, this alternative way of understanding and analysing phenomena, which is relatively new in the social sciences, offers great opportunities, as it allows to model and analyse relationships between variables (e.g. symptoms, psychological processes, personality traits, environmental factors, etc.) in a slightly different way than traditionally, to design new forms of prevention and intervention strategies or to improve the search for aetiological mechanisms (see e.g. Borsboom, 2017; Fonseca-Pedrero, 2018).

What is the network approach? A network is an abstract model that contains nodes and edges (Hevey, 2018). Nodes represent objects or variables in the research, while edges represent connections between nodes (Fonseca-Pedrero, 2018). In psychological research, nodes can be individuals or any kind of variable, such as, for example, psychopathological symptoms, personality traits, attitudes, environmental influences, risk factors, etc. (Fonseca-Pedrero, 2018; Isvoranu et al., 2017). Edges, on the other hand, are different types of connections, i.e. relationships between nodes (e.g. correlations, friendship relationships, etc.), which can be modeled from the collected data (Hevey, 2018). It is these connections that are central to network theory, and some researchers argue that scientific theories cannot ignore the network effects caused by the interconnectedness of variables (see e.g. Barabási, 2012).

One type of networks are social networks, to which this article is devoted. A social network is generally defined as a specific relationship or bond between a group or groups of nodes (Sweet, 2016). According to network theory, the relationships or bonds mentioned are the so-called edges. In social networks, nodes are most often individuals, but this is not necessarily always the case – as in some network contexts, nodes can be, for example, school classes, departments at a university, etc. (see e.g. Sweet, 2016). Social networks are encountered in a variety of situations – these can be, for example, friendships between children, collaboration and information exchange between teachers, participation in the same training courses, etc. Social Network Analysis (SNA), on the other hand, is a set of theories and methods that take into account direct and indirect relationships, in a clearly defined context (Gilman, Carboni, 2022). As McGloin and Kirk (2010) observe, the basic premise of SNA is that individuals are interdependent and that these dependencies influence their behaviour. On the one hand, SNA allows us to look at the functioning of a given person from the perspective of his or her relationships with others, and on the other hand, they enable us to take a comprehensive view of social networks – all interactions and connections in a given community or social group. Social networks can therefore be analysed both at the level of the individual and the group as a whole.

The main difference between traditional surveys and SNA is the type of data being operated on. Traditional research usually analyses the *individual attributes* of individuals that affect their functioning, in interpersonal relationships, in the school environment, etc. In contrast, in SNA, the basis of analysis is the relationship between nodes, i.e. the links between some objects (e.g. individuals or groups). Thus, it can be said that traditional research operates on *attributional data*, while SNA operates on *relational data*. McGloin and Kirk (2010) give the following example to explain the difference between the data mentioned: the extent of the deviant norms a person reports is an attribute of that person, whereas the intensity or frequency of his/her communication with friends about these norms is an exchange relationship. As already mentioned, it is implicit in SNA that the quantity and quality of links between individuals (or other network objects) can be an important factor influencing different behaviours (McGloin, Kirk, 2010).

Since, as mentioned earlier, SNAs operates on relational data, in order to carry it out we need data on the links between objects (i.e. links between nodes; McGloin, Kirk, 2010). The repertoire of such links is very wide, making the potential for exploiting SNA enormous. A link can be, for example, friendship, co-membership, communication, similar behaviour, etc. It should be added that, depending on the nature of the links or the hypotheses posed, relational links can be undirected or directed (this thread will be developed a little further). Links between nodes may have a specific value. For example, researchers may code relationships according to a certain level of attachment or commitment (e.g. the number of days per week that two people communicate). In addition, these values may reflect separate relationships (e.g. friends versus siblings) or combinations of these, which is called a *multirelational network* (McGloin, Kirk, 2010).

SNA is based on three mathematical foundations: (1) graph theory, (2) algebraic models, and (3) probability theory (Wasserman, Faust 1994, after: McGloin, Kirk, 2010).

Historically, network science initially developed using graphical approaches to represent relationships between nodes. Graph theory refers to well-known sociograms in which individuals (or any other nodes on which the study focuses) are represented by points, and social relationships are represented by lines between the points (Moreno, 1934, after: McGloin, Kirk, 2010). In classical sociograms, the graphical representation of the alignment and distance between nodes is of little importance. The edges of the network may be weighted or unweighted. In unweighted networks, nodes are connected without specifying the strength of this connection, whereas in weighted networks there is a coefficient that indicates the size or magnitude of this connection. This value oscillates between 0 and -/+1, representing the type of relationship and relative effect of a node on another node. In addition, the edges of the network can be undirected or directed. Undirected networks are those in which the direction of the relationship between nodes is not indicated, whereas in directed networks the direction of the relationship between nodes is specified, as shown by the arrows (Fonseca-Pedrero, 2018). These two types of graphs can help represent different types of networks, with the prior visualizing e.g. Facebook friends well, while the latter more accurately shows e.g. a work hierarchy.

Of course graphs are a great help to researchers, as they allow them to quickly visualise the network of interconnections and relationships between nodes. However, it is a fairly simple technique and insufficient for more advanced research. SNA allows for much deeper analyses as it includes a wide range of measures of social network properties. As mentioned earlier, some of these measures look at the characteristics of the network as a whole, while others allow us to look at a single entity, or node, in the context of the network as a whole. There are many different ways to describe how individuals relate or interact in the network. For example, measures of distance and shortest path length, centrality of connectivity and clustering can be used to analyse network structure (Fonseca-Pedrero, 2018). Only a few commonly used characteristics will be presented here. The interested reader will find a more complete list in the work by Costantini and colleagues (Costantini et al., 2015) or Wasserman and Faust (1994; after Sweet, 2016).

One obvious description of a network is the number of links between nodes in the network. The proportion of links occurring in a network to all possible links is called density. It is a measure of how well connected the network is, which in an analysis of network performance can indicate, for example, how quickly information flows, how much information is shared and even how well individuals are served (Sweet, 2016). Density, on the one hand, provides a common measure by which researchers can compare groups of different types and sizes (e.g. to test for cohesion across ethnic groups of different sizes), but also provides an opportunity to test theoretical models and hypotheses about the role of network density on group behaviour (e.g. whether more cohesive classes are more engaged in learning). Another frequently calculated network parameter is reciprocity, i.e. the reciprocity index, which is calculated as the proportion of found links that are reciprocal to the total number of links (Sweet, 2016) and being used for e.g. comparing ties in friendship nominations.

In addition to measures relating to the network as a whole, SNA also includes measures relating to individuals (or any other objects that are nodes) in the network. In the network structure, not all nodes are equally important. Centrality measures allow the importance of a node to be determined in the context of other nodes in the network (Borgatti et al., 2009). For example, a node is degree-central if it has many connections, and peripheral (i.e. outside the network) if it has few connections (Fonseca-Pedrero, 2018). Identifying such nodes can be very useful. For example, knowledge of the most popular and least popular students in a class would be useful for designating seating, managing group dynamics or disseminating important information (see e.g. Sweet, 2016). There are several centrality measures, and each of these measures reflects a slightly different aspect of what it means to be a central node in a network. The most common factors considered in the research are: degree centrality (i.e. the number of incidental connections to a node), node strength (i.e. how strongly a node is directly connected to other nodes; the indicator is based on a weighted sum of the number and strength of all connections of a given node in relation to all other nodes), closeness (i.e. how close a node is from other nodes in the network in terms of shortest path length), betweenness (i.e. how important a node is in the shortest paths between other pairs of nodes, i.e. how often it connects two other nodes lying on the shortest path between them), clustering (i.e. to what extent a node is part of a cluster of nodes; provides insight into a node's local redundancy – whether its removal affects the ability of neighbouring nodes to continue to influence each other; Hevey, 2018; Sweet, 2016). Although the application of these measures may at first sight seem purely theoretical, nothing could be further from the truth. As already mentioned, network measurement makes it possible not only to determine which people are the most "popular" members of a network (i.e., in-degree), but also to answer a number of other questions. For example, to what extent does communication within the network need to "go through" specific individuals (i.e. betweenness centrality; McGloin, Kirk, 2010), to whom students turn for help (whether most turn to one or a few selected individuals in the school or to many different ones), who in the group is most important to maintain group cohesion or how information spreads in the community (Sweet, 2016).

In addition to graphs and descriptive measures, network analysis allows for more advanced calculations such as network autocorrelation models. Many empirical studies rely on statistical methods that assume that individuals are independent of each other, which may not always be true. If there is an interdependence between the behaviour of individuals in a social network, researchers need an inference strategy that takes this into account. These needs are met, among others, by the aforementioned autocorrelation models of networks, which explicitly take into account the fact that there is interdependence between individuals, i.e. nodes, and allow certain social processes to be captured, such as, for example, the diffusion of ideas and innovations (McGloin, Kirk, 2010). Of course, networks differ in the extent of interdependence between entities/nodes. In some, this interdependence may be minimal; nevertheless, as McGloin and Kirk observe (2010, p. 176): "if the nodes cannot be assumed to be independent, then analytic methods that do assume independence may not be able to capture the true importance of group structure on behaviour".

2. Examples of the use of SNA in educational psychology research

Educational institutions, such as schools are environments in which students' knowledge, competences, attitudes, mental processes and, finally, behaviour are shaped and modified through relationships. Social interactions with teachers, peers and other members of the school community are an integral component of how students function and how they perceive themselves, their world and their future (see e.g. Gilman, Carboni, 2022; Grbić, Maksić, 2022). For this reason, there is an increasing demand in source literature for educational research to consider a broader pattern of social relations than has been the case to date, using a set of theories and methods that both complement and extend the most commonly used approaches (Neal, 2020; Sweet, 2016)

Although, as mentioned in the introduction, research within the SNA paradigm has seen an increase in popularity in the social sciences in recent years, educational psychology does not seem to have kept pace. Gilman and Carboni (2022) conducted an analysis of articles relating to "social networks", "social network analysis" and "networks", which showed that fewer than 20 articles on this topic had been published in English-language school psychology journals in the last two decades (up to 2022)! In addition, as the researchers point out, many of these texts date from more than a decade ago. Even less attention is paid to SNA in Polish educational research. The author of this article has not been able to find a single Polish study from the field of educational psychology conducted in the paradigm of network theory. This is surprising, given that many of the issues of interest in this field both influence – and are influenced by – the social context. This could include, for example, the cooperation between family and school, the functioning of school classrooms, or even the process of distributing information in the school social network. In addition, analyses to date have shown that even – as was previously believed- individual attributes and choices (such as cheating in learning, or literacy achievement, etc.), are partly determined by the social context. It would therefore be all the more expedient to broaden the research on them and to take into account the contribution of direct and indirect social relations (Gilman, Carboni, 2022).

To date relatively few works in educational psychology, conducted within the framework of network theory, have shown, that SNA provides a new perspective on how social interactions can affect, for example, aggression at school, friendships between students, the development of language skills, relationships within the same and diverse ethnic groups, the sense of belonging to the school community, and many other important issues related to education (Gilman, Carboni, 2022). At this point, it seems justified to give some examples of how SNA methods have been used to investigate, describe and explain selected problems in the field of educational psychology.

In social groups, such as school peer networks, children and young people often compete for power and dominance over others. In doing so, they may use, with varying degrees of success, diverse strategies to gain power, such as coercive or cooperative-oriented strategies. To understand patterns of power in peer groups, Andrews, McDowell, Spadafora and Dane (2022) applied social network methods to a study of several hundred grade 5 to grade 8 students attending a Canadian primary school (N = 466). The researchers examined whether and how social network centrality and social network prestige were linked to social strategies, social power and peer reputation. Peer nominations were used to assess the centrality and prestige of the social network (through friendship nominations), social power strategies (coercive and collaborative strategies), social power and peer reputation (popularity and likability). The results indicated that coercive and cooperative strategies were used by youth with both high centrality and prestige, but only high prestige was associated with power, popularity and likability. At the same time, the research carried out has shown that the SNA approach can broaden knowledge of the structure of social relations and power structures in the school environment, and has practical implications for teachers and educational psychologists.

Davila and Kornienko (2022), on the other hand, were interested in adolescents establishing and maintaining friendship relationships. Building on a developmental psychopathology perspective and previous research showing gender differences in social tasks and friendship structures, the researchers used longitudinal SNA methods to examine how fears of negative evaluations (FNE) and gender interact to jointly shape friendship dynamics, and to characterise their distinct roles in how adolescents make new friends, maintain existing friendships and become more like each other over time. The participants in the survey were 1,034 secondary school students, from grades 6 to 8. Peer networks were assessed at two time points, 1 year apart. The results showed that girls were more likely to make new friends and maintain existing friendships when they had lower levels of FNE. In contrast, boys were more likely to make new friends and maintain existing friendships when they had higher levels of FNE. In addition, girls with low FNE levels were more likely to maintain friendships with others who also had low FNE levels, while boys with high FNE levels were more likely to maintain friendships with friends who had low FNE levels. The results also showed a significant effect of peers on FNE, which resulted in friends becoming similar to each other in terms of FNE levels over time, while there were no significant gender differences in these processes. In light of the results, it can be concluded that FNE reinforces gender differences in adolescents' tendency to form and maintain friendship networks, while at the same time the influence of peers on FNE levels is the same for boys and girls.

In today's increasingly ethnically and culturally diverse world, the educational environment is also increasingly multicultural. Rambaran and colleagues (2022a) pointed out that ethnically and racially diverse schools provide students with opportunities for social interaction with peers of the same or different ethnicity, which can shape their sense of belonging at school. In their work, the researchers examined the extent to which friends of the same or different nationality influence the sense of belonging at school. The participants in the survey were 4,461 students from grades 9 to 12 attending two large US secondary schools. Data were collected from participants in three waves, at 6-month intervals. Using a longitudinal social network analytical approach, it was not found that students specifically selected friends of the same ethnicity. At the same time, however, it was discovered that students remain, or over time become, more and more similar to their friends of the same nationality, but not to their friends of another nationality. It can therefore be concluded that friendships of the same ethnic group shaped students' sense of belonging more than inter-ethnic friendships, although it should be noted that the strength of these effects varied according to the location of the school. Expanding on the knowledge that friends – especially those who are members of the same ethnic group – are a significant factor influencing feelings of belonging (or lack thereof) in the school environment has important implications for educational psychology.

At this point, it is also worth mentioning another study by Rambaran and colleagues (2022b) conducted in the SNA paradigm. Their aim was to answer the question to what extent the defence of bullying victims depends on the sympathy or antipathy towards them, and the relationship of the mentioned variables to the bullying norms operating in the school classroom. A total of 1,272 fifth-grade primary school students were surveyed. The SNA showed that children are more willing to defend those victims whom they themselves like, who like them, and towards whom they share sympathy with their classmates, while they are reluctant to defend victims whom they themselves dislike, who dislike them, and towards whom they share antipathy with their classmates. Furthermore, the analysis showed that norms of bullying had an ambiguous effect on the relationship between defence and sympathy or antipathy towards victims of bullying.

Tannoia and Lease (2022) used the SNA approach to explore in more depth the social relationships of young children who display symptoms of attention deficit hyperactivity disorder (ADHD). Drawing on the source literature, the researchers focused on the attention deficits (IA) and hyperactivity-impulsivity (HI) characteristic of ADHD, which are often associated with problems in interacting with peers. The main research problem was to answer the question: is the reluctance to play with a peer perceived as HI and/or IA, mediated by the perception of that peer as reactively aggressive, instrumentally aggressive and/or anxiously withdrawn? In other words, the aim was to investigate whether IA and HI are directly related to peer difficulties or indirectly through their association with problem behaviours, e.g. aggression. The participants were 387 fourth and fifth grade students nested in 21 class peer networks. Participants nominated their class peers as IA, HI, aggressive, anxiously withdrawn and least liked. Analyses were conducted separately for each class peer network, and meta-analytical procedures were used to compile the results and calculate effect sizes across networks. We found that reactive and instrumental aggression did not mediate the relationship between IA/HI and peer resentment. In addition, perceiving a peer as anxious and withdrawn was not associated with nominating them as IA, HI or disliked. As the researchers conclude, for children, the peer's IA and HI alone are sufficient to contribute to their aversion to peers who exhibit such behaviours, regardless of the co-occurrence of aggressive behaviours.

Based on the research cited, it can be concluded that thinking about empirical data in terms of networks and applying network analysis methods to research problem solving can provide unique insights into the psychological processes present in education.

3. Restrictions on the use of SNA

Like all statistical models, the network model is not a tool without certain limitations. One of the more frequently mentioned problems by SNA experts is access and data collection. McGloin and Kirk (2010), for example, highlight two problems. In their view, firstly, researchers should be very considerate about the sampling procedure. Ideally, the social network is complete and reflects the entire population of interest to the researcher. In some cases, it is possible to include the entire network in a survey, e.g. when surveying a specific class in a school or an entire department in a company. In such cases, the population has clearly defined boundaries. However, often sampling is much more complicated, both conceptually and practically, because the population boundary is unclear. The researchers give the example of a peer network or street gang study, where you start sampling people at school or on the street. In this case, in order to capture the network, the researcher should keep track of each identified friend and then "friend of a friend", etc., which can be an endless exercise. At some point he/she will therefore be faced with the need to decide when the network boundary has been "reached" and justify this accordingly Ideally, this boundary should have a conceptual value and not be based solely on ease of access to network members or previous research work. A similar sampling problem will be encountered by researchers interested in ego-centric networks. Ego-centric networks typically contain individuals with whom a given individual is connected (via any connections of interest), as well as any connections between the alters (i.e. nodes in a network other than the ego network). This means that researchers who record respondents' ego-centric peer networks, but limit them to identifying only a handful of friends, may have problems with the accuracy of the model (McGloin, Kirk, 2010).

The second problem highlighted by McGloin and Kirk (2010) is missing data and the different techniques for dealing with this. In network research, missing data can cause a domino effect. McGloin and Kirk cite the following example: we have a project that collects network data of young people at a summer camp. The researcher is asking about the friendship bonds between the campers and is interested in the alcohol consumption in their personal networks (i.e. "ego-centric" networks). If one participant was absent on the day of the survey, there will of course be no data on their friendship network. However, unlike typical data, his absence may also affect the extent to which other participants have missing data. While it could be argued that this would not affect the structure of the other participants' primary networks, as they were able to identify him as a friend even though he was not present, it could affect the extent to which their peer group appears to engage in alcohol consumption. If drinking behaviour among friends is based on friends' self-reports, then if that absent student was identified as a friend in 20 networks, those 20 people now have missing data on any variable measuring the degree of peer drinking. This is an example of how in the SNA, under certain circumstances, the impact of missing data can quickly grow and create a domino effect in network studies (McGloin and Kirk, 2010).

When selecting variables for modelling, it is therefore necessary to decide which variables will be included and which omitted, as well as how they are to be measured. Each of these two processes introduces some error into the modelling process. Thus, like other methods of analysis (e.g. regression, SEM), network analysis is sensitive to the variables in the model and to the specific estimation methods used (Hevey, 2018). Frequent objections to the networks relate to their replicability (see e.g. Forbes, Wright, Markon and Krueger, 2017; Hevey, 2018). Moreover, researchers emphasise that there is a lack of more conceptual and methodological studies to estimate both the accuracy and stability of the network (Fried, Cramer, 2017). Identifying useful thresholds of acceptability for these parameters would be very useful in interpreting network models (Hevey, 2018).

Of course, the outlined problems associated with the use of SNA cannot be ignored. However, it should be emphasised that most of the challenges, e.g. regarding replication of surveys and generalisation of results, do not only apply to network modelling, but also to other, more traditional, methods of data analysis. Furthermore, several assumptions can be checked based on the expected properties of the network, as given a certain size, networks oftentimes obey several patterns, which can then be used to verify the correctness of the modelling. Moreover, substantial efforts are currently being made to develop new techniques of ensuring network validity.

Conclusions

On the basis of the considerations presented in this article, it can be concluded that knowledge of social network analysis methods can be useful for both researchers and practitioners involved in education in its broadest sense. Complex social systems exist in the educational environment, and to understand them, we need to understand the networks that define the interactions between the different elements that interact with each other. Considering psychological processes from this perspective offers alternative ways of conceptualising and answering important questions posed by educational psychologists.

What SNA offers – network exploration, calculation of network centrality measures, estimation of network features and even simply visualising networks using graphs – can be very useful for research. Among other things, these methods allow researchers to identify potentially important people in the network, compare their place and importance in the networks, determine how information travels through the network, and how this affects behaviour. Thus, social network methods have the potential to greatly assist research in educational psychology. As McGloin and Kirk (2010) observe, analysis of social networks is more than a set of methods – it is an orientation to understanding human behaviour that focuses on the importance of social relationships, and a set of tools that enable the study of social relationships and their consequences.

References

Andrews, N. C. Z., McDowell, H., Spadafora, N., Dane, A.V. (2022). Using social network position to understand early adolescents' power and dominance within a school context. *School Psychology, 37*(6), 445-454. https://doi.org/10.1037/spq0000445

Barabási, A. L. (2012). The network takeover. *Nature Physics, 8*, 14-16. https://doi.org/10.1038/nphys2188

Borgatti, S. P., Mehra, A., Brass, D. J., Labianca, G. (2009). Network analysis in the social sciences. *Science, 323*(5916), 892-895. https://doi.org/10.1126/science.1165821

Borsboom, D. (2017). A network theory of mental disorders. *World Psychiatry, 16*, 5-13. https://doi.org/10.1002/wps.20375

Brass, D. J. (2022). New developments in social network analysis. *Annual Review of Organizational Psychology and Organizational Behavior, 9*, 225-246. https://doi.org/10.1146/annurev-orgpsych-012420-090628

Burt, S. A., Pearson, A. L., Rzotkiewicz, A., Klump, K. L., Neiderhiser, J. M. (2019). It really does take a village: The role of neighbors in the etiology of nonaggressive rule-breaking behavior. *Development and Psychopathology, 31*(2), 713-725. https://doi.org/10.1017/S0954579418000366

Costantini, G., Epskamp, S., Borsboom, D., Perugini, M., Mõttus, R., Waldorp, L. J., Cramer, A. O. J. (2015). State of the aRt personality research: A tutorial on network analysis of personality data in R. *Journal of Research in Personality, 54*, 13-29. https://doi.org/10.1016/j.jrp.2014.07.003

Davila, M., Kornienko, O. (2022). Making, keeping, and influencing friends: The role of fear of negative evaluation and gender in adolescent networks. *School Psychology, 37*(6), 455-466. https://doi.org/10.1037/spq0000481

Fonseca-Pedrero, E. (2018). Network analysis in psychology. *Papeles del Psicólogo*, *39*(1), 1-12. https://doi.org/10.23923/pap.psicol2018.2852

Forbes, M. K., Wright, A. G. C., Markon, K. E., Krueger, R. F. (2017). Evidence that psychopathology symptom networks have limited replicability. *Journal of Abnormal Psychology, 126*(7), 969-988. https://doi.org/10.1037/abn0000276

Fried, E. I., Cramer, A. O. J. (2017). Moving forward: Challenges and directions for psychopatho-logical network theory and methodology. *Perspectives on Psychological Science, 12*(6), 999-1020. https://doi.org/10.17605/OSF.IO/BNEK

Gilman, R., Carboni, I. (2022). Introduction to the special issue: Social network analysis and its application to schools. *School Psychology, 37*(6), 421-423. https://doi.org/10.1037/spq0000530

Grbić, S., Maksić, S. (2022). Adolescent identity at school: Student self-positioning in narratives concerning their everyday school experiences. *Journal of Constructivist Psychology, 35*(1), 295-317. https://doi.org/10.1080/10720537.2020.1816235

Hevey, D. (2018) Network analysis: a brief overview and tutorial. *Health Psychology and Behavioral Medicine, 6*(1), 301-328. https://doi.org/10.1080/21642850.2018.1521283

Isvoranu, A. M., van Borkulo, C. D., Boyette, L. L., Wigman, J. T. W., Vinkers, C. H., Borsboom, D. (2017). A network approach to psychosis: Pathways between childhood trauma and psychotic symptoms. *Schizophrenia Bulletin, 43*, 187-196. https://doi.org/10.1093/schbul/sbw055

Kornienko, O., Rivas-Drake, D. (2021). Adolescent intergroup connections and their developmental benefits: Exploring contributions from social network analysis. *Social Development,* 31, 9-26 https://doi.org/10.1111/sode.12572

Lambe, L. J., & Craig, W. M. (2022). The co-evolution of friendship, defending behaviors, and peer victimization: A short-term longitudinal social network analysis. *Social Development, 31*(4), 984-1000. https://doi.org/10.1111/sode.12599

McGloin, J. M., Kirk, D. S. (2010) An overview of social network analysis. *Journal of Criminal Justice Education, 21*(2), 169-181.https://doi.org/10.1080/10511251003693694

Neal, J. W. (2020). A systematic review of social network methods in high impact developmental psychology journals. *Social Development, 29*, 923-944. https://doi.org/10.1111/sode.12442

Quinn, A., Ralph Woehle & Kathleen Tiemann (2012) Social Network Analysis for Analyzing Groups as Complex Systems, *Journal of Social Service Research*, *38*(5), 605-618. https://doi.org/10.1080/01488376.2012.721278

Rambaran, J. A., Hoffman, A. J., Rivas-Drake, D., Schaefer, D. R., Umaña-Taylor, A. J., Ryan, A. M. (2022a). Belonging in diverse contexts: Sociability among same-ethnic and cross-ethnic peers. *School Psychology, 37*(6), 467-477. https://doi.org/10.1037/spq0000480

Rambaran, J. A., van Duijn, M. A. J., Dijkstra, J. K., Veenstra, R. (2022b). The relation between defending, (dis)liking, and the classroom bullying norm: A cross-sectional social network approach in late childhood. *International Journal of Behavioral Development*, *46*(5), 420-431. https://doi.org/10.1177/01650254211029715

Sweet, T. M. (2016). Social network methods for the educational and psychological sciences. *Educational Psychologist, 51*(3-4), 381-394. https://doi.org/10.1080/00461520.2016.1208093

Tannoia, D. P., Lease, A. M. (2021). The relation of inattention and hyperactivity-impulsivity to peer dislike: An examination of potential mediators. *School Psychology, 37*(6), 478-487. https://doi.org/10.1037/spq0000446

van den Bos, W., Crone, E. A., Meuwese, R., Güroğlu, B. (2018). Social network cohesion in school classes promotes prosocial behavior. *PLOS ONE, 13*(4), Article e0194656. https://doi.org/10.1371/journal.pone.0194656

Zimmerman, G. M., Rees, C., Posick, C., Zimmerman, L. A. (2016). The power of (Mis)perception: Rethinking suicide contagion in youth friend-ship networks. *Social Science & Medicine, 157*, 31-38. https://doi.org/10.1016/j.socscimed.2016.03.046