Symptoms of Aggression Functions and Sleep: A Network Analysis Approach

By

Elizabeth C. Tampke
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B.A., University of Kansas, 2015

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Chair: Paula J. Fite, Ph.D.

Omar G. Gudino, Ph.D., ABPP

Matthew Mosconi, Ph.D., ABPP

Meagan Patterson, Ph.D.

Michael Vitevitch, Ph.D.

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The dissertation committee for Elizabeth C. Tampke certifies that this is
the approved version of the following dissertation:

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Chair: Paula J. Fite, Ph.D.

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Abstract

More research is needed to understand how aggression is associated with problematic sleep, which is both a cause and consequence of aggression. Previous work has used factor analytic models to examine the distinct, yet overlapping, functions (i.e., proactive and reactive) of aggression. However, network analysis may be a useful statistical tool for examining aggression because it identifies key symptoms through evaluating the associations between specific symptoms (rather than their higher-order factors). Furthermore, this method could identify which aggression symptoms are associated with specific symptoms of poor sleep quality. The current study used network analysis to (1) evaluate the symptomatology structure of proactive and reactive aggression as well as aggression and sleep quality (i.e., communities), (2) identify the core symptoms of proactive and reactive aggression as well as sleep quality (i.e., centrality), (3) identify the aggression and sleep symptoms that are the most salient targets for interventions to reduce aggression (i.e., "key players"), and (4) evaluate differences in these outcomes based on child- and teacher-report of aggression. Results indicated that both child- and teacher-reported Aggression networks resulted in a two-community structure (i.e., proactive and reactive) and child- and teacher-reported Aggression Plus Sleep networks resulted in a 3-community structure (i.e., proactive aggression, reactive aggression, and sleep quality); however, communities were not as well defined as anticipated. Child- and teacher-reported networks were found to be similar to each other overall but demonstrated some differences. In contrast to expectations, proactive and reactive aggression symptoms were equally central in child- and teacher-reported Aggression and Aggression Plus Sleep networks. However, centrality indices of strength, closeness, and betweenness were not statistically robust and, therefore, should be interpreted with caution. While different symptoms were identified as key players in the teacher and child networks, in both Aggression networks proactive aggression symptoms were identified as key players over reactive aggression symptoms. In both Aggression Plus Sleep networks, *sleep onset latency* (Falling_Asleep) was identified as a key player. In contrast to expectations, both reactive and proactive aggression symptoms were both positively and negatively correlated with sleep quality symptoms in teacher- and child-reported networks. Findings suggest that proactive aggression symptoms are important to target for aggression interventions and that improvements in sleep quality may enhance aggression interventions. Additional findings and their implications are discussed in turn.

Keywords: proactive aggression, reactive aggression, sleep quality, middle childhood, network analysis

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Table of Contents

Aggression is present in a variety of psychological disorders (e.g., ADHD, PTSD, DMDD, and ODD; American Psychiatric Association, 2013) and childhood aggression is associated with a variety of immediate and long-term negative outcomes into adulthood (e.g., internalizing problems, conduct problems, and substance use; Card & Little, 2006; Marsee et al., 2011). On a societal level, aggressive youth incur significantly more public cost-per-child than typically developing youth (Foster & Jones, 2005); moreover, aggression victims are at increased risk for a series of physical, emotional, and economic negative outcomes (e.g., Martin et al., 2011). Therefore, successful prevention and intervention programs for aggressive youth could significantly contribute to the betterment of society and individuals. Intervention and prevention programs may be particularly valuable in middle to late childhood, when aggression levels peak (Fite et al., 2008). One way to improve aggression interventions is through examining aggression symptomatology via network analysis, which includes the evaluation of which symptoms of unique aggression functions are most central to the network and which symptoms would be the most salient targets for aggression interventions.

Previously, aggression functions have been studied through a factor analytic approach (e.g., Dodge & Coie, 1987; Marsee et al., 2011; Raine et al., 2006) with results suggesting that all symptoms of aggression stem from central "disorder factors" (Borsboom & Cramer, 2013). Network analysis, in contrast, examines the associations that lower-level symptoms have with each other. In doing this, network analysis can be used to identify which symptoms are at the core of the construct(s), which symptoms are most closely related, and which symptoms connect related constructs. In this way network analysis can determine (theoretically) which symptoms are causes and consequences of each other within a disorder (Borsboom & Cramer, 2013). Clinical psychology research has just recently begun to employ network analysis for psychological disorders, such as ADHD and eating disorders (Forbush et al., 2016; Martel et al., 2016), and this statistical technique has led to valuable discoveries. For example, in a study of adults (ages 18 to 55), Forbush and colleagues (2016) were able to identify that the behavior of "Body Checking" (i.e., "trying on different outfits because one did not like how one looked") was the most important symptom in a network of eating disorder symptomatology and recommended that intervention programs focus more on "Body Checking" behaviors. Alternatively, in a cross-sectional study of ADHD in preschool, childhood, adolescence, and young adulthood, Martel and colleagues (2016) identified significant changes in the symptom structure of ADHD based on the developmental period; however, they also demonstrated that two symptoms of ADHD (i.e., "often easily distracted" and "difficulty sustaining attention") remained central to the disorder across all ages. While network analysis has been valuable for re-conceptualizing the pathology of several psychological disorders, it has not yet been applied to the study of aggression.

Network analysis may be particularly useful in examining the development of aggression and its correlates due to the way aggression has been conceptualized and dichotomized in the past. Throughout the scientific literature, aggression has traditionally been characterized by distinct, yet highly correlated, functions of proactive and reactive aggression, which can be both physical and relational in form (e.g., Card et al., 2008; Dodge & Coie, 1987; Marsee et al., 2011). Proactive aggression is utilized to achieve a goal, is typically planful and controlled, and can be explained by the social-cognitive learning theory, which posits that aggression is adopted by youth who find it adaptive (Bandura, 1973; Dodge & Coie, 1987). Conversely, reactive aggression is the defensive use of aggression in response to a perceived threat, is more impulsive and emotional, and can be explained by the frustration-aggression theory, which states that a barrier or threat to expected goal attainment instigates impulsive, emotional aggression (Berkowitz, 1993; Dodge & Coie, 1987). While proactive and reactive aggression have each been associated with unique risk factors and negative outcomes in middle childhood and adolescence (Fite et al., 2014; Fite et al., 2016), they are also highly correlated and often comorbid in youth from early childhood to adolescence (Card & Little, 2006).

Despite the high rate of comorbidity between the constructs, much of the scientific literature focuses on separating out the forms and functions of aggression and has called for tailored interventions for each type (Marsee et al., 2011; Smeets et al., 2015). It is important to note that understanding distinct subtypes of aggression is necessary and that research which separates the distinct aggression subtypes has played a valuable role in elucidating the underlying mechanisms of each function (e.g., Behavioral Inhibition and Behavioral Activation Systems for proactive aggression and maladaptive Social Information Processing for reactive aggression; Crick & Dodge, 1996; Dodge, 2006; Gray, 1972). However, this approach fails to evaluate aspects of the subtypes of aggression that may link the constructs together. Perhaps as a result of this, interventions that account for both functions of aggression attempt to target proactive and reactive aggression in a sequential manner. Unfortunately, these interventions have effect sizes that are small to moderate, tend to focus on reactive, rather than proactive, aggression, and are not equally successful in reducing both aggression functions in middle childhood and early adolescence (i.e., 10- to 13-years-old; Daunic et al., 2012; Smith et al., 2014; Stoltz et al., 2013; Van Manen et al., 2004; Vitaro & Brendgen, 2011).

Of potential significance, network analysis provides an opportunity to identify symptoms that connect related constructs (e.g., Forbush et al., 2016). Therefore, network analysis can be used to identify the symptoms that link proactive and reactive aggression, which could enable psychologists to better conceptualize aggression and optimize interventions to target key behaviors for both aggression subtypes. Examining the symptomatology of aggression functions in middle childhood is especially important given that most aggression interventions are designed for youth in this developmental period (Leff et al., 2018; Lochman et al., 2018) and that both proactive and reactive aggression peak in this period (i.e., 6th grade) before declining for most youth throughout late childhood and adolescence (Fite et al., 2008).

Evaluating differences in symptom networks for aggression based on informant (i.e., teacher- and child-report) may offer valuable insight into aggression symptomatology. Previous studies have found that child-reports of aggressive behavior often differ from teacher- or peer-reports on aggression, with children tending to report lower levels of aggressive behavior for themselves than their teachers or peers in first through seventh grade (Johnson & Hannon, 2014; Ledingham et al., 1982). While teachers have previously been identified as valid reporters of externalizing behavior in youth (e.g., 13-year-olds; Stanger & Lewis, 1993), research suggests youth in middle childhood (e.g., 3rd to 5th graders) also provide valuable insight on their own problem behavior (Rubens et al., 2017). Specifically, children may be able to better report behaviors that are more covert in nature, such as proactive aggression. Therefore, collecting reports of aggression from multiple informants would provide valuable insight into which symptoms of aggression are most important from both child and teacher perspectives.

Aggression and Sleep

In accordance with the developmental psychopathology framework, biological factors are important to consider in the development of aggression (Cummings et al., 2002). Sleep may be a particularly important factor to evaluate given that a wide range of research in youth aged 4- to 13-years-old has demonstrated links between aggression and sleep-related problems (e.g., Becker, 2014; Coulombe et al., 2011; Rubens et al., 2017). Moreover, middle childhood youth are at increased risk for poor sleep due to the onset of biological changes they incur at the beginning of pubertal development (Blakemore et al. 2010; Sadeh et al., 2000).

The majority of research on sleep-related problems and aggression examines inappropriate sleep duration (i.e., too little or too much sleep) and has demonstrated that both too little and too much sleep are associated with increased aggression, hostility, and delinquency in youth 4- to 19-years-old (Coulombe et al., 2011; Ireland & Culpin, 2006; Lin & Yi, 2015; Meijer et al., 2010; Rubens et al., 2017). However, the categorization of "problematic" sleep duration has been inconsistent (and sometimes arbitrary) throughout the literature (e.g., Lin & Yi, 2015; Na & Park, 2018); moreover, youth may not be accurate reporters of their own sleep duration (Bauer & Blunden, 2008). Given these limitations, examining other sleep problems beyond sleep duration, such as sleep quality, is warranted. Symptoms of low sleep quality (e.g., night wakings, sleep onset latency, sleep maintenance insomnia, and subjective poor sleep) are important to consider as previous research suggests they are uniquely linked to increased aggression across development in youth 8- to 19-years-old (e.g., Ireland & Culpin, 2006; Rubens et al., 2017).

Existing evidence suggests sleep-related problems may be a physiological cause and consequence of aggression (Ireland & Culpin, 2006; Kamphuis et al., 2012; Meijer et al., 2010). While mechanistic research in youth is limited, research in adults suggests that problematic sleep may contribute to aggression via impairment in the functioning of the prefrontal cortex (PFC), which results in decreased emotional intelligence, increased impulsivity, and decreased behavioral inhibition (Kamphuis et al., 2012). Some research indicates that poor sleep weakens the connectivity between the amygdala and the medial PFC, which reduces the ability of the medial PFC to exert top-down control of the amygdala and results in context-inappropriate emotional responses and heighted threat response (Kamphuis et al., 2012). Alternatively, aggression may also cause sleep problems. Engaging in aggression may be a stressful experience for youth which results in deregulation of the hypothalamic-pituitary-adrenal (HPA) axis. This deregulation results in increases in cortisol levels at bedtime which makes it difficult to attain high quality sleep (Kamphuis et al., 2012; Na & Park, 2018).

Some research indicates that sleep is more strongly related to reactive aggression than proactive aggression in elementary through high school-age youth (Becker, 2014; Fite et al., 2015; Rubens et al., 2017). For example, multiple studies have found that sleep quality is negatively associated with reactive aggression, but not proactive aggression in elementary and high school youth (Becker, 2014; Fite et al., 2015; Rubens et al., 2017). This may be because (1) reactive aggression is more strongly linked to heightened threat response and impulsivity and/or (2) youth who are reactively aggressive are more likely to feel stressed after engaging in aggression. Alternatively, it may be that third factors, such as internalizing symptoms, link poor sleep to reactive aggression (e.g., Fite et al., 2015). However, it should be noted that there is very limited research examining mechanisms connecting sleep quality to aggression in youth and more research is needed before firm conclusions about children can be drawn (Kamphuis et al., 2012).

In sum, a variety of sleep quality symptoms may be associated with aggression in middle childhood. Using symptom networks to study the link between sleep and aggression may be particularly useful because it allows researchers to examine which specific symptoms of low-quality sleep are associated with the unique symptoms of aggression functions in middle childhood. This approach differs significantly from other studies on sleep and aggression which have used composite scores of sleep quality measures (e.g., Becker, 2014) and can provide valuable insight on which specific symptoms of problematic sleep would be valuable to target in interventions.

Current Study

The current study sought to better understand the associations between the functions of aggression through evaluating the symptom networks of proactive and reactive aggression in middle childhood. Network analysis was used to (1) evaluate the symptomatology structure of proactive and reactive aggression as well as aggression and sleep quality (i.e., communities), (2) identify the core symptoms of proactive and reactive aggression as well as aggression and sleep quality (i.e., centrality), (3) identify the aggression and sleep symptoms that are the most salient targets for interventions to reduce aggression (i.e., "key players"), and (4) evaluate differences in these outcomes based on child- and teacher-report of aggression. Specific symptoms of aggression and sleep problems were represented as nodes, associations between nodes were represented as edges (i.e., lines that connect associated nodes), and closely related nodes were visually represented through communities of nodes (i.e., individual nodes located close to each other; see Data Analytic Plan for more detail). The symptom networks were evaluated to determine whether and how the network shifted depending on the informant (i.e., teacher versus child).

This study could significantly advance the scientific literature because it was the first time that network analysis was used to evaluate the functions of aggression and their associations with specific sleep quality symptoms. The statistical approach and study design have the potential to dramatically change how aggression in middle childhood is conceptualized, as it allowed for the identification of key symptoms of the different functions of aggression and their associations with problematic sleep in middle childhood. Findings from this study could inform aggression interventions, as psychologists could then target key symptoms of both functions of aggression. Associations with sleep-related symptoms were especially important to examine, as this may identify “modifiable biological contributors” to specific aggression symptoms (Na & Park, 2018, p. 786). Improving aggression interventions would not only minimize the harm done by aggressive individuals to others but would also improve the aggressor’s quality of life. Finally, given that problematic sleep and aggression are key components of a variety of comorbid psychological disorders, further evaluation of their associations has the opportunity to inform the pathology of other psychological disorders and identify key symptoms to target in middle childhood.

In our evaluation of aggression symptoms, we expected that two symptom communities would emerge: proactive and reactive aggression. Further, we expected to identify core symptoms of proactive and reactive aggression through measures of closeness, strength, and betweenness, and we expected that reactive aggression symptoms would be more central to the network given that they are more common in youth (e.g., Cui et al., 2016). We also expected to identify symptoms that may be essential in connecting proactive and reactive functions (i.e., “key players”; see Data Analytic Plan).

In subsequent analyses of aggression with sleep quality symptoms, we expected that 3 symptom communities would emerge: proactive aggression, reactive aggression, and sleep quality. Regarding associations between communities, we expected that reactive aggression, rather than proactive aggression, would be more closely related to sleep symptoms. Additionally, we expected that symptom networks of teacher- and child-reported aggression would differ because of the covert nature of proactive aggression (Card & Little, 2006). Specifically, in

Aggression networks, we expected that symptoms of proactive aggression would be more central to the network in child-reported networks than teacher-reported networks.

Methods

Participants

Participants were elementary students (n =375; 51% female) aged 8-11 years (mean = 9.24 years, SD = 0.94) and their classroom teachers (n = 17) in a rural community in the Midwestern United States in Fall of 2014. Our sample consisted of third graders (n = 140), fourth graders (n = 118), and fifth graders (n = 117). Notably, the number of children for which data was available shifted depending on the network estimated, with teachers reporting on aggression symptoms of 375 youth (approximately 18 to 25 children per teacher) and 295 children providing self-report of their aggression and sleep symptoms. Therefore, the teacher networks consisted of 375 youth, while the child networks consisted of 295 youth. For teachers, the consent and participation rate was 100%. For children, the consent rate was 80.65% and the participation rate was 79.30%. Some children who consented did not participate in the study because they declined assent (n = 3) or were absent during data collection (n = 2).

While the school did not provide specific information about student demographics, national census data for the community in which the school was located indicated that approximately 90% of the population was white, the primary language spoken at home was English, the average per capita income was $25,369, and 5% of individuals lived below the federal poverty line (U. S. Census Bureau, 2010). According to school records data, approximately 40% of students received free or reduced-price lunch.

Measures

Proactive and Reactive Aggression

Aggression functions were assessed via the Proactive/Reactive Aggression (PRA) scale for teacher- and child-report (Dodge & Coie, 1987). In both the child and teacher version, the PRA had 6 items which assessed both functions of aggression using a 5-point scale (1 = *Never*, 2 = *Very Rarely*, 3 = *Sometimes*, 4 = *Often*, and 5 = *Almost Always).* Three items assessed proactive aggression and three items assessed reactive aggression. Each item was treated as an individual symptom of aggression in the networks (see Appendix A). Previously, the PRA's construct, concurrent, and content validity have been established through the evaluation of internal consistency, factor structure, and behavioral associations (Dodge & Coie, 1987). Additionally, previous work has established the predictive validity of the PRA through high scores on proactive and reactive domains predicting elevated levels of expected outcomes (McAuliffe et al., 2007; Smithmyer et al., 2000). The PRA was originally developed as a teacher-report measure; however, it has demonstrated adequate to good internal consistency in previous studies utilizing self-report in children 5- to 13-years-old (Fite et al., 2009; Fite et al., 2011; Rubens et al., 2017). In the current study, internal consistencies were good for teacher-reports of proactive (α = 0.79) and reactive (α = 0.95) aggression and modest to good for child-reports of proactive (α = 0.57) and reactive (α = 0.72) aggression, which is consistent with previous research (Connor et al., 2003; Fite et al., 2017; Rubens et al., 2017).

Sleep Quality

Child sleep quality was assessed via a 4-item child self-report measure which utilized a 3-point scale. The measure assessed for sleep onset latency (i.e., *When you're in bed and the lights are turned off:* (1) *It takes you a long time to fall asleep, (2) You stay awake for a while, (3) You fall asleep at once),* frequency of night wakings (i.e., *Do you sometimes wake up during the night? (1) Nearly Every Night, (2) Sometimes, (3) Never*), sleep maintenance insomnia (or difficulty returning to sleep; *If you wake up during the night: (1) It takes you a while to fall asleep again, (2) You fall asleep again soon, (3) Mostly you don't notice*), and a subjective rating of overall sleep quality (*Do you sleep well at night? (1) No (2) Sometimes (3) Yes, always*; Meijer et al., 2000). Each item was treated as an individual symptom of sleep quality, with higher scores indicating higher sleep quality (see Appendix A). Previous research has demonstrated concurrent validity for child self-reports of sleep by comparing it to objective sleep measures, such as actigraphy (Meltzer et al., 2013). In the current study, internal consistencies were adequate (α = 0.60), which is consistent with previous research utilizing self-report in middle childhood and adolescent youth (Meijer et al., 2000).

Procedures

All study procedures were approved by the Institutional Review Board of the researchers and the school administrators.

Child Data Collection

Students' parents were given information about the ability for their child to participate in the study via online back-to-school packets. Consented students were asked to provide verbal assent at the commencement of data collection. Only students with both parental consent and child assent were allowed to participate in the study. Data collection occurred in the Fall of 2014. Children who declined to participate or were not able to complete the survey without assistance and all school personnel were removed from the classroom before data collection commenced. Data collection occurred in a group format during the regular school day and the survey took students 20 to 30 minutes to complete. Students were given a paper questionnaire to complete, which was read aloud to students by a reader so that items could be paced based on student needs. One to three additional research personnel (in addition to the reader) remained in the room to answer questions, ensure students were not sharing answers, and discourage disruptive behavior. Students received a pencil as compensation for completing the survey.

Teacher Data Collection

Teachers from the elementary school were informed of the study and its purpose at school staff meetings and given the opportunity to consent to participate. During the consent process, the voluntary nature of their participation was emphasized, and teachers were informed that a lack of participation would not negatively impact them. Teachers were given paper and electronic instructions for accessing the online survey, which was estimated to take 10 minutes to complete per student. Teachers completed surveys on children in their homeroom class (n = 18-25) and were paid $50 for completing measures on all of the students in their classroom and $25 if they completed measures on only a portion of their students.

Data Analysis

All analyses were run in R Core Team (2020). The current study utilized a Gaussian graphical model (GGM; Costantini et al., 2015; Lauritzen, 1996), which is a type of pairwise Markov random field (PMRF) network analysis (Costantini et al., 2015, Epskamp et al., 2018; van Borkulo et al., 2014). In a GGM, specific variables (i.e., symptoms) are represented by nodes and the associations (i.e., partial correlation coefficients) between those nodes are represented as undirected edges (i.e., if node A is associated with node B, node B *must* be associated with node A). In the current study, edges appeared visually in the network as lines that connected nodes, with thicker and darker edges representing stronger partial correlation coefficients (Epskamp et al., 2018). Networks were color-coded, such that blue edges represented positive associations and red edges represented negative associations.

Ordered categorical data were utilized in which several variables were non-normally distributed (i.e., all proactive and reactive aggression items). A recent comprehensive evaluation of best practices for GGM in the social sciences determined that data transformation for non-normal categorical ordinal variables does not improve network evaluation (and can be deleterious for some network parameters; Isvoranu & Epskamp, 2021 PREPRINT). Therefore, non-normal data was not transformed and polychoric correlations were used to attenuate potential effects of data skewness (Epskamp & Fried, 2016; Isvoranu & Epskamp, 2021 PREPRINT).

The data regularization techniques of graphical least absolute shrinkage and selection operator (GLASSO; Friedman et al., 2008; Tibshirani, 1996) and Extended Bayesian Information Criterion (EBIC; Chen & Chen, 2008) were used to estimate and select the optimal network structure for each estimated network. GLASSO is a regularization technique, which limits the total sum of absolute parameter values via a tuning parameter (λ), resulting in the shrinkage of many edge estimates to zero, which drops them from the model; therefore, reducing the network to a relatively small number of meaningful edges and thus increasing the interpretability of the model (Epskamp et al., 2018; Epskamp & Fried, 2016). Notably, GLASSO estimates a range of networks depending on the value of the tuning parameter selected (which can be as many as 100 different values); therefore, EBIC was used to select the most optimal network out of the range of networks estimated (Epskamp & Fried, 2016).

Proactive and reactive aggression and sleep symptoms were evaluated in a sequential manner. GGM was used to estimate four symptom networks: (1) child-report of aggression symptoms (child-reported Aggression), (2) teacher-report of aggression symptoms (teacher-reported Aggression), (3) child-report of aggression and sleep quality symptoms (child-reported

Aggression Plus Sleep), and (4) teacher-report of aggression symptoms and child-report of sleep quality symptoms (teacher-reported Aggression Plus Sleep). Each item of the PRA and sleep questionnaire represented a symptom node.

Networks were compared to determine whether there were statistically significant differences across network structures using the Network Comparison Test (van Borkulo et al., 2016). The Network Comparison Test determined statistically significant differences between the networks based on three indicators of invariance: (1) network structure invariance (i.e., whether the network structure was identical between networks), (2) global strength invariance (i.e., whether the weighted absolute sum of edges were similar between networks), and (3) edge invariance (i.e., whether specific edges were equally strong between networks; van Borkulo et al., 2016).

The Spinglass Community Detection method (Newman & Girvan, 2004; Reichardt & Bornholdt, 2006; Traag & Bruggeman, 2009) was used to identify sub-groups of nodes (referred to as communities) in each network (Siew, 2013; Siew et al., 2017). Communities are comprised of nodes that are more connected to each other than they are to other nodes in the network that are not a part of their communities (Newman, 2006). In this way, community detection can identify which symptoms tend to occur together (e.g., symptoms of proactive aggression were expected to occur together more than symptoms of both proactive and reactive aggression). For child- and teacher-reported Aggression networks a 2-community model was expected to emerge (i.e., one community for proactive aggression symptoms and one community for reactive aggression symptoms). For child- and teacher-reported Aggression Plus Sleep networks a 3-community model was expected to emerge (i.e., proactive aggression, reactive aggression, and sleep quality).

Additionally, each network was evaluated to determine which symptoms (i.e., nodes) were most important to the network via node centrality. Centrality is an indicator of how strongly a specific symptom is related to other symptoms in the network and its involvement in other network pathways. Consistent with previous literature (Forbush et al., 2016; Siew et al., 2017), centrality was measured by three indicators: (1) strength (i.e., how well a node is directly connected to other nodes), (2) closeness (i.e., how well a node is *indirectly* connected to other nodes), and (3) betweenness (i.e., how important a node is in the average path between two other nodes; Epskamp et al., 2018; Opsahl & Panzarasa, 2009). For all indices, higher numbers indicated higher centrality. In theory, centrality indices can be used to hypothesize which symptoms are causal players in the symptom network (Borsboom & Cramer, 2013); however, recent literature has called into question the utility of centrality indices for skewed ordered-categorical data (Isvoranu & Epskamp, 2021 PREPRINT) and has emphasized the importance of assessing stability and accuracy of centrality indices (Dablander et al., 2019). The accuracy and stability of centrality indices were evaluated via the methods proposed by Epskamp et al. (2018): (1) the accuracy of edge-weights (i.e., value of partial correlation coefficients) were evaluated by *bootstrapped Confidence Intervals*, (2) the stability of the order of centrality indices were evaluated via *case-dropping subset bootstrapping,* in which networks of subsets of our sample were examined, and were quantified using the *correlation stability coefficient*, and (3) significant differences between edge-weights and centrality indices were evaluated via *bootstrapped differences tests*.

In addition to strength, closeness, and betweenness centrality, a key players analysis was used to identify which nodes maintain the cohesiveness in the network through measuring their fragmentation centrality (An & Liu, 2016; Borgatti, 2008; Forbush et al., 2016). In this way, a key players analysis identifies which nodes, when removed from the network, result in the maximum fracturing of the network. Notably, the number of key players identified in a network is determined by the analyst, rather than the parameters of the network itself. In order to account for redundancy, the key players that are selected may differ depending on the number of key players identified. Key players analysis provides unique information regarding which symptoms may be most important to target for treatment depending on how many symptoms one wishes to target.

While issues of sample size contributing to limited power seem to be regularly acknowledged in the psychological literature about network analysis (e.g., Eddinger et al., 2020; Epskamp et al., 2018; Forbush et al., 2016), clear recommendations about sample size and number of nodes do not seem to exist in the field to date and methods to evaluate statistical power of specific types of networks are just starting to emerge (e.g., longitudinal networks; Stadtfeld et al., 2020). Thus, the manuscript includes a table of current psychological symptom networks in the literature, their sample size, and the number of nodes evaluated (see Appendix B). Based on this table, our sample size and number of nodes were generally comparable to other psychological studies.

Results

Descriptive Statistics

Means and distributions for the individual items are reported in Table 1. Children generally reported higher means for reactive aggression symptoms than teachers, while teachers generally reported higher means for proactive aggression than children, which is consistent with previous literature (Mildrum Chana et al., 2020). Also consistent with previous literature, both teachers and children reported higher levels of reactive aggression than proactive aggression

(Fite et al., 2016). All aggression variables were non-normally distributed. All sleep variables were normally distributed.

Given that child-reported networks only included children with child-reported data, while teacher-reported networks included students with teacher-reported data for aggression and child-reported data for sleep, the sample size differed substantially between teacher- and child-reported networks (n = 80). Independent samples t-tests were conducted to evaluate whether the sample characteristics were significantly different from each other. Results indicated that there were no significant differences in study variables between youth with child-reported data and youth with only teacher-reported data.

Description of Networks

Child-Reported Aggression Network

In the child-reported Aggression network (Figure 1) all proactive and reactive aggression nodes were positively correlated with at least 4 other aggression nodes. All nodes were only positively correlated with nodes they were connected to, with the exception of proactive aggression item *threatens or bullies others in order to get his/her own way* (PA_Threatens) and reactive aggression item *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) which were negatively associated.

Teacher-Reported Aggression Network

In the teacher-reported Aggression network (Figure 2), all nodes were positively connected with at least two other nodes in the network. While the majority of nodes were positively associated with each other, some nodes were negatively associated with each other. The proactive aggression symptom *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical) and the reactive aggression symptom *claims that* *other children are to blame in a fight and feels that they started the trouble* (RA_Blames) were negatively associated. Similarly, the proactive aggression symptom *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up) and the reactive aggression symptom *when someone accidentally hurts the child, assumes that the peer meant to do it and then reacts with anger/fighting* (RA_Accident) were negatively associated.

Child-Reported Aggression Plus Sleep Network

In the child-reported Aggression Plus Sleep network (Figure 3), all sleep symptoms that were associated were positively correlated with each other, with the exception of a weak negative association between *frequency of night wakings* (Nightwakings _Freq) and *sleep onset latency* (Falling_Asleep). All sleep quality nodes were negatively associated with at least two aggression nodes. Most notably, high *frequency of night wakings* (Nightwakings _Freq) was associated with high levels of the proactive aggression symptom *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical). Further, long *sleep onset latency* (Falling_Asleep) was associated with high levels of the proactive aggression node *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up). Some symptoms of sleep quality were positively associated with symptoms of aggression. Low *frequency of night wakings* (Nightwakings _Freq) was positively associated with the proactive aggression symptom *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up) and the reactive aggression symptom *when teased or threatened, gets angry easily and strikes back* (RA_Teased). High levels of the proactive aggression symptom *threatens or bullies others in order to get his/her own way* (PA_Threatens) was associated with short *sleep onset latency* (Falling_Asleep), low levels of *sleep maintenance insomnia* (ReturntoSleep), and high *subjective sleep quality* (SubQuality).

Teacher-Reported Aggression Plus Sleep Network

In the teacher-reported Aggression Plus Sleep network (Figure 4), all sleep symptoms that were associated with each other were positively correlated. Aligning with expectations, low scores on every sleep quality symptom were associated with high scores on at least one aggression symptom (i.e., negatively associated). Most notably, experiencing high levels of *sleep maintenance insomnia* (ReturntoSleep) was associated with the reactive aggression symptom *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) and low *subjective sleep quality* (SubQuality) was associated with the proactive aggression symptom *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical). In contrast to expectations, high scores on some sleep quality nodes were also associated with high scores on aggression nodes (i.e., positively associated). Most notably, low levels of *sleep maintenance insomnia* (ReturntoSleep) were positively associated with *when teased or threatened, gets angry easily and strikes back* (RA_Teased), and experiencing short *sleep onset latency* (Falling_Asleep) was positively associated with *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA _Physical).

Characteristics of Edge-Weights

The characteristics of edge-weights were evaluated using *bootstrapped Confidence Intervals* and *bootstrapped differences tests* for each network (Epskamp et al., 2018). *Bootstrapped Confidence Intervals* indicated the confidence intervals for child- and teacher-reported Aggression and Aggression Plus Sleep networks were relatively wide, therefore interpreting the order of similarly weighted edges should be done with caution (see Figures 5 and 6).

However, results from the *bootstrapped differences tests* indicated that multiple edge-weights did differ significantly from one another (see Figure 7). In the child-reported Aggression network, most edges were not significantly different from each other, except that the edge between *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up) and *threatens or bullies others in order to get his/her own way* (PA_Threatens) tended to significantly differ from edges that connected different aggression functions (see Figure 7). This suggests that the association between these two nodes is significantly stronger than the associations between differing aggression functions. In contrast, in the teacher-reported Aggression network, results indicated that edges that connected nodes from alike aggression functions typically differed significantly from nodes that connected different aggression functions (see Figure 8). This suggests that teachers viewed associations between nodes of the same aggression function as stronger than associations between nodes of differing aggression functions.

In the child-reported Aggression Plus Sleep network, the edge between *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up) and *threatens or bullies others in order to get his/her own way* (PA_Threatens) tended to significantly differ from edges that connected different aggression functions and edges that connected sleep to aggression symptoms, and, to a lesser extent, the edge between *when teased or threatened, gets angry easily and strikes back* (RA_Teased) and *when someone accidentally hurts the child, assumes the peer meant to do it and reacts with anger/fighting* (RA_Accident) also followed this pattern (see Figure 9). This suggests that these nodes are more strongly associated with each other than the associations between nodes that connect different aggression functions and aggression with sleep. Similarly, in the teacher-reported Aggression Plus Sleep network, the edge that connected *frequency of* *night wakings* (Nightwakings_Freq) and *subjective sleep quality* (SubQuality) and the edges that connected alike aggression functions typically were significantly different than edges that connected different aggression functions or edges that connected aggression nodes to sleep nodes (see Figure10). This suggests that these nodes are more strongly connected to each other than other nodes are connected to each other in the network.

Network Comparisons

The network structures for child- and teacher-reported Aggression and Aggression Plus Sleep networks were compared using the Network Comparison Test (NCT; van Borkulo et al., 2016). NCT evaluated networks for invariance of (1) network structure (i.e., whether the entire network structure is identical), (2) edge strength (i.e., whether specific edges are equally strong across networks), and (3) global strength.

Child- and Teacher-Reported Aggression Networks

For the child- and teacher-reported Aggression networks, the evaluation of network structure invariance indicated that differences between network structures were marginally statistically significant (M = 0.40, $p = 0.09$). Therefore, while the symptom structures between networks were similar overall, differences between specific edges were still examined. Analysis of edge invariance indicated that there were significant differences between the networks for associations between *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) and *when teased or threatened, gets angry easily and strikes back* (RA_Teased; $p = 0.01$), *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical; $p < 0.001$), and *threatens or bullies others in order to get his/her own way* (PA_Threatens; $p = 0.05$). Specifically, *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) and *uses physical force (or* *threatens to use physical force) in order to dominate other kids* (PA_Physical) were negatively associated in the teacher-reported Aggression network, but positively associated in the child-reported Aggression network. Similarly, *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) and *threatens or bullies others in order to get his/her own way* (PA_Threatens) were positively associated in the teacher-reported Aggression network, but negatively associated in the child-reported Aggression network. While *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) and *when the child has been teased or threatened, gets angry easily and strikes back* (RA_Teased) were positively associated in both networks, the association was stronger in the teacher-reported than the child-reported Aggression network. Evaluation of global strength invariance indicated that the difference between the networks was significant (S = 0.22, $p < 0.001$), with global strength of the teacher-reported Aggression network (sum = 2.80) significantly larger than the child-reported Aggression network (sum = 2.58). This suggests the nodes in the teacher-reported Aggression network were more strongly associated with one another, even though there were fewer connections between nodes when compared to the child-reported Aggression network.

Child- and Teacher-Reported Aggression Plus Sleep Networks

For the Aggression Plus Sleep networks, evaluation of network structure invariance indicated that differences between network structures were not significant (M = 0.34, $p = 0.56$), suggesting that the networks were similar. Therefore, testing differences between specific edges was not warranted (van Borkulo et al., 2016). However, the test of global strength invariance indicated the difference was significant (S = 0.62, $p = 0.02$), with global strength of the teacher-reported network (sum = 4.04) significantly larger than the child-reported network (sum = 3.43). Similar to the Aggression networks, this indicates that the nodes in the teacher-reported

Aggression Plus Sleep network were more strongly associated with one another than the nodes in the child-reported Aggression Plus Sleep network.

Community Detection

The Spinglass community detection method (Newman & Girvan, 2004; Reichardt & Bornholdt, 2006; Traag & Bruggeman, 2009) was used to identify communities in all networks. Modularity (or Q) is a measure of the degree to which communities are distinct and well-defined within a network. Q values range from 0 to 1, with 1 indicating that a community is particularly distinct and well defined and values ranging from 0.30-0.70 indicating the presence of communities (Newman, 2006; Newman & Girvan, 2004). The child-reported Aggression network resulted in a 2-community structure (i.e., proactive aggression community and reactive aggression community) with a modularity value indicating that the communities were not defined ($Q = 0.16$), while the teacher-reported Aggression network resulted in a 2-community structure (i.e., proactive aggression community and reactive aggression community) with a modularity value indicating the communities were marginally defined ($Q = 0.25$). This suggests that while two communities were identified in the Aggression networks, neither the teacher- nor child-reported network resulted in distinct communities for proactive and reactive aggression. The child-reported Aggression Plus Sleep network resulted in a 3-community structure (i.e., proactive aggression community, reactive aggression community, and sleep community) that was marginally defined ($Q = 0.29$), while the teacher-reported Aggression Plus Sleep network resulted in a 3-community structure (i.e., proactive aggression community, reactive aggression community, and sleep community) with a modularity value indicating it was moderately defined ($Q = 0.39$). The relatively low modularity across networks indicates that the nodes within a community are also well-connected to other nodes that are outside of their communities. Results also suggest that teachers perceived children's reactive and proactive aggression behaviors as more distinct than children perceived their own proactive and reactive behaviors.

Centrality Indices

Child-Reported Aggression Network

As shown in centrality plots (Figure 11), nodes in the child-reported Aggression network that had the highest strength (in descending order) are: *threatens or bullies others in order to get his/her own way* (PA_Threatens), *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames), and *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up). This suggest that these nodes are directly connected to the most other nodes in the network. Nodes in the network that had the highest closeness (in descending order) are: *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames), *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical), and *threatens or bullies others in order to get his/her own way* (PA_Threatens). This suggest that these nodes are the nodes best indirectly connected to other nodes in the network. Nodes that had the highest betweenness (in descending order) are: *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) and *when someone accidentally hurts the child, assumes that the peer meant to do it and then reacts with anger/fighting* (RA_Accident). This suggest that these nodes are the most important in the average path between two other nodes.

Teacher-Reported Aggression Network

As shown in centrality plots (Figure 12), items in the teacher-reported Aggression network that had the highest strength (in descending order) are: *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames), *when someone accidentally* *hurts the child, assumes that the peer meant to do it and then reacts with anger/fighting* (RA_Accident), and *when teased or threatened, gets angry easily and strikes back* (RA_Teased). This suggests that these nodes are directly connected to the most other nodes in the network. Nodes that had the highest closeness (in descending order) are: *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical), *when teased or threatened, gets angry easily and strikes back* (RA_Teased), and *when someone accidentally hurts the child, assumes that the peer meant to do it and then reacts with anger/fighting* (RA_Accident). This suggests these nodes are the nodes that are best indirectly connected to other nodes in the network. Nodes that had the highest betweenness are equally: *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) and *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical). This suggest that these nodes are the most important in the average path between two other nodes.

Child-Reported Aggression Plus Sleep Network

As shown in centrality plots (Figure 13), nodes in the child-reported Aggression Plus Sleep network that had the highest strength (in descending order) are: *threatens or bullies others in order to get his/her own way* (PA_Threatens), *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up), *frequency of night wakings* (Nightwakings_Freq), *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical), and *sleep maintenance insomnia* (ReturntoSleep). This suggests that these nodes are the nodes that are directly connected to the most other nodes in the network. Nodes in the network that had the highest closeness (in descending order) are: *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical), *threatens or bullies others in order to get his/her own way* (PA_Threatens), *gets other kids to gang up on somebody that he/she doesn't* *like* (PA_Gang_Up), *frequency of night wakings* (Nightwakings_Freq), *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames), and *sleep maintenance insomnia* (ReturntoSleep). This suggest these nodes are the nodes that are best indirectly connected to other nodes in the network. Nodes that had the highest betweenness (in descending order) are: *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical), *threatens or bullies others in order to get his/her own way* (PA_Threatens), *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up), *frequency of night wakings* (Nightwakings_Freq), *when teased or threatened, gets angry easily and strikes back* (RA_Teased), and *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames). This suggests that these nodes are the most important in the average path between two other nodes.

Teacher-Reported Aggression Plus Sleep Network

As shown in centrality plots (Figure 14), nodes in the teacher-reported Aggression Plus Sleep network that had the highest strength (in descending order) are: *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames), *when teased or threatened, gets angry easily and strikes back* (RA_Teased), *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical), *threatens or bullies others in order to get his/her own way* (PA_Threatens), *subjective sleep quality* (SubQuality), and *when someone accidentally hurts the child, assumes that the peer meant to do it and then reacts with anger/fighting* (RA_Accident). This suggests that these nodes are directly connected to the most other nodes in the network. Nodes that had the highest closeness (in descending order) are: *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical), *when teased or threatened, gets angry easily and strikes back* (RA_Teased), *claims that other* *children are to blame in a fight and feels that they started the trouble* (RA_Blames), *when someone accidentally hurts the child, assumes that the peer meant to do it and then reacts with anger/fighting* (RA_Accident), *threatens or bullies others in order to get his/her own way* (RA_Threatens), and *subjective sleep quality* (SubQuality). This suggest that these nodes are the nodes that are best indirectly connected to other nodes in the network. Aggression and sleep items that had the highest betweenness (in descending order) are: *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical), *sleep maintenance insomnia* (ReturntoSleep), *when teased or threatened, gets angry easily and strikes back* (RA_Teased), *threatens or bullies others in order to get his/her own way* (PA_Threatens), *subjective sleep quality* (SubQualilty), and *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames). This suggests that these nodes are the most important in the average path between two other nodes.

Stability of Centrality Indices

The stability of centrality was evaluated via a *case-dropping subset bootstrap*, in which networks of subsets of our sample were examined. Stability of centrality indices were quantified using the *correlation stability coefficient (CS-coefficient*), which in the current study measured the maximum proportion of data that could be dropped and still retain a correlation of 0.70 in at least 95% of the samples within a network. To indicate that the centrality metric is stable, the *CS-coefficient* should not fall below 0.25 and preferably fall above 0.50 (Armour et al., 2017; Epskamp et al., 2018). For the child-reported Aggression network, the *CS-coefficient* indicated that strength (CS(cor = .7)=0), betweenness (CS(cor = .7)= 0), and closeness (CS(cor = .7)=0) were not stable under subsetting cases (see Figure 15). For the teacher-reported Aggression network, the *CS-coefficient* indicated that strength (CS(cor = .7)=.05), betweenness (CS(cor =

.7)= 0) and closeness (CS(cor = .7)=0) were not stable under subsetting cases (see Figure 16). For the child-reported Aggression Plus Sleep network, the *CS-coefficient* indicated that strength (CS(cor = .7)= 0.13, betweenness (CS(cor = .7)= 0), and closeness (CS(cor = .7)= 0) were not stable under subsetting cases (see Figure 17). For the teacher-reported Aggression Plus Sleep network, the *CS-coefficient* indicated that strength (CS(cor = .7)= 0.128), betweenness (CS(cor = .7)= 0), and closeness (CS(cor = .7)= 0.05) were not stable under subsetting cases (see Figure 18). Overall, these results suggest that the centrality indices of strength, betweenness, and closeness are not stable for the estimated networks, which aligns with previous research evaluating the utility of centrality indices of strength, betweenness, and closeness in non-normally distributed ordinal data (Isvoranu & Epskamp, 2021 PREPRINT).

Significant differences between centrality indices were evaluated via *bootstrapped differences tests*. Results indicated that strength, closeness, and betweenness did not differ significantly between nodes with the child- and teacher-reported Aggression and Aggression Plus Sleep networks. This suggests that the order of centrality indices (e.g., highest strength) should be interpreted with caution.

Key Players Analysis

A key players analysis was conducted to determine which nodes would result in the maximum fracturing of the network when removed (Borgatti, 2006; Borgatti, 2008). The impact of key players is measured via fragmentation, which ranges from 0 (no fracturing) to 1 (entire network fractured) and represents the proportion of nodes that are isolated in a network once the key player nodes are removed (Borgatti, 2006). The number of nodes removed impacts which key players should be selected for removal, given that some nodes may be redundantly connected (Borgatti, 2006).

Child- and Teacher-Reported Aggression Networks

For child- and teacher-reported Aggression networks, we conducted a key players analysis for the removal of one node (17% of the network) and two nodes (33% of the network).

Child-Reported Aggression Network. For the child-reported Aggression network, when one node was selected for removal, *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical; fragmentation = 0.84) was identified as the key player, indicating that the removal of this node resulted in a fracturing of 84% of the network. When two nodes were selected, *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical) and *when someone accidentally hurts the child, assumes that the peer meant to do it and then reacts with anger/fighting* (RA_Accident) were identified as key players (fragmentation = 0.87), indicating that the removal of these two nodes resulted in a fracturing of 87% of the network.

Teacher-Reported Aggression Network. For the teacher-reported Aggression network, when one node was selected for removal *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up; fragmentation = 0.84) was identified as the key player, indicating that the removal of this node resulted in a fracturing of 84% of the network. When two nodes were selected, *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up) and *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) were identified as key players (fragmentation = 0.89), indicating that the removal of this node resulted in a fracturing of 89% of the network.

Child- and Teacher-Reported Aggression Plus Sleep Networks

For child- and teacher-reported Aggression Plus Sleep networks, a key players analysis was conducted for the removal of one node (10% of the network), two nodes (20% of the network), and four nodes (40%) of the network.

Child-Reported Aggression Plus Sleep Network. For the child-reported Aggression Plus Sleep network, when one node was selected for removal, *sleep onset latency* (Falling_Asleep) was identified as the key player (fragmentation = 0.92), indicating that the removal of this node resulted in a fracturing of 92% of the network. When two nodes were selected, *sleep onset latency* (Falling_Asleep) and *when someone accidentally hurts the child, assumes the peer meant to do it and reacts with anger/fighting* (RA_Accident) were identified as key players (fragmentation = 0.93), indicating that the removal of these nodes resulted in a fracturing of 93% of the network. When four nodes were selected, *when someone accidentally hurts the child, assumes the peer meant to do it and reacts with anger/fighting* (RA_Accident), *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up), *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical), and *sleep onset latency* (Falling_Asleep) were identified as key players (fragmentation= 0.96), indicating that the removal of these nodes resulted in a fracturing of 96% of the network.

Teacher-Reported Aggression Plus Sleep Network. For the teacher-reported Aggression Plus Sleep network, when one node was selected for removal, *sleep maintenance insomnia* (ReturntoSleep) was identified as the key player (fragmentation = 0.92), indicating that the removal of this node resulted in a fracturing of 92% of the network. When two nodes were selected, *sleep maintenance insomnia* (ReturntoSleep) and *sleep onset latency* (Falling_Asleep) were identified as key players (fragmentation = 0.94), indicating the removal of these nodes resulted in a 94% fracturing of the network. When four nodes were selected, *claims that other* *children are to blame in a fight and feels that they started the trouble* (RA_Blames), *sleep onset latency* (Falling_Asleep), *sleep maintenance insomnia* (ReturntoSleep), and *subjective sleep quality* (SubQuality) were identified as key players (fragmentation= 0.97), indicating that the removal of these nodes results in a 97% fracturing of the network.

Taken together these results indicated that for the child- and teacher-reported Aggression and Aggression Plus Sleep networks, removing even one node from the networks resulted in a high percentage of network fracturing. Additionally, for both Aggression networks, proactive aggression symptoms were identified over reactive aggression symptoms and for both Aggression Plus Sleep networks, *sleep onset latency* (Falling_Asleep) was identified as a key player.

Discussion

The current study utilized network analysis to evaluate the symptomatology of teacher-reported and child-reported proactive and reactive aggression and sleep quality symptoms in a middle childhood sample. Aligning with expectations, child- and teacher-reported Aggression networks resulted in a two-community structure (i.e., proactive and reactive) and Aggression Plus Sleep networks resulted in a 3-community structure (i.e., proactive aggression, reactive aggression, and sleep); however, communities were not as well defined as anticipated. Child- and teacher-reported networks were found to be similar to each other overall but demonstrated some differences. However, specific study predictions about differences in network structure were not supported given that proactive and reactive aggression symptoms were equally central in both child- and teacher-reported Aggression and Aggression Plus Sleep networks. Notably, centrality indices of strength, closeness, and betweenness were not statistically robust and, therefore, should be interpreted with caution. In line with our predictions, we were able to identify symptoms that may be essential to target for aggression interventions via a key players analysis, and different nodes were selected for removal depending on whether the network was comprised of child- or teacher-reported aggression. However, for both child- and teacher-reported Aggression networks, proactive aggression symptoms were identified as key players over reactive aggression symptoms, and for both Aggression Plus Sleep networks, *sleep onset latency* (Falling_Asleep) was identified as one of the key players. In contrast to expectations, both reactive and proactive aggression symptoms were both positively and negatively correlated with sleep quality symptoms in child- and teacher-reported networks. Findings and their implications are discussed in turn.

Evaluation of Network Structures

Aligning with expectations, child- and teacher-reported Aggression networks demonstrated a 2-community structure (i.e., proactive and reactive); however, communities were not as well defined as anticipated. The two-community structure identified in the Aggression networks aligns with previous construct research on proactive and reactive aggression that demonstrated a two-factor structure of proactive and reactive aggression in teacher- and child-reported measures (Dodge & Coie, 1987; Poulin & Boivin, 2000; Raine et al., 2006). While neither aggression network resulted in communities that were well-defined, this finding aligns with previous construct research of proactive and reactive aggression, which has allowed latent factor aggression functions to substantially correlate with one another within models (Poulin & Boivin, 2000) or included a third factor for co-occurring aggression functions (Fite et al., 2006). Indeed, community detection analysis evaluates the degree to which nodes within a community are more strongly connected to each other than to nodes outside of that community (Newman, 2006); therefore, the low to moderate modularity indexes may be a result of the general interconnectedness of proactive and reactive aggression symptoms in youth, especially given that the PRA scale may be biased towards evaluating a singular form of aggression functions (i.e., physical; Dodge & Coie, 1987; Fite et al., 2016; Poulin & Boivin, 2000).

However, while the teacher-reported Aggression network communities were marginally defined, the child-reported Aggression network communities were particularly poorly defined. It is important to consider that our measure for aggression (the PRA) was developed for use in teachers (Dodge & Coie, 1987) and then adapted for use in children. While self-reports on the PRA have demonstrated internal consistency and concurrent validity (Fite et al., 2011; Fite et al., 2009; Rubens et al., 2017), to our knowledge a factor analytic approach has not been applied to establish the construct validity of this measure utilizing self-report in youth. Moreover, other aggression measures specifically developed for use in children (e.g., Peer Conflict Scale and Reactive–Proactive Aggression Questionnaire) are able to effectively demonstrate distinct proactive and reactive latent factors (Marsee et al., 2011; Raine et al., 2006). While the behaviors described and item phrasing are similar across the PRA and the measures developed for self-report, substantially more items are used to capture aggression functions in the Peer Conflict Scale (40 items; Marsee et al., 2011) and the Reactive-Proactive Aggression Questionnaire (23 items; Raine et al., 2006) than the PRA (6 items; Dodge & Coie, 1987). Thus, while the PRA is a valuable tool for succinctly capturing proactive and reactive aggression, it may lend itself to better capturing aggression functions that are teacher-reported, rather than child-reported. In the current study, perhaps teachers were better able to distinguish between proactive and reactive aggressive behavior because they were more adept at attending to the situational contexts that occurred around aggressive behavior (e.g., being provoked by a peer versus intentionally manipulating others), and therefore, were able to accurately do so with fewer items assessing behavior. Future work would benefit from examining symptom communities for child-reported aggression utilizing aggression measures that were originally developed for self-report.

As anticipated, both child- and teacher-reported Aggression Plus Sleep networks demonstrated a 3-community structure (i.e., proactive, reactive, and sleep quality). The Aggression Plus Sleep networks were better defined than the Aggression networks, which is likely due to the introduction of a separate construct (i.e., sleep quality) into the network. Similar to the Aggression networks, the teacher-reported Aggression Plus Sleep network was better defined than the child-reported Aggression Plus Sleep network (moderately defined versus marginally defined). These results are consistent with additional study findings which indicated that for teacher-reported networks, more so than child-reported networks, edges that connected alike aggression functions typically were significantly different than edges that connected different aggression functions or edges that connected aggression symptoms to sleep symptoms (see Figure 9 and Figure 10). In sum, the relatively low modularity indexes across both child- and teacher-reported networks, even when sleep symptoms were included, indicated that nodes within communities were also well-connected to other nodes that were outside of their communities (Newman, 2006), therefore reflecting that multiple sleep quality symptoms were associated with aggression symptoms.

Predictions about differences in network structure between child- and teacher-reported aggression symptoms were somewhat supported in that child- and teacher-reported Aggression and Aggression Plus Sleep networks were similar overall but also demonstrated some differences. The evaluation of network invariance for teacher- and child-reported Aggression Plus Sleep networks was not statistically significant; therefore, differences between edges were not examined (van Borkulo et al., 2016). The evaluation of network invariance for child- and teacher-reported Aggression networks was marginally statistically significant (p = 0.09), indicating that some differences between child- and teacher-reported networks emerged. The examination of specific edge differences (i.e., edge invariance) between the child- and teacher-reported Aggression networks indicated that the networks differed based on how the reactive aggression symptom *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) was associated with other nodes in the network. While *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) and *when teased or threatened, gets angry easily and strikes back* (RA_Teased) were positively associated in both networks, the association was stronger in the teacher-reported network than the child-reported network. Notably, the mean score of *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) was substantially higher in child-reported than teacher-report data, which may indicate that a multitude of children may view themselves as not to blame when there is an altercation, whereas teachers may view this as indicative of more aggressive behavior. Indeed, *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) was identified as a key player in the teacher-reported, but not child-reported, aggression networks (see below). Alternatively, while *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) was positively associated with *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical) in the child-reported Aggression network, these nodes were negatively associated in the teacher-reported Aggression network. These results partially support previous research findings on the associations between child self-report of externalizing of blame and teacher- and child-reported aggression in early adolescents, which found that child-reported externalizing of blame was positively associated with child-reported physical aggression but was not associated with teacher-reported physical aggression (Stuewig et al., 2010). Current findings may indicate that children perceive themselves as more likely to use physical force to dominate other children while simultaneously blaming that peer for their own physical aggression; whereas teachers are more likely to distinguish between instigating physical altercations and blaming others for starting fights. Similarly, *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) was negatively associated with *threatens or bullies others in order to get his/her own way* (PA_Threatens) in the child-reported network, while these nodes were positively associated in the teacher-reported network. These findings also partially support previous research on the associations between child-report of externalization of blame and teacher- and child-reported aggression in early adolescents, which found that externalization of blame was *positively* associated with both child- and teacher-reported verbal aggression (Stuewig et al., 2010). Current findings may indicate that children view these behaviors more distinctly, perceiving themselves as a reactive bystander when they blame others for starting fights (RA_Blames) and as a planful aggressor when they threaten or bully others to get their own way (PA_Threatens), whereas teachers may be more likely to view blaming others in fights (RA_Blames) and threatening others to get their way (PA_Threatens) as similarly manipulative. Taken together, these findings highlight the differences in how teachers and children attend to the situational contexts of aggression, specifically indicating that the behavior of blaming others in middle childhood merits future research.

In addition to evaluating the nature of the associations between specific nodes in child- and teacher-reported networks, the differences between the general strength of all associations within a network were compared (i.e., global strength). For the child- and teacher-reported Aggression and Aggression Plus Sleep networks, evaluation of global strength invariance indicated that the global strength of the teacher-reported networks were significantly larger than the global strength of the child-reported networks. When examining networks visually, this finding may seem counterintuitive given that connections between nodes in the child-reported Aggression and Aggression Plus Sleep networks were more numerous than the connections in the teacher-reported Aggression and Aggression Plus Sleep networks. However, these findings reflect a general pattern of edge strength in the networks, indicating that the associations between nodes that were interconnected in the teacher-reported networks were more strongly associated with one another than the nodes that were interconnected in the child-reported networks (even though nodes in the child-reported networks were connected with more nodes within their network). These findings are consistent with our community detection results which demonstrated that teacher networks had communities that were less interconnected and more strongly defined. Findings provide further support that teachers view proactive and reactive aggression behaviors as distinct from each other on the PRA, whereas children may view their own aggressive behaviors as more interconnected. Additionally, the differences in global edge strength may be partially explained by the study methods in which teachers reported on multiple children, therefore their pattern of responding may be similar across youth.

Core Symptoms of Proactive and Reactive Aggression and Sleep Quality

Aligning with expectations, the order of centrality indices of betweenness, closeness, and strength differed between teacher- and child-reported Aggression and Aggression Plus Sleep networks. However, inconsistent with expectations, these centrality indices were not statistically robust in their stability nor their order. Therefore, while results were visually striking (Figures 11-14), differences in node strength, betweenness, and closeness for both child- and teacher-reported Aggression networks should be interpreted with caution. Our findings align with recent literature that has called into question the utility of strength, betweenness, and closeness for skewed ordinal categorical data (Isvoranu & Epskamp, 2021 PREPRINT). It is important to note that the evaluation of the statistical robustness in network analysis is a relatively recent phenomenon (Epskamp et al., 2018) and a large portion of existing research on network analysis does not evaluate centrality robustness in any way (e.g., Crossley & Langdridge, 2005; Forbush et al., 2016; Martel et al., 2016). Thus, to align with previous work, our centrality findings and their potential implications will be discussed; however, the findings should be interpreted with caution.

In contrast with hypotheses, proactive and reactive aggression were equally central in child- and teacher-reported Aggression networks. For the child-reported Aggression network, the proactive symptom *threatens or bullies others in order to get his/her own way* (PA_Threatens) had the highest strength, indicating that it was directly connected to the most other nodes in the network; while the reactive aggression symptom *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) had the highest closeness and betweenness, indicating it was the node that was best indirectly connected to other nodes and that it was the most important node on the average path between two other nodes. On the other hand, for the teacher-reported Aggression network, the reactive aggression symptom *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) had the highest strength and the proactive aggression symptom *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical) had the highest closeness; while both of these nodes (RA_Blames and PA_Physical) were the highest on betweenness. Without consideration of the robustness and stability of these centrality indices, these findings indicate that *claims that other children are to blame in a fight and feels that they started the trouble*

(RA_Blames) was a core symptom of both teacher- and child-reported Aggression networks (even though this node was differentially associated with other nodes in child- versus teacher-reported networks, see above). While the current study did not examine forms (i.e., physical vs. relational) of aggression functions, our general pattern of results indicated that blaming others (RA_Blames) tended to be positively associated with more physical forms of aggression (e.g., using physical force to dominate others; PA_Physical) than verbal forms of aggression (e.g., threatening others; PA_Threatens) in the child-reported Aggression network and the opposite occurred in the teacher-reported network. Furthermore, study findings contrasted with previous work evaluating associations between externalizing of blame and teacher- and child-reported aggression in youth (Stuewig et al., 2010). Taken together, these findings highlight the differences in how teachers and children attend to the situational contexts of aggression and indicate that the behavior of blaming others in the context of proactive and reactive aggression in middle childhood merits further research, particularly using measures that distinguish both form and functions of aggression.

Similarly, in contrast with expectations, teacher- and child-reported Aggression Plus Sleep networks indicated that reactive aggression symptoms were not more central than proactive aggression symptoms when symptoms of sleep quality were introduced to the network. Surprisingly, in the child-reported Aggression Plus Sleep network, the proactive aggression symptom *threatens or bullies others in order to get his/her own way* (PA_Threatens) was consistently high across strength, closeness, and betweenness, and the proactive aggression symptom *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical) demonstrated the highest closeness and betweenness. These findings indicated that proactive aggression symptoms were more central to the child-reported Aggression Plus

Sleep network than reactive aggression symptoms, which contrasts with previous research demonstrating that child- and teacher-reported reactive, but not proactive, aggression symptoms were significantly associated with sleep quality (Becker, 2014; Rubens et al., 2017) and that proactive aggression is only correlated with sleep when comorbid reactive aggression is not accounted for (Fite et al., 2015). Both *threatens or bullies others in order to get his/her own way* (PA_Threatens) and *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical) were negatively associated with low *nighttime wakings frequency* (Nightwakings_Freq), indicating that children who frequently woke up at night were at increased risk for engaging in proactive aggression (or that youth who engaged in proactive aggression were at increased risk for waking up at night). This supports previous research in adolescents (12- to 16-year-old youth) demonstrating that frequent nightmares (but not other aspects of sleep quality) were associated with increased self-reported aggression (Coulombe et al., 2011). However, it should be noted that *threatens or bullies others in order to get his/her own way* (PA_Threatens) was *positively* associated with all other sleep quality symptoms (i.e., besides Nightwakings_Freq), indicating that youth with short sleep onset latency (Falling_Asleep), low sleep maintenance insomnia (ReturntoSleep), and high subjective quality (SubQuality) were actually *more likely* to threaten or bully others to get their way (and that youth who threatened or bullied others to get their own way were more likely to attain high quality sleep). Findings may indicate that youth who are prone to aggressive behavior are more likely to choose to engage in proactive aggression than reactive aggression when they experience high quality sleep due to enhanced ability to exert top-down control and increased emotional intelligence (Kamphuis et al., 2012) or that youth who engage in proactive aggression do not find aggression to be stressful experience and therefore are not at increased risk for poor sleep (Baglioni et al., 2010; Kamphuis et al., 2012; Na & Park, 2018). These findings are interesting to consider in the context of previous research linking enhanced sleep to aggression. In a sample of 12- to 16-year-old youth, Coulombe et al. (2011) found that sleeping more than others, but not subjective reports of “trouble sleeping,” were associated with increased adolescent-rated aggression. Similarly, in a sample of school-age youth, Rubens et al. (2017) found that sleeping more than others was marginally associated with higher levels of child-reported reactive and proactive aggression. Further, in a study of adults, larger amounts of restorative sleep (i.e., slow-wave sleep) were found in aggressive individuals than in nonaggressive individuals (Lindberg et al., 2009). While the current study did not examine sleep duration, it may be that both time in bed and sleep quality are important to consider in the understanding of aggressive behavior (Meijer et al., 2010). For example, in a sample of 12- to 15-year-old youth, Meijer et al. (2010) found that low sleep quality interacted with long sleep duration to result in the highest level of physical aggression. Additional findings in relation to sleep and aggression are discussed in the context of key players analysis (see below).

For the teacher-reported Aggression Plus Sleep network, the proactive aggression symptom *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical) and the reactive aggression symptom w*hen teased or threatened, gets angry easily and strikes back* (RA_Teased) were consistently high across strength, closeness, and betweenness. However, as in the child-reported networks, associations with sleep were unexpected. While *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical) was negatively and positively associated with sleep quality symptoms, w*hen teased or threatened, gets angry easily and strikes back* (RA_Teased) was only positively associated with sleep quality symptoms. Specifically*, uses physical force (or threatens to use* *physical force) in order to dominate other kids* (PA_Physical) was negatively associated with *subjective sleep quality* (SubQuality) and positively associated with short *sleep onset latency* (Falling_Asleep), indicating that youth who use physical force to dominate other children report not sleeping well while simultaneously falling asleep quickly once the lights are shut off (Falling_Asleep). Findings regarding associations between low subjective sleep quality (SubQuality) and using physical force to dominate others (PA_Physical) align with previous work demonstrating a link between low sleep quality and physical aggression in a sample of 12- to 15-year-old youth (Meijer et al., 2010). Additionally, the positive link between using physical force to dominate others (PA_Physical) and shortened sleep onset latency (Falling_Asleep) may indicate that proactively aggressive youth do not find engaging in aggression to be stressful and therefore do not experience deregulation of the HPA axis at bedtime (Baglioni et al., 2010; Kamphuis et al., 2012; Na & Park, 2018). In contrast to expectations, w*hen teased or threatened, gets angry easily and strikes back* (RA_Teased) was positively associated with low levels of *sleep maintenance insomnia* (ReturntoSleep) and was not correlated with any other sleep quality symptoms, indicating that children who found it easy to return to sleep after waking up in the middle of the night (ReturntoSleep) also reported getting angry easily and striking back when teased (RA_Teased). This result contrasts with previous research demonstrating negative associations between sleep quality and reactive aggression, emotion dysregulation, impulsivity, and hostility (Becker, 2014; Ireland & Culpin, 2006; Meijer et al., 2010; Wang et al., 2019), as well as research demonstrating links between sleep maintenance insomnia and emotional reactivity (e.g., becoming angry easily; Baglioni et al., 2010). Notably, previous work examining the links between sleep quality and reactive aggression have utilized composite scores of low sleep quality (i.e., combined symptoms of sleep quality; e.g., Becker, 2014) and has not examined specific associations between sleep maintenance insomnia and reactive aggression. Therefore, the links between sleep maintenance insomnia and reactive aggression merit further investigation.

Identification of Key Players

In addition to measures of closeness, betweenness, and strength, a key players analysis was conducted to evaluate which nodes, when removed, would result in the maximum fracturing of the network (i.e., fragmentation). In this way key players analysis determined which nodes are (theoretically) the most salient symptoms to target in aggression interventions. Aligning with expectations, different nodes were identified as key players in the teacher- and child-reported Aggression networks; however, in contrast with expectations, proactive aggression symptoms were identified over reactive aggression symptoms as key players in both child- and teacher-reported networks.

When one node was selected for removal from the child-reported Aggression network, *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical) was identified as the key symptom, which resulted in an 84% fracturing of the network. This suggests that children perceived using physical force to dominate others as the aggressive behavior that was most interconnected with other behaviors and that it would be the most important behavior to target in aggression interventions. It is important to note that during middle childhood most, but not all, youth begin to replace physically aggressive behaviors with relationally aggressive ones (Casas & Bower, 2018; Ostrov et al., 2018). Some have theorized that the small subset of youth who persist in physical aggression may do so because they fail to respond to social and environmental cues to desist in physical aggression (Casas & Bower, 2018; Hymel & Espelage, 2018; Ostrov et al., 2018). In line with the Social-Cognitive Learning theory and Social Information Processing theory, these youth may have developed a cognitive schema in which physical aggression is an adaptive solution (Bandura, 1973; Crick & Dodge, 1996; Dodge, 2006); therefore, they are likely to engage in aggression in a variety of contexts, including when they want to achieve a goal (proactive aggression) as well as when acting impulsively and when faced with potentially threatening interactions with peers (i.e., reactive aggression). Therefore, it may be that utilizing physical force to dominate other children (PA_Physical) is representative of engaging in a wider array of aggressive behaviors and is an important target for interventions. This suggests youth may benefit from learning to utilize alternative means, rather than physical force, to attain their goals, such as problem solving.

When one node was selected for removal from the teacher-reported Aggression network, *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up) was identified, resulting in a fracturing of 84% of the network. This suggests that teachers perceived getting others to gang up on a disliked peer was the aggressive behavior that was most interconnected with other aggressive behaviors and that it would be the most important behavior to target in aggression interventions. It is noteworthy that while this is a proactive aggression symptom, this behavior is centered on utilizing others to punish a disliked peer rather than attaining a goal. Relational aggression becomes more common in middle childhood and while it desists for most youth throughout adolescence, a small portion of highly aggressive individuals continue to engage in relational aggression throughout adolescence and adulthood (Fite & Pederson, 2018). Therefore, youth who utilize their peers to help them aggress against a disliked peer may also be indicative of youth who are highly aggressive and likely to continue engaging in aggression throughout development. While findings provide valuable insight into why interventions aimed at reducing relational aggression and bullying often result in a variety of other positive outcomes for youth (e.g., Leff et al., 2018), these interventions may benefit from also targeting underlying mechanisms of proactive aggression (e.g., beliefs about aggression being an adaptive solution).

When two nodes were selected for removal, reactive symptoms were selected in addition to the previously identified proactive symptoms in both child- and teacher-reported Aggression networks. In the child-reported Aggression network, the reactive aggression symptom *when someone accidentally hurts the child, assumes that the peer meant to do it and then reacts with anger/fighting* (RA_Accident) was selected in addition to the previously identified proactive aggression symptom (PA_Physical), resulting in a fracturing of 87% of the network. This suggests that children perceived responding impulsively to ambiguous situations (RA_Accident) as closely tied to other aggression symptoms. This finding supports the maladaptive Social Information Processing theory for aggression which purports that aggressive youth may have a hostile attribution bias and respond to ambiguous situations negatively (Crick & Dodge, 1996; Dodge, 2006). Similarly, in the teacher-reported Aggression network, the reactive aggression symptom *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) was selected in addition to the previously identified proactive aggression symptom (PA_Gang_Up), resulting in a fracturing of 89% of the network. This indicates that teachers perceived externalizing blame in altercations as connected with a multitude of other aggressive behaviors. Previous research in early adolescence has indicated that externalizing blame was positively associated with teacher-reported verbal, but not physical, aggression (Stuewig et al., 2010) and thus further supports theorizing that teachers may perceive relationally oriented aspects of aggression as more connected to the aggression network. Again, while the PRA does not explicitly distinguish between relational/verbal and physical aspects of proactive and reactive aggression, differences in the aggression symptoms identified as key players in teacher- and child-reported Aggression networks may indicate that children view physical aggression (i.e., using physical force to dominate others and striking back when threatened) as more integral to aggression symptomatology and teachers view relational/verbal aggression as more integral (i.e., utilizing social resources to punish disliked peers and blaming others).

In sum, findings from the teacher- and child-reported Aggression networks (surprisingly) indicated that proactive aggression symptoms are the most salient targets for intervention followed by reactive aggression symptoms. We had assumed reactive, rather than proactive, aggression symptoms would play a key role in connecting the aggression functions because reactive aggression is more common in youth (e.g., Cui et al., 2016). Indeed, even in the current study, means for reactive aggression were higher than proactive aggression via child- and teacher-report. However, results may indicate that even though proactive aggression symptoms are less common, they are more salient targets for interventions because they are more likely to be associated with a variety of other aggressive behaviors when they are present. This finding may have important implications for current aggression intervention and prevention programs, given that they usually focus on mechanisms underlying reactive aggression (e.g., empathy, social skills, and emotion regulation; for reviews see Leff et al., 2018 and Lochman et al., 2018), which are not necessarily helpful for reducing proactive aggression and in some cases may inadvertently train youth how to better proactively aggress (e.g., empathy training; Day et al., 2010; McMahon & Washburn, 2003; Tampke et al., 2020). Instead, current findings indicate that interventions would benefit from incorporating more proactive components, such as behavioral interventions (e.g., time-out or other punishment for aggression), problem-solving skills, and cognitive reframing centered on how aggression negatively impacts the aggressor (rather than the victim).

Identification of Key players: Aggression and Sleep

A key players analysis was also conducted in the teacher- and child-reported Aggression Plus Sleep networks. When one node was selected for removal, a sleep quality node, rather than an aggression node, was identified in both teacher- and child-reported networks. Results support previous research indicating that sleep quality is an important component of aggression in youth (e.g., Becker, 2014; Rubens et al., 2017); however, in contrast with expectations the sleep quality nodes identified as key players were both positively and negatively associated with aggression symptoms in the networks.

For the child-reported Aggression Plus Sleep network, *sleep onset latency* (Falling_Asleep) was identified as the key player, which resulted in a 92% fracturing of the network. While short *sleep onset latency* (Falling_Asleep) was negatively associated with *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up), it was positively associated with *threatens or bullies others to get his/her way* (PA_Threatens). This suggests that children who struggle to fall asleep quickly (i.e., delayed sleep onset latency; Falling_Asleep) are more likely to gang up on a peer they dislike (PA_Gang_Up) but are less likely to threaten or bully others to get their way (PA_Threatens). Additionally, differences in these associations were not statistically significant, indicating that a short sleep onset latency functions simultaneously as a protective factor and risk factor for aggression (and that aggression functions as a risk and protective factor for short sleep onset latency; see Figure 9). At first glance, these results are puzzling given the similarity in the items (i.e., both proactive items and both involve language around bullying/ganging up). However, the items differ in that *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up) is centered on punishing a disliked peer, while *threatens or bullies others to get his/her way* (PA_Threatens) is centered on attaining a goal. This may indicate that delayed sleep onset latency contributes to underlying anger and irritability (Kamphuis et al., 2012), leading to spiteful and hostile proactive aggression (i.e., PA_Gang_Up). On the other hand, short sleep onset latency (indicative of high sleep quality) may result in enhanced ability to problem solve to achieve goals, resulting in youth utilizing proactive aggression to achieve desired outcomes (PA_Threatens). Additionally, youth who engage in proactive aggression to solve their problems may not find aggression to be a stressful experience and therefore do not experience deregulation of the HPA axis at bedtime (perhaps unlike youth who engage in other forms of aggression; Kamphuis et al., 2012).

For the teacher-reported Aggression Plus Sleep network, *sleep maintenance insomnia* (ReturntoSleep) was identified as the key player, which resulted in a fracturing of 92% of the network. Similar to the child-reported network, *sleep maintenance insomnia* (ReturntoSleep) was negatively associated with *claims other children are to blame in a fight and feels that they started the trouble* (RA_Blames) and was positively associated with *when teased or threatened gets angry easily and strikes back* (RA_Teased) and *threatens or bullies others in order to get his/her way* (PA_Threatens). The edge weights were not significantly different from each other, indicating sleep maintenance insomnia functions as both a risk and protective factor for aggression and that these aggression symptoms functioned as either risk (RA_Blames) and protective (RA_Teased and PA_Threatens) factors for sleep maintenance insomnia. Therefore, findings suggest that children who found it difficult to fall asleep after waking up in the middle of the night (ReturntoSleep) also reported high levels of blaming others (RA_Blames) and low levels of getting angry easily and striking back when teased (RA_Teased) and bullying others to get their way (PA_Threatens). These seemingly paradoxical findings may be explained by the strong association between sleep maintenance insomnia and anxiety (Baglioni et al., 2010).

Aligning with previous work which found that anxiety mediated the link between low sleep quality and reactive aggression (Fite et al., 2015), youth who struggle with sleep maintenance insomnia may be anxious as well as aggressive. Given anxious youth's fear of punishment and heightened sensitivity to threat response (Bar-Haim et al., 2007) these youth may fear getting in trouble at school and, therefore, from the teacher's perspective, be more likely to shift blame to others during altercations as well as resist engaging in other behaviors that may get them in trouble (e.g., striking back when threatened or bullying others to get their way).

When two nodes were identified as key players in the child-reported Aggression Plus Sleep network, the reactive aggression symptom *when someone accidentally hurts the child, assumes that the peer meant to do it and then reacts with anger/fighting* (RA_Accident) was selected in addition to the previously identified sleep symptom (Falling_Asleep), resulting in a 93% fracturing of the network. Partially aligning with expectations, *when someone accidentally hurts the child, assumes that the peer meant to do it and then reacts with anger/fighting* (RA_Accident) was negatively associated with all sleep quality symptoms with the exception of *sleep onset latency* (Falling_Asleep; no association). This suggests that reacting negatively to an ambiguous situation (RA_Accident) is associated with increased difficulties with sleep maintenance insomnia (ReturntoSleep), waking up frequently at night (Nightwakings_Freq), and poor subjective sleep quality (SubQuality). These findings support previous research linking reactive aggression to composite scores of poor sleep quality (Becker, 2014; Fite et al., 2015; Rubens et al., 2017). This item may have been more consistently associated with low sleep quality than other reactive aggression items because it more overtly assesses Hostile Attribution Bias (i.e., attributing hostile intent to others; Crick & Dodge, 1994), which has been proposed as a mechanism linking poor sleep to aggression (Freitag et al., 2017; Ireland & Culpin, 2006).

For the teacher-reported Aggression Plus Sleep network, when two sleep nodes were selected *sleep onset latency* (Falling_Asleep) was identified in addition to the previously identified sleep symptom (ReturntoSleep), resulting in a 94% fracturing of the network. Short *sleep onset latency* (Falling_Asleep) was negatively associated with *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) and positively associated with *child uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical) and the edges were not significantly different from each other. The negative association between short *sleep onset latency* (Falling_Asleep) and blaming others for starting fights (RA_Blames) aligns with previous work linking reactive aggression to poor sleep (e.g., Fite et al., 2015) and may support theorizing that youth find engaging in reactive aggression to be a stressful experience which results in deregulation of the HPA axis, therefore making it more difficult to fall asleep (Kamphuis et al., 2012). Alternatively, similar to the child-reported network, short sleep onset latency (indicative of high sleep quality; Falling_Asleep) may result in enhanced ability to problem solve to achieve goals, resulting in youth utilizing proactive aggression to achieve desired outcomes (PA_Physical) or may indicate that proactively aggressive youth do not find engaging in aggression to be a stressful experience (Kamphuis et al., 2012).

When four nodes were selected from the child-reported Aggression Plus Sleep network, two proactive aggression symptoms were identified (PA_Gang_Up and PA_Physical) in addition to the previously identified reactive aggression symptom (RA_Accident) and sleep symptom (Falling_Asleep), which resulted in a 96% fracturing of the network. The two proactive symptoms selected were *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up) and *uses physical force (or threatens to use physical force) in order to dominate* *other kids* (PA_Physical). The proactive aggression symptom *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up) was negatively associated with most sleep quality symptoms (i.e., Falling_Asleep, SubQuality, and ReturntoSleep), but was positively associated with *frequency of night wakings* (Nightwakings_Freq). Notably, *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up) was more strongly negatively associated with short *sleep onset latency* (Falling_Asleep), than it was positively associated with low *frequency of night wakings* (Nightwakings_Freq). Taken together, these findings support previous research linking hostility to poor sleep in youth, especially given that the proactive symptom identified (PA_Gang_Up) centers on punishing a disliked peer (Freitag et al., 2017; Ireland & Culpin, 2006). On the other hand, *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical) was negatively linked with frequency of night wakings, indicating that youth who use physical force to dominate others are more likely to wake up at night (and that youth who wake up more at night are more likely to use physical force to dominate others). Night wakings' differential associations in the child-reported network may highlight how it behaves differently than other sleep quality symptoms and aligns with previous research in adolescents indicating that frequent nightmares (but not other aspects of sleep quality) were associated with increased self-reported aggression (Coulombe et al., 2011).

Alternatively, when four nodes were removed from the teacher-reported Aggression Plus Sleep network, one additional sleep quality symptom (SubQuality) and a reactive aggression symptom (RA_Blames) were selected in addition to the two previously identified sleep symptoms (Falling_Asleep and ReturntoSleep), resulting in a fracturing of 97% of the network. The reactive aggression symptom *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames) was negatively associated with falling asleep quickly (i.e., short *sleep onset latency*; Falling_Asleep) and quickly returning to sleep after waking up in the night (i.e., low *sleep maintenance insomnia*; ReturntoSleep). This suggests that youth who blamed others for altercations (RA_Blames) also reported struggling with falling asleep (Falling_Asleep) and returning to sleep after waking up in the night (ReturntoSleep). This finding supports the previous theorizing that insomnia-related sleep problems may be indicative of youth with anxiety, who may be motivated to externalize blame in order to avoid getting in trouble (Baglioni et al., 2010; Bar-Haim et al., 2007; Fite et al., 2015). Additionally, *subjective sleep quality* (SubQuality) was negatively associated with *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical) and positively associated with *when someone accidentally hurts the child, assumes that the peer meant to do it and then reacts with anger/fighting* (RA_Accident) and *threatens or bullies others in order to get his/her own way* (PA_Threatens). Indicating that, from a teacher perspective, youth who reported subjective poor sleep quality were more likely to use force to dominate others (PA_Physical) but were less likely to respond poorly in ambiguous situations (RA_Accident) or to threaten others to attain a goal (PA_Threatens). The link between low sleep quality and using physical force to dominate others (PA_Physical) aligns with previous work demonstrating associations between low sleep quality and physical aggression (Meijer et al., 2010). Similarly, findings that high sleep quality is associated with threatening others to achieve a goal (PA_Threatens) may be explained by increased sleep quality enhancing emotion regulation abilities and the use of proactive aggression as a means of achieving desired outcomes. Alternatively, it may be that youth who engage in this type of aggression do not experience aggression as associated with negative emotions and therefore are not at increased risk for poor sleep (Kamphuis et al., 2012; Na & Park, 2018). However, the links between high sleep quality and reacting negatively to ambiguous situations (RA_Accident) directly contrasts with research linking poor sleep to aggression via hostility (Ireland & Culpin, 2006; Freitag et al., 2017) and contrasts with findings in the child-reported Aggression Plus Sleep network. In addition to the somewhat surprising results, current findings also highlight the importance of considering a multitude of sleep quality symptoms when evaluating links with aggression. Key players analysis considers redundancy in its selection and thus does not select nodes that would result in similar fracturing of the symptom network. Therefore, three sleep nodes being selected as key players further emphasizes that each component of sleep quality interacted with aggression symptoms in a unique way.

Limitations and Future Directions

The current study had several strengths including its use of both teacher and child reports, its evaluation of specific sleep symptoms, and its utilization of a novel statistical technique to evaluate associations between aggression symptoms. In addition to its many strengths, the current study has several limitations which should be used to inform future research.

The first set of limitations revolve around the theoretical and practical constraints of our analyses. First, evaluation of traditional centrality indices (i.e., strength, closeness, and betweenness) indicated results were not statistically robust, while methods to evaluate the stability of fragmentation, to our knowledge, do not exist. Future research would benefit from utilizing a larger sample size, which would increase the statistical robustness of effects and lead to networks with increased accuracy. Secondly, the current study utilized cross-sectional, between subject data to estimate networks and make inferences about the symptomatology of aggression and sleep, which may not necessarily translate to how these symptoms are connected with each other *within* an individual (de Boer et al., 2021; Fisher et al., 2018). As network analysis techniques become more sophisticated, future work would benefit from examining symptom networks within a subject (de Boer et al., 2021). Moreover, there is some debate over the degree to which symptom networks can be said to theoretically represent the causal nature of symptoms within psychological disorders, especially when symptoms are not highly differentiated from one another (e.g., Borsboom & Cramer, 2013; de Boer et al., 2021). Future work could bolster current study findings through assessing how symptom networks change as a result of interventions specifically targeted at the proactive aggression symptoms identified as key players (e.g., PA_Gang_Up and PA_Physical). Additionally, given that the current study was cross-sectional in nature, we were unable to determine temporal or causal links between aggression symptoms and sleep. Future work would benefit from utilizing longitudinal designs to further elucidate associations. Future work would also benefit from examining associations between sleep and aggression with additional (potentially explanatory) factors included in the network (e.g., anxiety; Fite et al., 2015).

The second set of limitations concerns the characteristics of the sample utilized. The current study sample was from a single elementary school, which was largely white and not racially or ethnically diverse; therefore, results may not be generalizable to other populations. Future work would benefit from examining aggression symptomatology in more diverse groups. Similarly, the current sample had a low base-rate of aggression, as demonstrated by the skewness of all the aggression items. Future work would benefit from examining the symptomatology of aggression in highly aggressive samples, such as adjudicated youth. Additionally, some research suggests there are gender differences between aggression forms and functions in children (e.g., Fite & Pederson, 2018; Rieffe et al., 2016). Future research would benefit from examining gender differences in network symptomatology, as this may indicate that different symptoms are important to target for boys and girls. Additionally, the current study only examined youth in middle childhood and therefore implications are limited to this developmental time period. Given that aggression evolves throughout development (Cui et al., 2016; Fite et al., 2008; Fite & Pederson, 2018) and that past work indicates symptom networks for disorders change throughout development (e.g., Martel et al., 2016), future work would benefit from examining aggression symptomatology in multiple developmental periods. In the current study the sample size for child- and teacher-reported networks differed, which may have resulted in differences in results (even though the samples were not significantly different from each other across variables). Future work comparing networks symptomatology between reporters would benefit from having identical samples.

The third set of limitations concern how aggression and sleep symptoms were measured. The current study was limited in that it only evaluated the functions of aggression. Given the differences we found in aggressive behaviors that seemed more physically or relationally based, future work would benefit from explicitly examining the network symptomatology of both forms (i.e., physical and relational) and functions (i.e., proactive and reactive) of aggression. Additionally, the current study used a measure developed for teachers which may have impacted how youth self-reported on their own symptoms. Perhaps because of this, internal consistency for child-report of proactive aggression was modest. Future work would benefit from utilizing measures specifically developed for children (e.g., Peer Conflict Scale; Marsee et al., 2011). The study has a strength in that it utilized teacher- and child-report of aggression symptoms; however, future work would also benefit from including parent-report of aggression symptoms (e.g., Martel et al., 2016). Additionally, the current study utilized a sleep measure which was very brief and used single items to assess multiple aspects of sleep quality with a scale that is not necessarily consistent across items. Future work may benefit from using more widely used sleep measures that have been more robustly validated with children that feature more items and consistent scaling, such as the PROMIS measures for sleep or the Children's Report of Sleep Patterns (Forrest et al., 2018; Meltzer et al., 2013; Yu et al., 2011). While the study had a strength in that it evaluated many aspects of sleep quality, we used single items to assess these aspects. Future research utilizing network analysis may benefit from utilizing composite scores of individual components of sleep quality (e.g., composite scores of sleep onset latency). Similarly, future work would benefit from examining additional sleep symptoms, such as daytime sleepiness and sleep duration, given that these sleep components have also been associated with aggression in youth (Lin & Yi, 2015; Na & Park, 2018; O'Brien et al., 2011) and the evidence supporting combined effects of problematic sleep duration and sleep quality (e.g., Meijer et al., 2010). Finally, future work would benefit from using objective measures of sleep quality in conjunction with subjective measures of sleep quality, as this may provide unique insight into how youth experience and perceive their sleep difficulties.

Summary and Implications

Overall, findings support that proactive and reactive aggression are unique constructs that are interrelated in middle childhood youth. Patterns in the differences of network structure suggest that teachers view proactive and reactive aggression symptoms as more distinct, whereas children view them as more interconnected. Of particular importance, *claims that other children are to blame in a fight and feels that they started the trouble* (RA_Blames), which was identified as a core symptom in teacher- and child-reported networks, behaved differently in teacher- and child-reported networks. This highlights the conceptualization of blaming in the context of aggression as an important area for future research. Differences in child- and teacher-reported networks could suggest that teachers are more attuned to the situational contexts that occur around aggressive behavior and therefore are better able to distinguish between proactively and reactively aggressive behavior. Alternatively, these differences could be due to study methodology, such as using a measure that was originally developed for teacher use or the effects of each teacher reporting on multiple youth.

Aligning with expectations, different nodes were identified as key players in the teacher- and child-reported Aggression networks; however, in contrast to expectations, proactive aggression symptoms were identified over reactive aggression symptoms as key players in both child- and teacher-reported networks. Specifically, *uses physical force (or threatens to use physical force) in order to dominate other kids* (PA_Physical) was identified as the most important symptom to target in the child-reported Aggression network, while *gets other kids to gang up on somebody that he/she doesn't like* (PA_Gang_Up) was the most important symptom to target in the teacher-reported Aggression network. These findings align with previous empirical research that has supported the utility of targeting proactive, over reactive, aggression symptoms (Phillips & Lochman, 2003). For example, in an experimental study which evaluated two aggression intervention strategies for reactive aggression (e.g., anger management, impulse control, and relaxation) and proactive aggression (e.g., recognizing domineering behavior and thinking about the positive consequences of non-aggressive solutions for the aggressors) in 10- to 12-year-old boys, the proactive aggression intervention resulted in decreases in aggression for both aggression functions, while the reactive aggression intervention only decreased reactive aggression (Phillips & Lochman, 2003). This suggests that aggression interventions would benefit from incorporating more components that target proactive, rather than reactive, aggression (e.g., behavioral interventions focused on positive and negative reinforcement, problem-solving skills, recognizing domineering behavior, and cognitive reframing centered on how aggression negatively impacts the aggressor, rather than the victim). While multiple aggression interventions already incorporate problem-solving skills into interventions (e.g., Daunic et al., 2012; Smith et al., 2014; Van Manen et al., 2004), surprisingly, there is a lack of emphasis on behavioral reinforcement and how non-aggressive solutions positively impact the aggressor and a substantial portion of each intervention is focused on targeting underlying mechanisms of reactive, rather than proactive aggression. Coping Power, a well-known aggression intervention, provides a useful model of a multicomponent cognitive-behavioral approach that incorporates proactive aggression components (e.g., rewards for non-aggressive behavior and social problem-solving abilities) as well as other elements (i.e., emotion awareness, perspective-taking abilities, and anger management; Wells et al., 2008). Previous evaluations of the Coping Power program have demonstrated its effectiveness in reducing both proactive and reactive aggression in middle childhood (Lochman et al., 2014; Lochman & Wells, 2002). However, Coping Power is a lengthy and time-intensive program (i.e., 1 hour per week for 2 years) that involves parents and children, and efforts to streamline the intervention have had mixed effects (Lochman et al., 2014; Lochman et al., 2012). Moreover, the program material is presented in a way that assumes children want to reduce their aggressive behavior and does not overtly address with youth the ways in which aggressive behavior negatively impacts the aggressor themselves (Wells et al., 2008). In light of current study findings, future intervention research would benefit from evaluating the impact of a streamlined intervention approach that prioritizes targeting proactive aggression (e.g., explicitly addressing how aggressive behavior towards peers negatively impacts the aggressor and focusing on problem-solving abilities, over emotion regulation and anger management).

When symptom networks were evaluated through traditional centrality indices (i.e., strength, betweenness, and closeness) and key players analysis (i.e., fragmentation), findings regarding aggression symptoms and sleep were surprising across both teacher- and child-reported networks. For both teacher- and child-reported networks, there was not a clear distinction between proactive and reactive aggression symptoms and their association with sleep, including that almost all sleep nodes were positively and negatively associated with both aggression functions and that reactive aggression symptoms were not found to be more central to the Aggression Plus Sleep networks. These findings contrast with study hypotheses and previous findings indicating that reactive aggression, but not necessarily proactive aggression, is closely tied to sleep quality (e.g., Fite et al., 2015; Rubens et al., 2017). Moreover, it was surprising that the key players analysis in the teacher-reported Aggression Plus Sleep network identified multiple sleep quality symptoms. Given that key players analysis considers redundancy in its selection (and therefore would not select nodes that result in similar fracturing), these findings provide support for the importance of considering multiple aspects of sleep quality in future research and highlight that specific aggressive behaviors are differentially correlated above and beyond cognitive motivations for engaging in aggression.

Taken together, findings indicate that aggression interventions would benefit from targeting children’s ability to fall asleep quickly and return to sleep when awoken in the night *in tandem* with targeting mechanisms for proactive aggression, such as an emphasis on non-aggressive rather than aggressive ways to resolve problems and conflicts. Both networks indicate that providing children with tools to fall asleep and return to sleep quickly (e.g., meditation apps or relaxation strategies) could provide some buffering for proactive and reactive aggression symptoms; however, high quality sleep may also confer risk for aggression if youth view aggression as an adaptive, effective, and beneficial way to resolve problems. Thus, while poor sleep quality is an important target of intervention for both proactive and reactive functions of aggression, improvements in sleep alone are not sufficient for reducing aggression. Instead, children would benefit from increased ability to fall asleep and maintain sleep throughout the night, perhaps through methods such as improved sleep hygiene (i.e., predictable bedtime routine, reduced blue light exposure, use of bed only for sleep), consistent bedtimes, and reduced interactions with caregivers during night wakings (Brown & Malow, 2016), in addition to increased likelihood to select non-aggressive (over aggressive) solutions (e.g., through programs such as Coping Power; Wells et al., 2008). Additionally, findings indicate that reducing aggressive behavior itself may improve sleep quality.

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Table 1

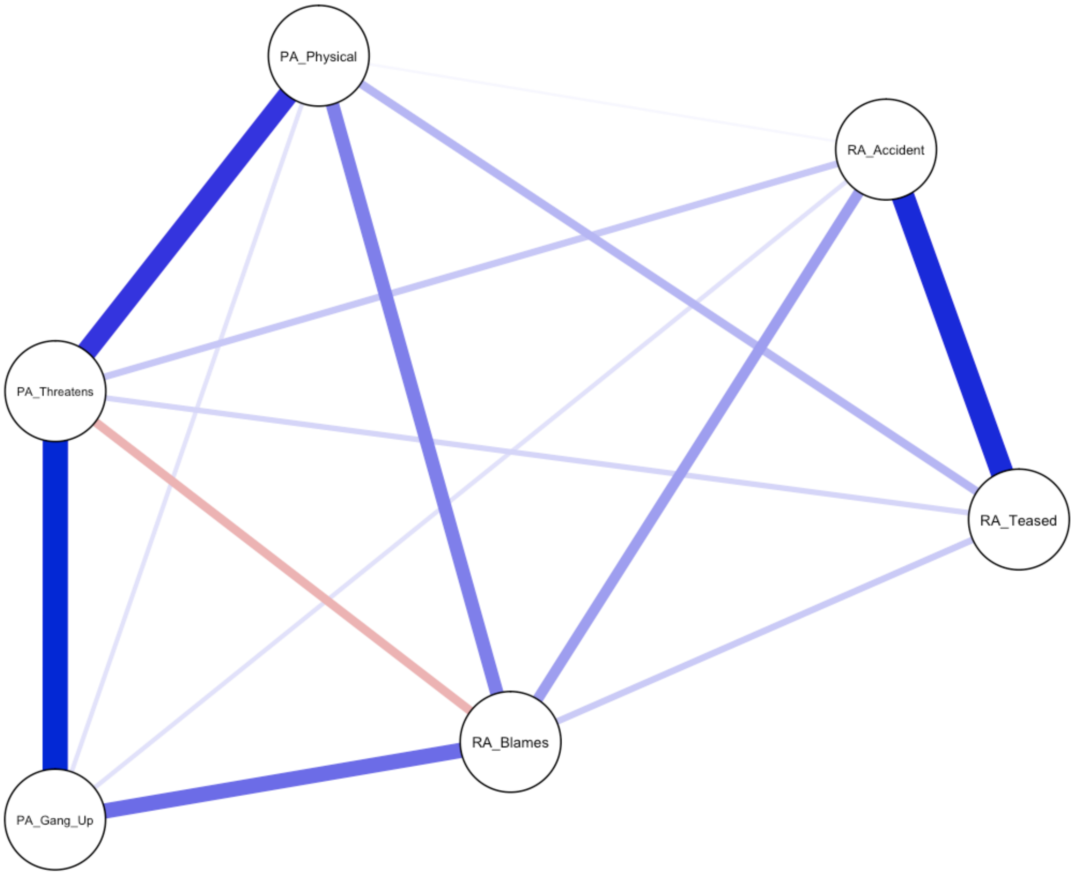
Node means, standard deviations, and skewness/kurtosis

			Skewness		Kurtosis	
Nodes	Mean	SD	Statistic	Std. Error	Statistic	Std. Error
Age	9.24	0.94	-	-	-	-
Grade	3.94	0.83	-	-	-	-
Gender	0.51	0.50	-	-	-	-
Teacher-reported Nodes						
RA_Teased	1.42	0.86	2.19	0.13	4.37	0.25
RA_Blames	1.49	0.94	2.02	0.13	3.48	0.25
RA_Accident	1.37	0.81	2.47	0.13	6.05	0.25
PA_Gang_Up	1.22	0.59	2.95	0.13	9.29	0.25
PA_Physical	1.12	0.43	4.20	0.13	19.63	0.25
PA_Threatens	1.18	0.52	3.16	0.13	10.24	0.25
Child-reported Nodes						
RA_Teased	1.90	1.14	1.31	0.14	0.96	0.28
RA_Blames	1.86	1.08	1.24	0.14	0.82	0.28
RA_Accident	1.46	0.88	2.34	0.14	5.61	0.28
PA_Gang_Up	1.11	0.43	5.32	0.14	34.48	0.28
PA_Physical	1.14	0.55	4.97	0.14	27.58	0.28
PA_Threatens	1.05	0.32	8.55	0.14	88.13	0.28
Falling_Asleep	1.94	0.67	0.064	0.14	-0.73	0.28
Nightwakings_Freq	1.88	0.55	-0.05	0.14	0.12	0.28
ReturntoSleep	1.88	0.66	0.14	0.14	-0.74	0.28
SubQuality	2.34	0.64	-0.44	0.14	-0.69	0.28

Note. SD = Standard Deviation, Std. Error = Standard Error

Figure 1

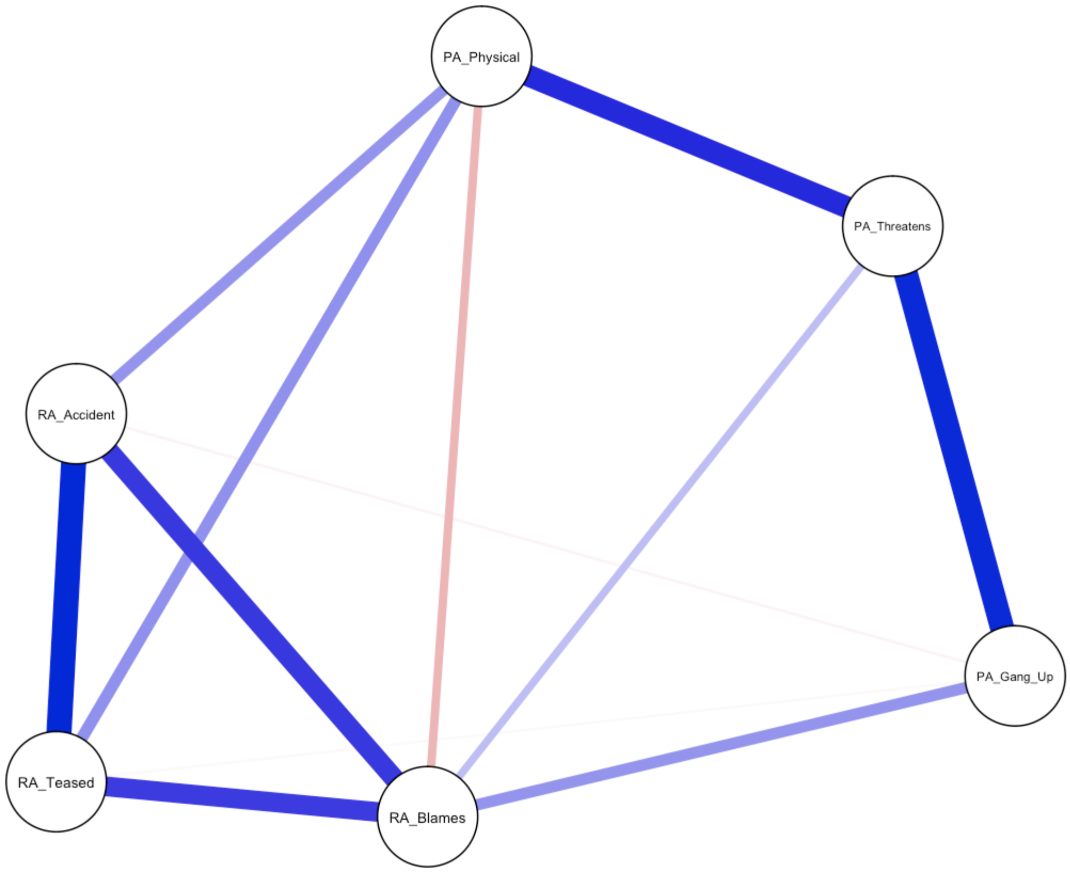
Child-Reported Aggression Network



Note. Blue edges indicate positive associations and red edges indicate negative associations.

Figure 2

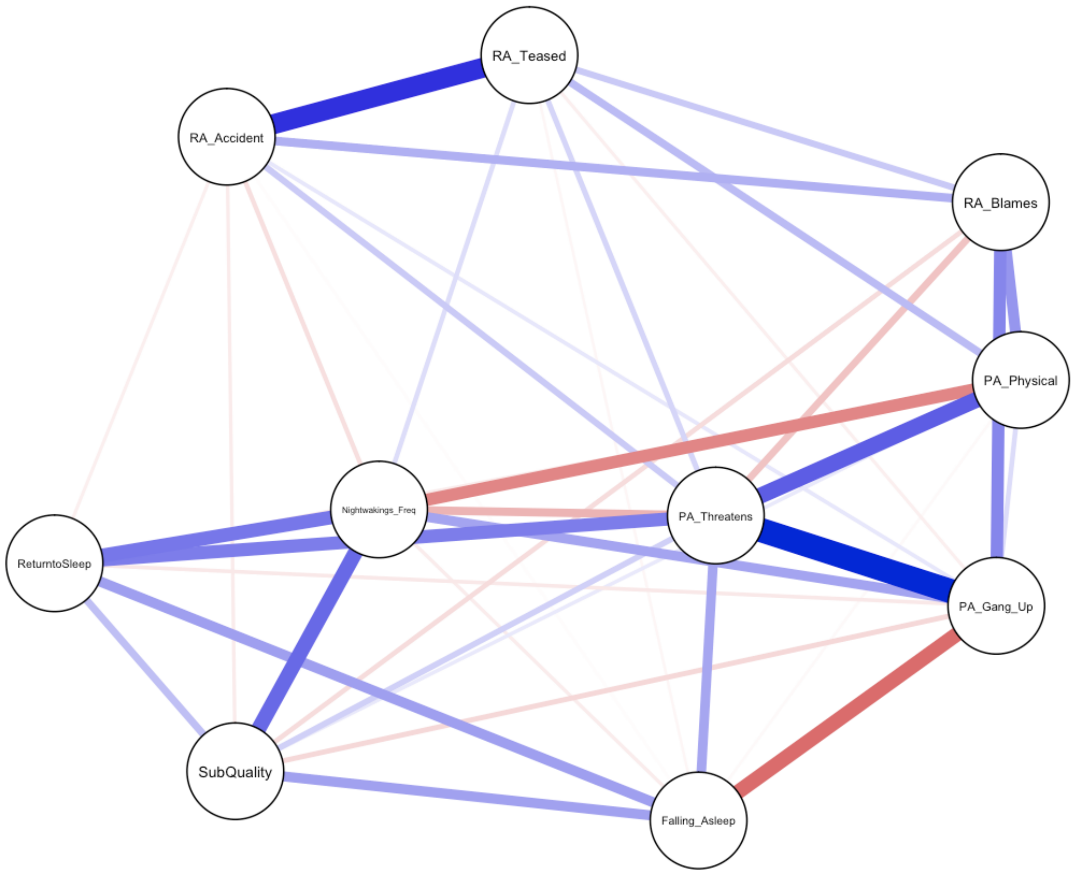
Teacher-Reported Aggression Network



Note. Blue edges indicate positive associations and red edges indicate negative associations.

Figure 3

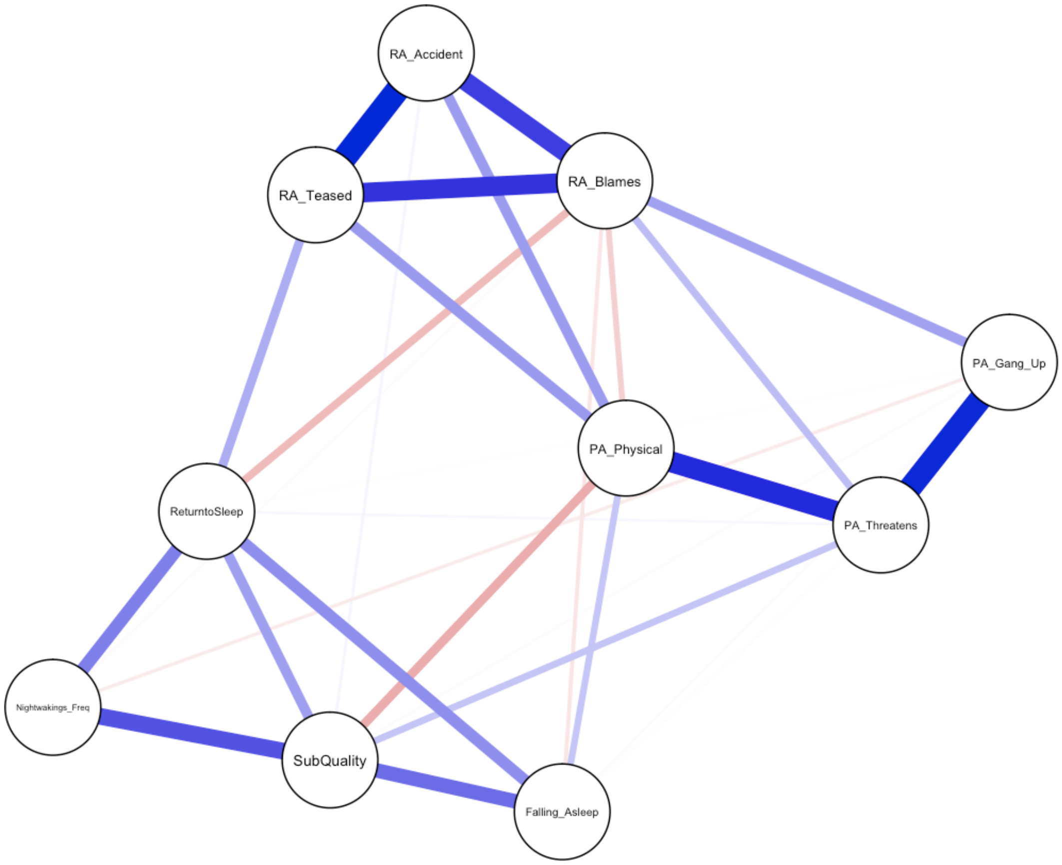
Child-Reported Aggression Plus Sleep Network



Note. Blue edges indicate positive associations and red edges indicate negative associations.

Figure 4

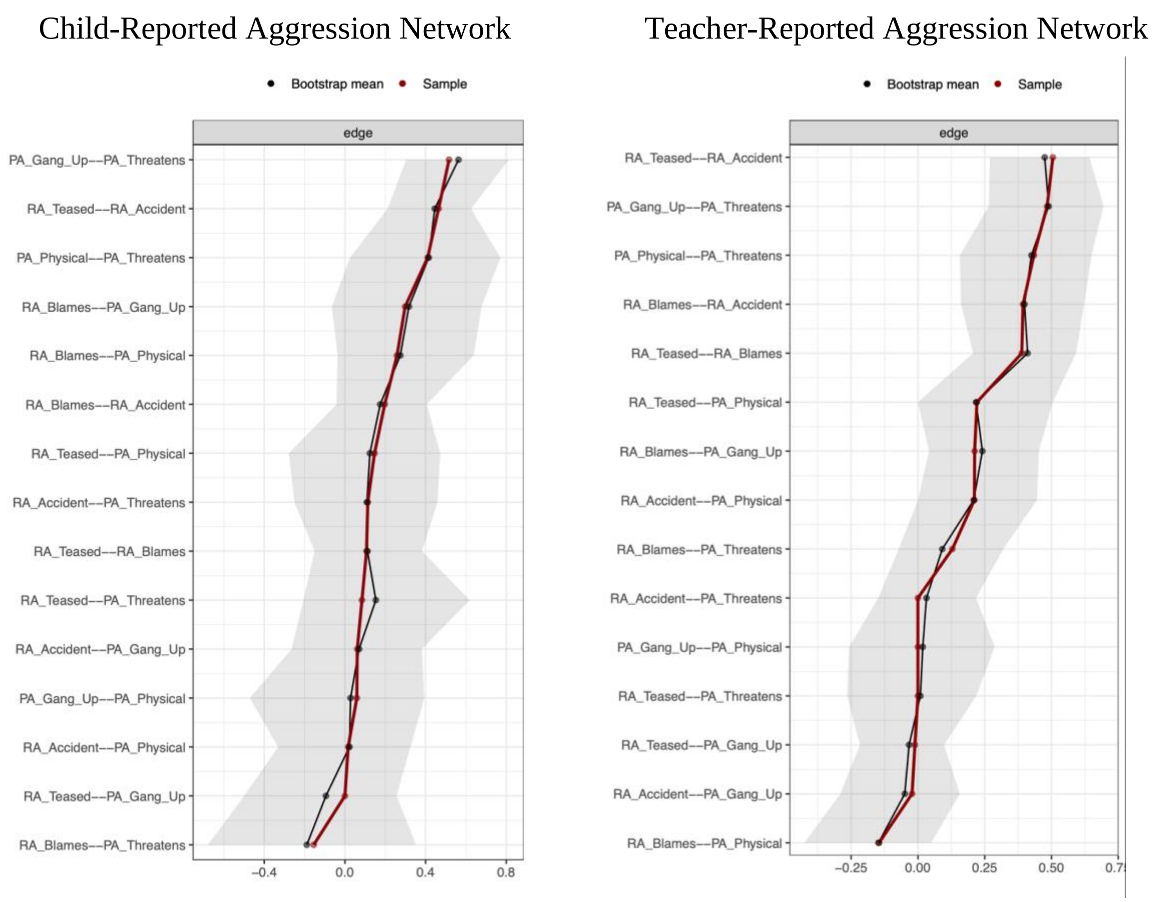
Teacher-Reported Aggression Plus Sleep Network



Note. Blue edges indicate positive associations and red edges indicate negative associations.

Figure 5

Edge-Weight Bootstrapped Confidence Intervals for Aggression Networks



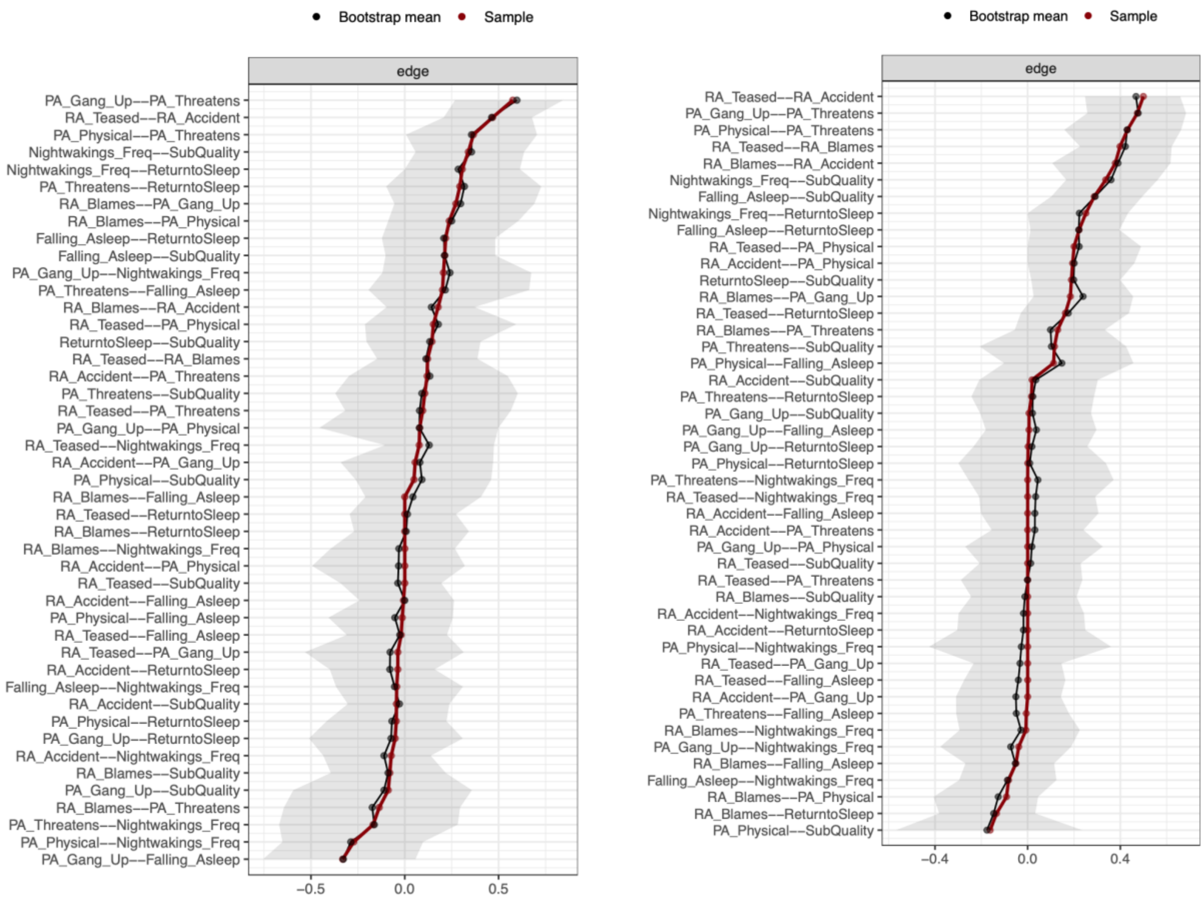
Note. The red line are the sample edge-weight values, the gray area representes the bootstrapped confidence intervals. The mean of the bootstrapped samples was used to order the edges.

Figure 6

Edge-Weight Bootstrapped Confidence Intervals for Aggression Plus Sleep Networks

Child-Reported Aggression Plus Sleep Network

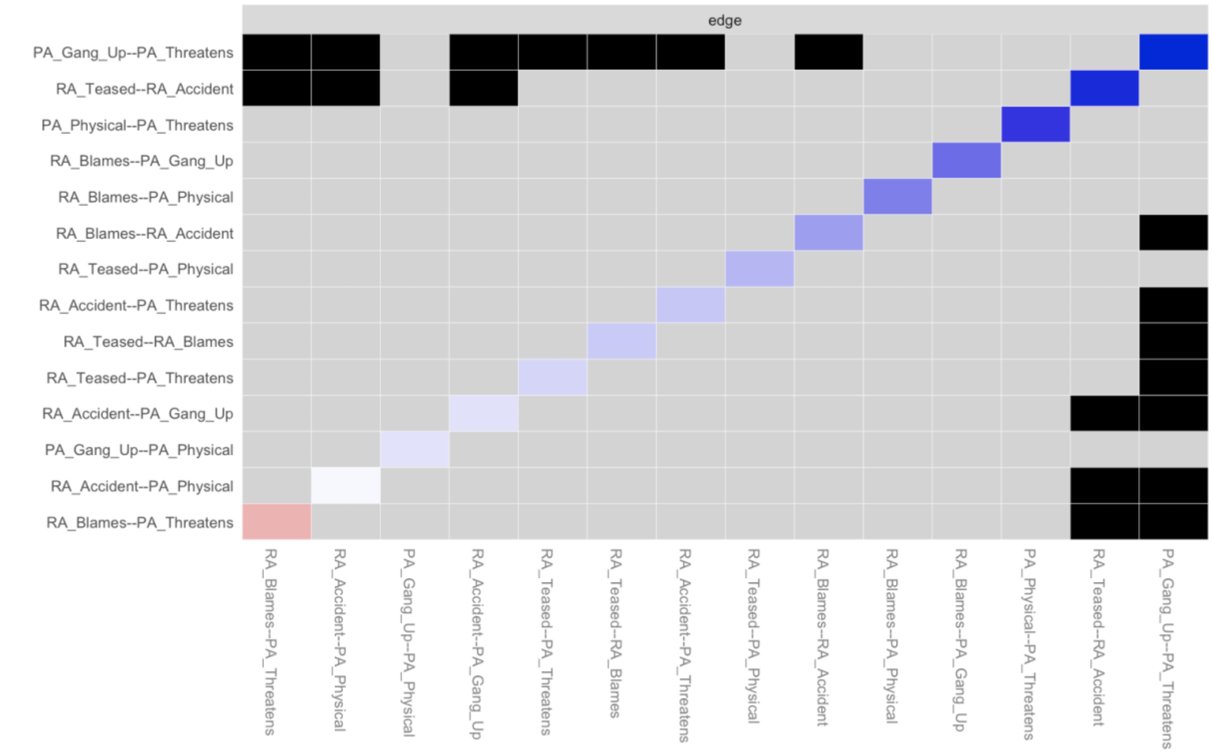
Teacher-Reported Aggression Plus Sleep Network



Note. The red line are the sample edge-weight values, the gray area representes the bootstrapped confidence intervals. The mean of the bootstrapped samples was used to order the edges.

Figure 7

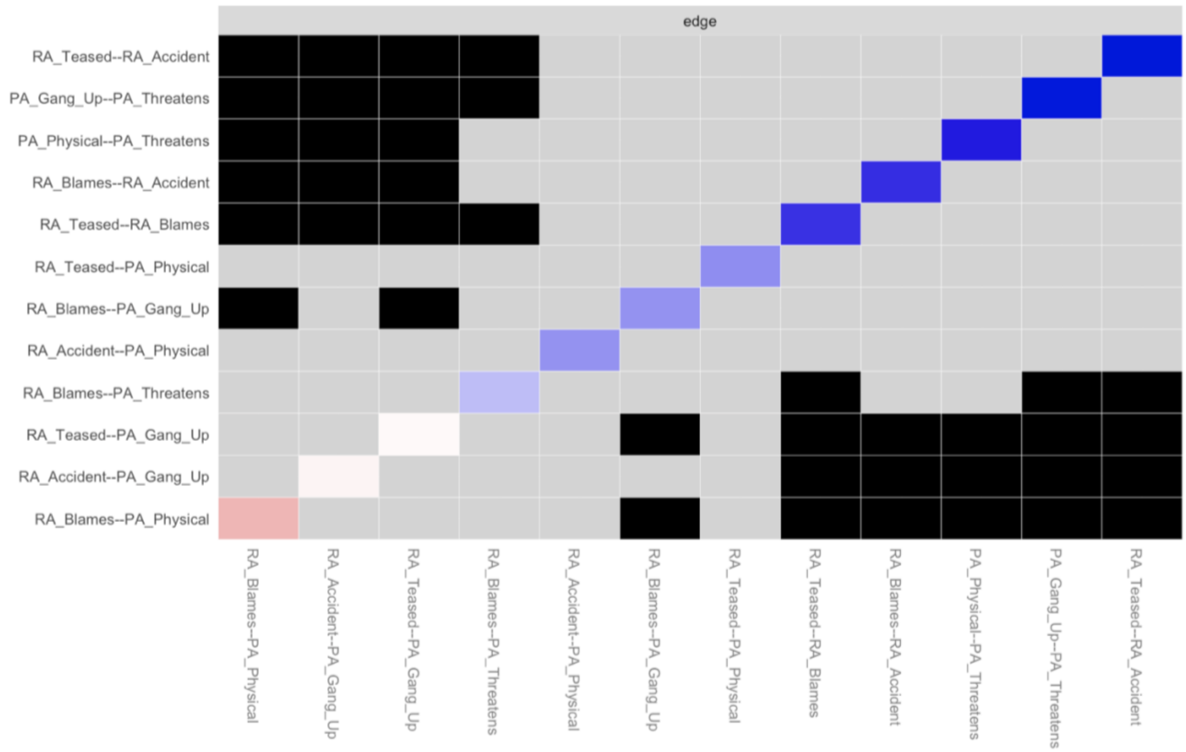
Bootstrapped Difference Test for Edge-Weights of the Child-Reported Aggression Network



Note. Black boxes indicate a significant difference between edge-weights, gray boxes indicate no significant difference between edge-weights.

Figure 8

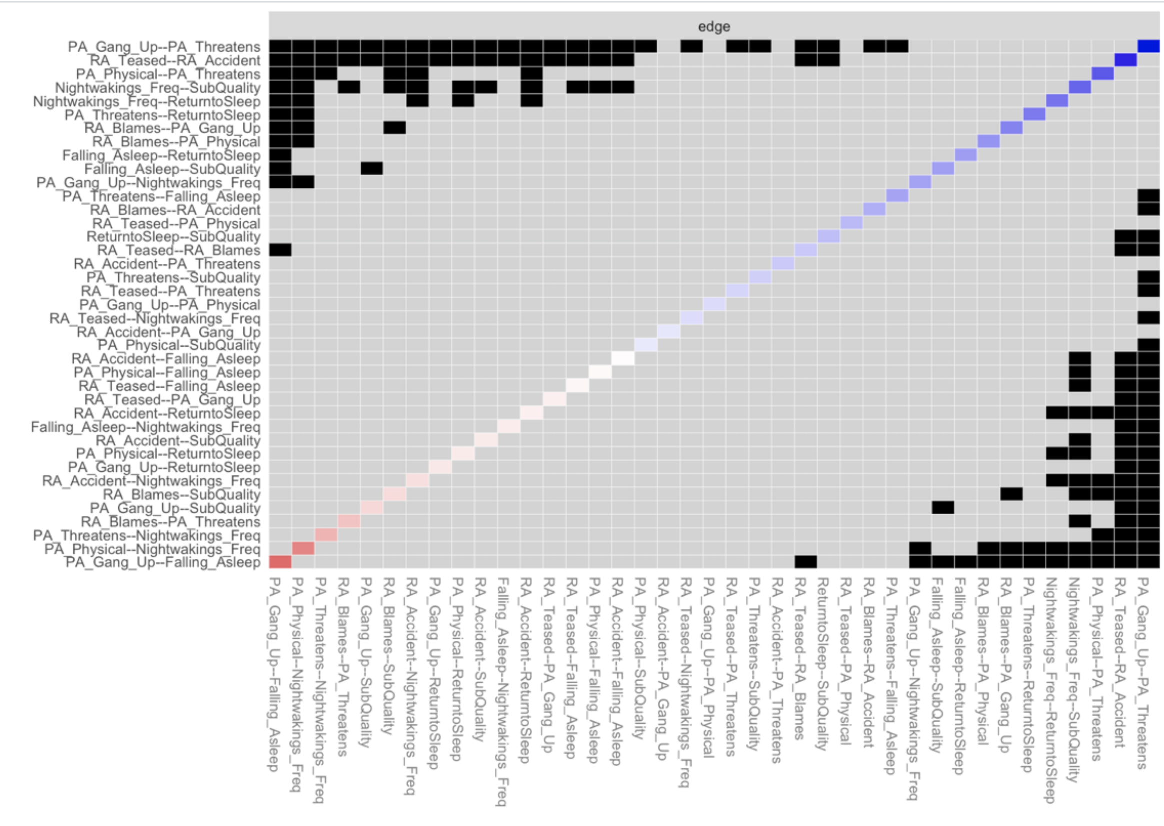
Bootstrapped Difference Test for Edge-Weights of the Teacher-Reported Aggression Network



Note. Black boxes indicate a significant difference between edge-weights, gray boxes indicate no significant difference between edge-weights.

Figure 9

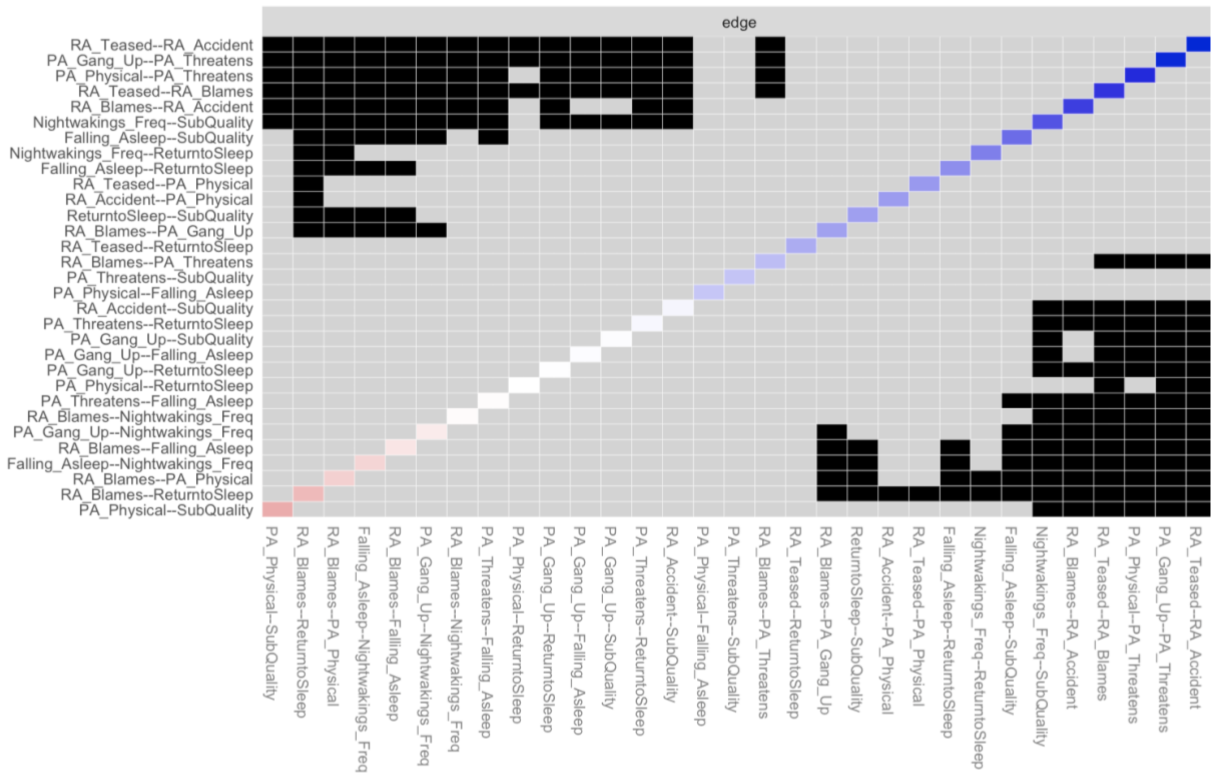
Bootstrapped Difference Test for Edge-Weights of the Child-Reported Aggression Plus Sleep Network



Note. Black boxes indicate a significant difference between edge-weights, gray boxes indicate no significant difference between edge-weights.

Figure 10

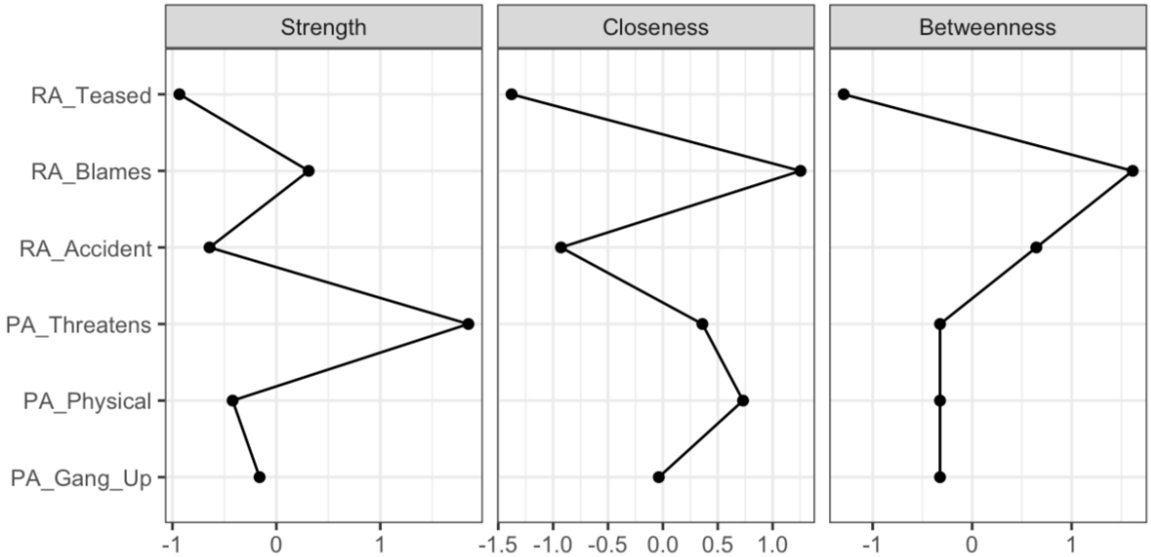
Bootstrapped Difference Test for Edge-Weights of the Teacher-Reported Aggression Plus Sleep Network



Note. Black boxes indicate a significant difference between edge-weights, gray boxes indicate no significant difference between edge-weights

Figure 11

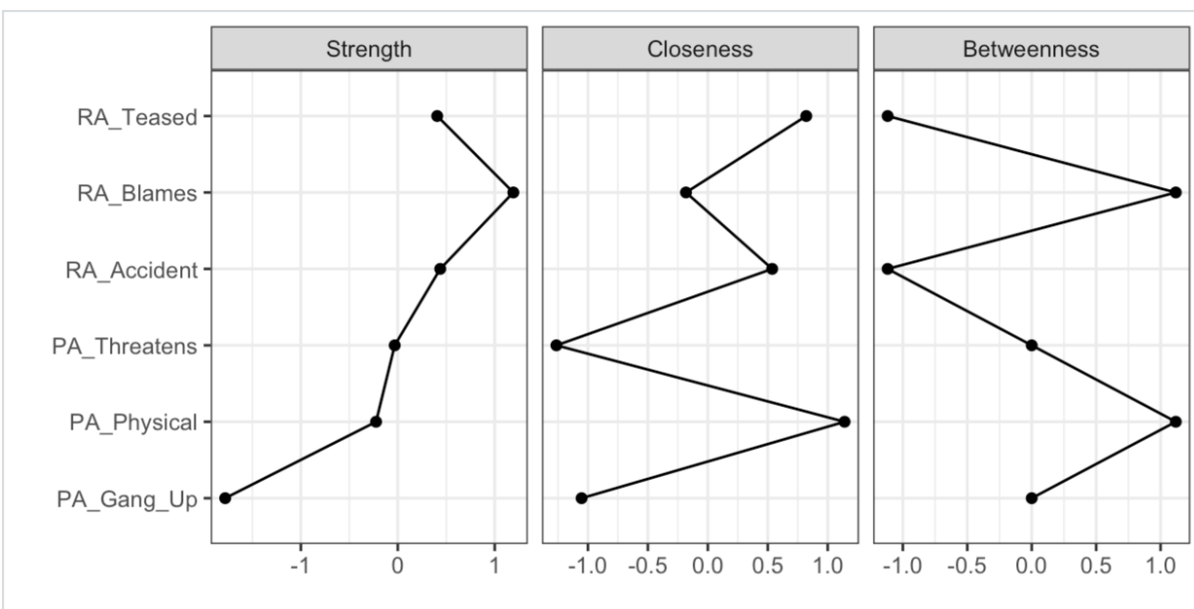
Strength, Closeness, and Betweenness Centrality Plots for the Child-Reported Aggression Network



Note. Standardized centrality scores are reported

Figure 12

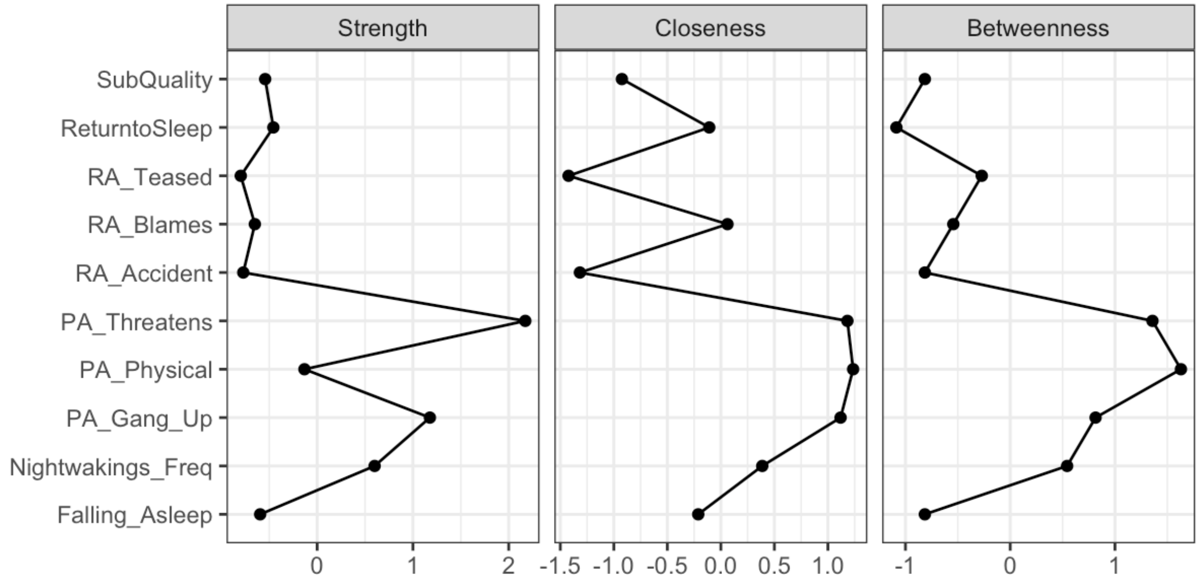
Strength, Closeness, and Betweenness Centrality Plots for Teacher-*Reported Aggression Network*



Note. Standardized centrality scores are reported.

Figure 13

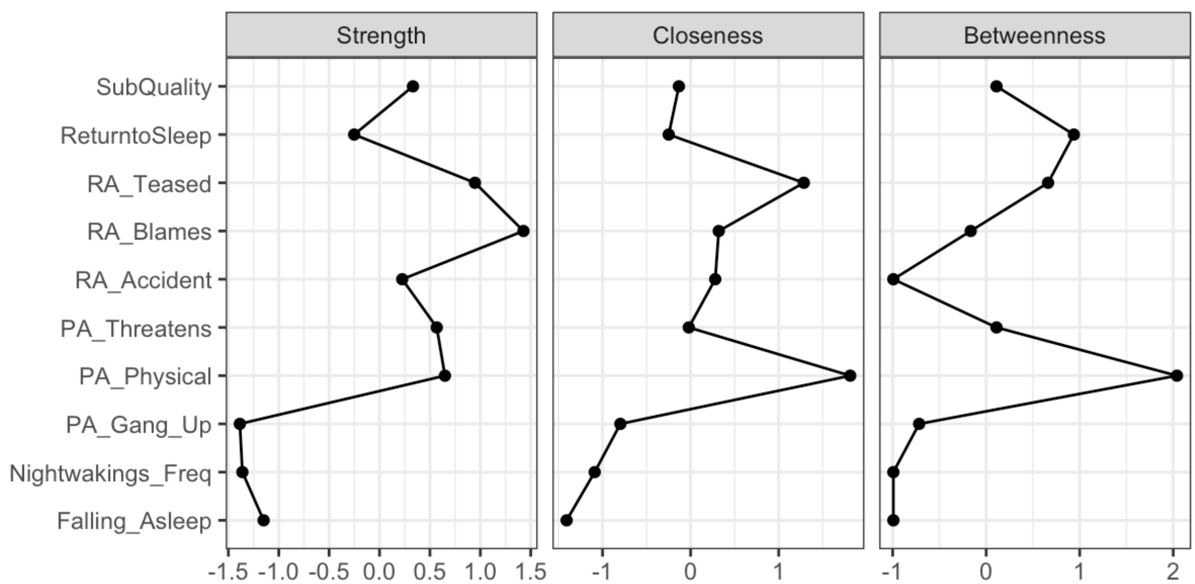
Strength, Closeness, and Betweenness Centrality Plots for the Child-Reported Aggression Plus Sleep Aggression



Note. Standardized centrality scores are reported.

Figure 14

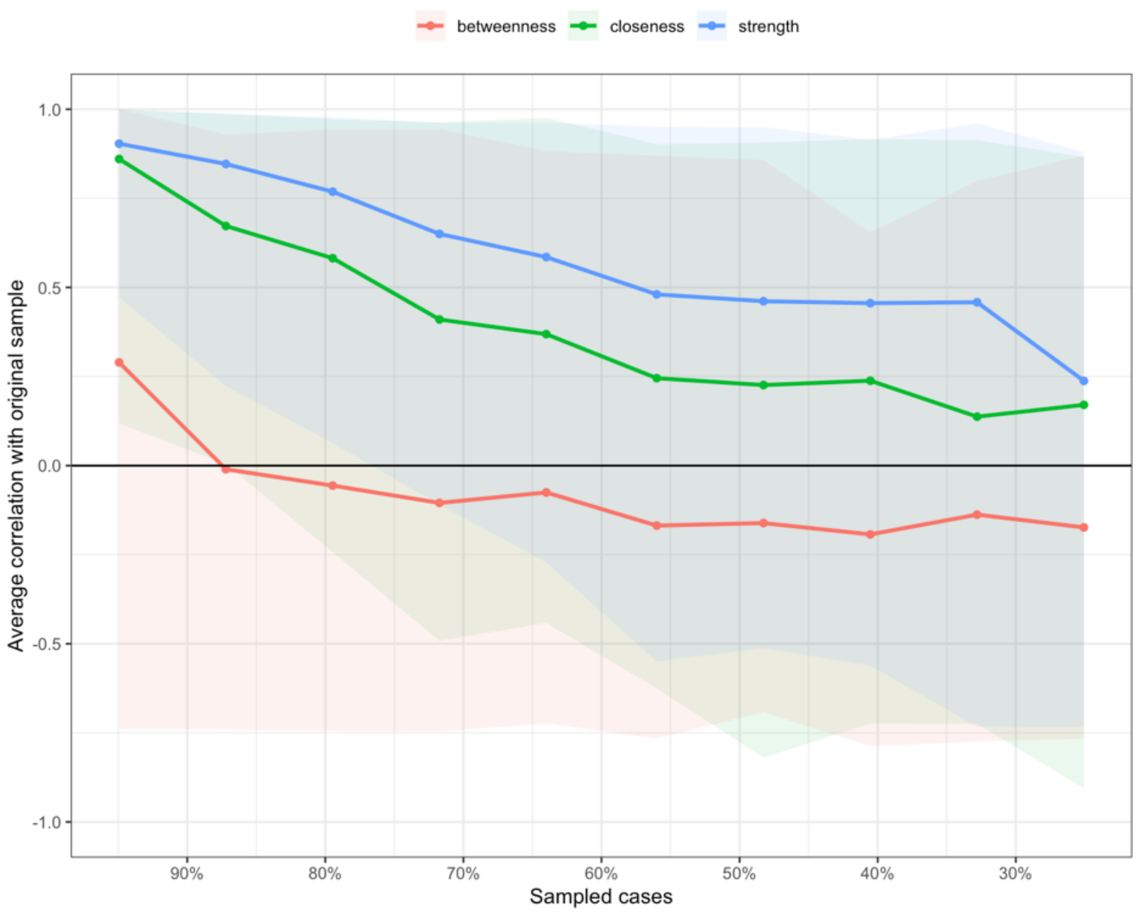
Strength, Closeness, and Betweenness Centrality Plots for the Teacher-Reported Aggression Plus Sleep Network



Note. Standardized centrality scores are reported.

Figure 15

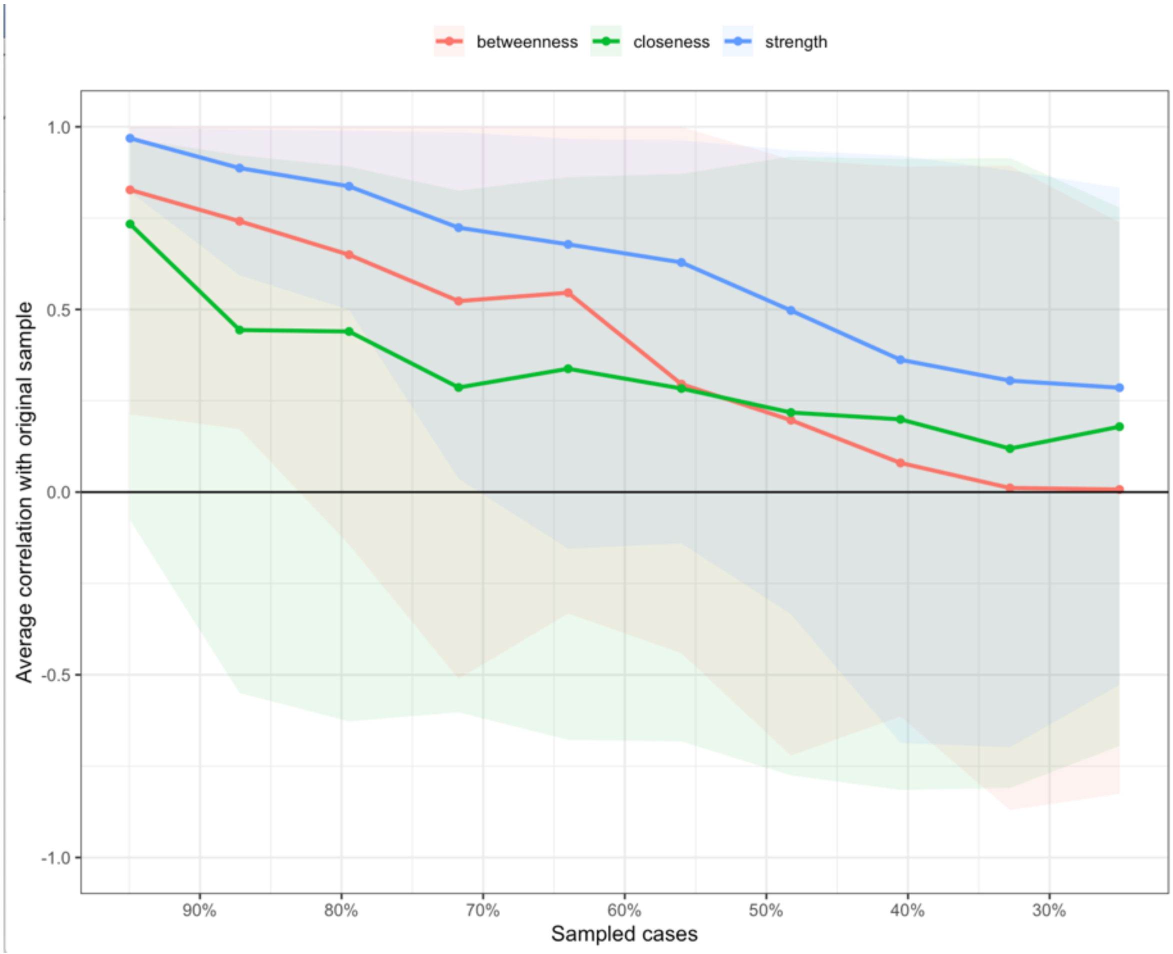
Centrality Stability of Child-Reported Aggression Network



Note. Lines represent the means of the correlation between centrality indices of network with persons dropped and of the network with the original sample. Shaded areas represent the range of the correlations from the 2.5th quantile to the 97.5th quantile.

Figure 16

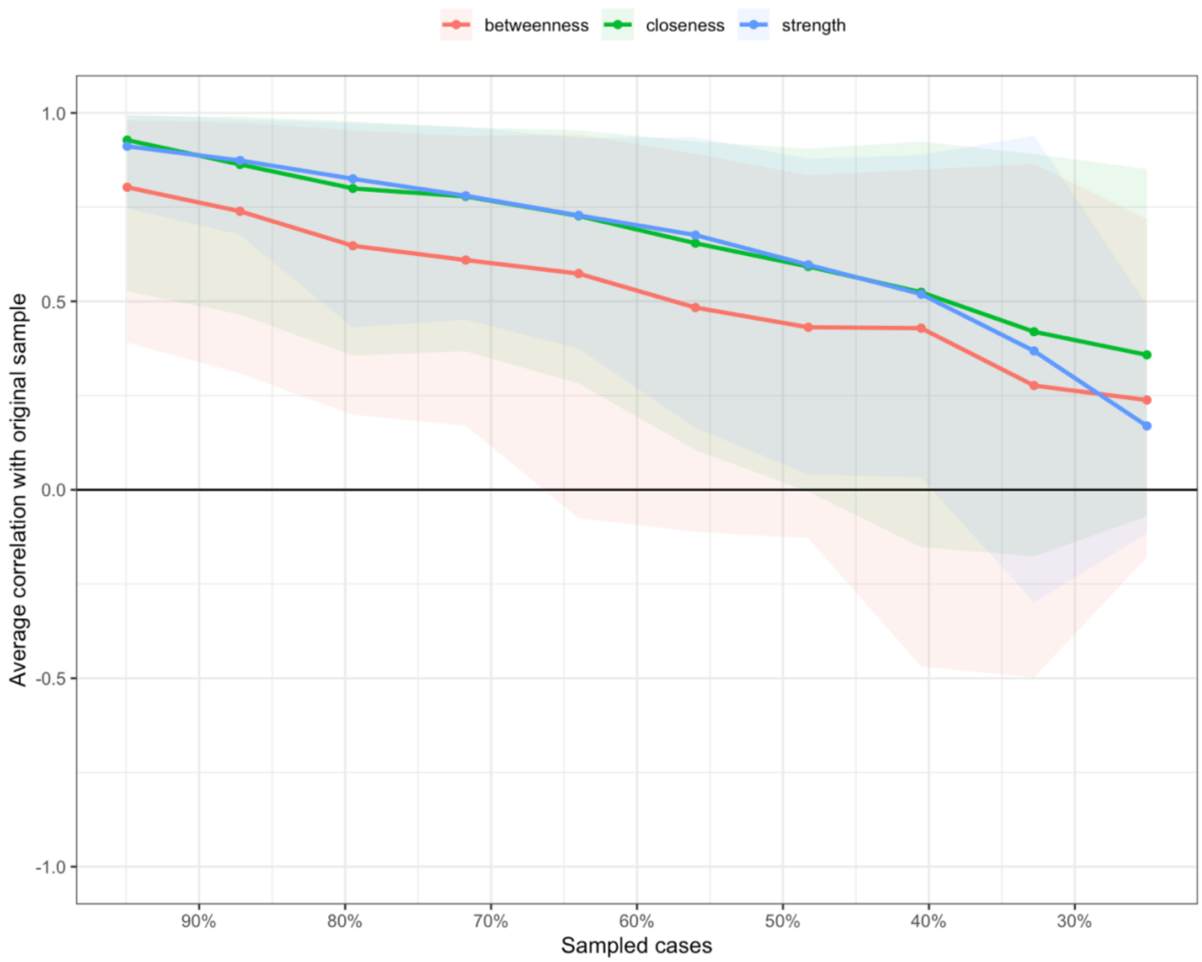
Centrality Stability of the Teacher-Reported Aggression Network



Note. Lines represent the means of the correlation between centrality indices of network with persons dropped and of the network with the original sample. Shaded areas represent the range of the correlations from the 2.5th quantile to the 97.5th quantile.

Figure 17

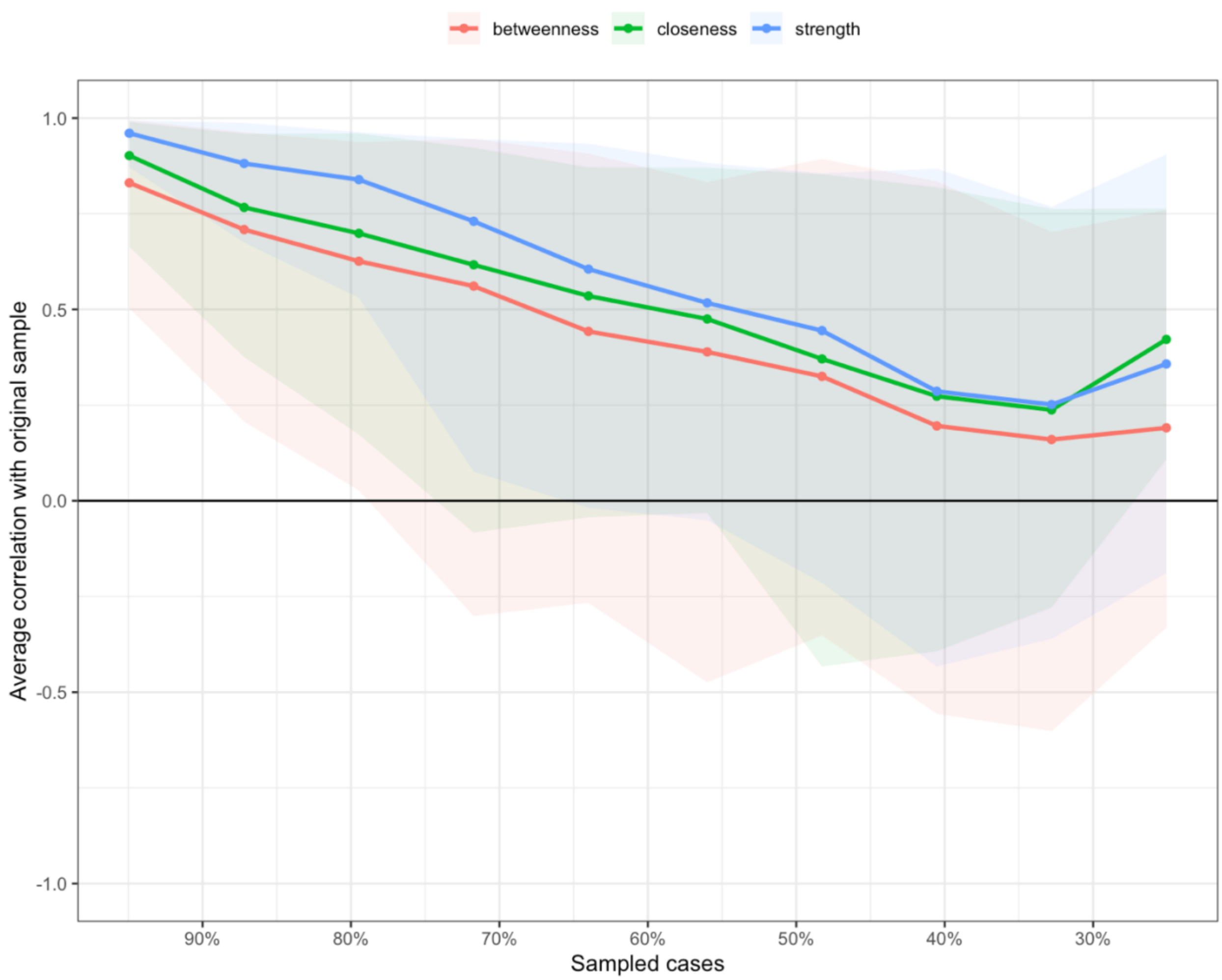
Centrality Stability of the Child-Reported Aggression Plus Sleep Network



Note. Lines represent the means of the correlation between centrality indices of network with persons dropped and of the network with the original sample. Shaded areas represent the range of the correlations from the 2.5th quantile to the 97.5th quantile.

Figure 18

Centrality Stability of Teacher-Reported Aggression Plus Sleep Network



Note. Lines represent the means of the correlation between centrality indices of network with persons dropped and of the network with the original sample. Shaded areas represent the range of the correlations from the 2.5th quantile to the 97.5th quantile.

Appendix A.

Proactive-Reactive Aggression Questionnaire

Item	Node Name
1. When the child has been teased or threatened, he/she gets angry easily and strikes back.	RA_Teased
2. The child always claims that other children are to blame in a fight and feels that they started the trouble.	RA_Blames
3. When someone accidentally hurts the child (such as bumping into him/her), he/she assumes that the peer meant to do it and then reacts with anger/fighting	RA_Accident
4. The child gets other kids to gang up on somebody that he/she doesn't like.	PA_Gang_Up
5. The child uses physical force (or threatens to use physical force) in order to dominate other kids.	PA_Physical
6. The child threatens or bullies others in order to get his/her own way.	PA_Threatens

RA = Reactive Aggression; PA = Proactive Aggression

Sleep Quality Items

Item	Node Name
1. When you're in bed and the lights are turned off: 1 = It takes you a long time to fall asleep 2 = You stay awake for a while 3 = You fall asleep at once	Falling_Asleep
2. Do you sometimes wake up during the night? 1 = Nearly Every Night 2 = Sometimes 3 = Never	Nightwakings_Freq
3. If you wake up during the night: 1= It takes you a while to fall asleep again 2 = You fall asleep soon again 3 = Mostly you don't notice	ReturntoSleep
4. Do you sleep well at night? 1 = No 2 = Sometimes 3 = Yes, always	SubQuality

Appendix B.

Study	Number of Participants	Number of Nodes in Network
Armour et al. (2017)	221	27
Bernstein et al. (2019)	403	20
Brown et al. (2020)	428	43
Choi et al. (2017)	296	38
Cramer et al. (2020)	557	22
Crossley & Langdridge (2005)	Sample 1: 20 Sample 2: 20	32
Curtiss & Klemanski (2016)	Sample 1: 70 Sample 2: 41	41
De Paoli et al. (2020)	753	18
Djelantik et al. (2020)	458	22
Forbush et al. (2016)	143	45
Forrest et al. (2019)	248	27
Hoorelbeke et al. (2016)	69	5
Jayawickreme et al. (2017)	337	84
Levinson et al. (2017)	196	27
Malgaroli et al. (2018)	Sample 1: 260 Sample 2: 263 Sample 3: 271	16
Martel et al. (2016)	Sample 1: 109 Sample 2: 548 Sample 3: 357 Sample 4: 406	18
McNally et al. (2017)	179	17
McWilliams et al. (2017)	216	9
Miers et al. (2020)	Time 1: 331 Time 2: 248 Time 3: 236	15
Monteleone et al. (2019)	405	20
Olatunji et al. (2019)	574	26
Perko et al. (2019)	Sample 1: 674 Sample 2: 674	35
Preszler et al. (2018)	Sample 1: 277 Sample 2: 871	Sample 1: 18 Sample 2: 12
Rogers et al. (2019)	167	57
Ruzzano et al. (2015)	213	17
Siew et al. (2017)	183	100
Smith et al. (2019)	446	38
Solmi et al. (2018)	Sample 1: 955 Sample 2: 813 Sample 3: 300	21
Thompson et al. (2019)	169	7
Vanzhula et al. (2019)	Sample 1: 158 Sample 2: 300	42