The Tangled Webs We Wreak: Examining the Structure of Aggressive Personality Using Psychometric Networks

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Acknowledgements. The analyses in this manuscript constitute secondary data analysis as the datasets used were collected for other projects. However, our analysis plan for each dataset was preregistered (Sample 1: https://osf.io/3j4ya, Sample 2: https://osf.io/vuze8, Sample 3: https://osf.io/h9jr5), and is available along with all the code, data needed to replicate our findings, and supplemental documents (https://osf.io/kqxd5/files/).This manuscript is not currently under review or consideration at other publication outlets. We have no conflicts of interest to disclose. Research reported in this publication was supported by the NIAAA under award K01AA026647 (PI: Chester). All data collection procedures were subjected to and approved via ethical review.

Abstract

Objective

Trait aggression is a prominent construct in the psychological literature, yet little work has sought to situate trait aggression among broader frameworks of personality. Initial evidence suggests that trait aggression may be best couched within the nomological network of the Five Factor Model (FFM). The current work sought to locate the most appropriate home for trait aggression among the FFM.

Method

We applied a preregistered regimen of psychometric network analyses to three datasets (combined $N = 2{,}927$) that contained self-reports of trait aggression and the FFM traits.

Results

Trait aggression was highly central in the factor-level networks, which contained associations consistent with the conceptualization of this construct as a lower-order component of low agreeableness. The facet-level networks revealed that the behavioral facets of trait aggression reflected low agreeableness, but that the anger and hostility facets reflected high neuroticism. The item-level network suggested that the *intent to initiate* aggressive encounters was the primary bridge that empirically linked trait aggression to agreeableness.

Conclusions

Our results indicate that trait aggression is primarily a lower-order facet of agreeableness, advance our understanding of trait aggression, integrate it with broader frameworks of personality, and suggest future directions to refine this complex dispositional tendency.

Keywords: network analysis, trait aggression, five factor model, antagonism, big five

Introduction

Despite a large body of research spanning many disciplines, trait aggression remains a fuzzy concept with unclear links to hierarchical frameworks of personality such as the Five Factor Model (FFM). Theoretical ambiguity may undermine research on trait aggression, as poorly defined constructs with ambiguous nomological networks yield poorly understood results (Cronbach & Meehl, 1955). A potential haven for the currently-adrift trait aggression construct is the Five Factor Model (FFM), which provides a framework for the structure of trait aggression within five broader dimensions of personality (Digman, 1990). To examine trait aggression's place within this broader FFM framework and the nature of its connections with the FFM traits we estimated a series of psychometric networks and examined the centrality of and connections among the FFM constructs and trait aggression. In doing so, we sought to examine the structure of trait aggression within the context of the FFM hierarchy, articulate this construct from other closely-related traits, and outline future directions for this important area of inquiry.

Defining Trait Aggression

Aggression, as a momentary state of behavior, is defined as any attempt to harm another person who does not wish to be harmed (e.g., Allen & Anderson, 2017). Yet aggressive behaviors do not occur in a vacuum, as they exhibit regular patterns of frequency and intensity that vary from one person to the next. Indeed, *trait aggression* reflects the stable, dispositional tendency to engage in aggression across situations and over time. A seminal longitudinal study of trait aggression found those exhibiting greater trait aggression at the onset of the study were also more aggressive at the end of a 22-year period, and that individual differences in trait aggression predicted violent behaviors outside of the laboratory (Huesmann et al., 1984). Further, dispositions towards aggressive behavior are not simply caused by environmental circumstances, but are also heritable (Caspi et al., 2002). Trait aggression is also associated with distinct patterns of neural activation during aggressive acts and hostile cognitions (Chester et al., 2018; Denson et al., 2009). The temporal stability, heritability, and neural bases of aggression indicate that aggressiveness is indeed a personality trait.

A commonly accepted model of trait aggression is instantiated in the Buss-Perry Aggression Questionnaire, which articulates four facets of trait aggression: physical aggression, verbal aggression, anger, and hostility (Buss & Perry, 1992). This four facet model has become the dominant paradigm in trait aggression research — the original publication has been cited 8,196 times (according to Google Scholar, as of November 14th, 2021). The physical aggression and verbal aggression facets refer to the tendency to engage in these two overt forms of aggression and comprise the behavioral component of trait aggression. The anger facet reflects the tendency to experience and express feelings of anger, reflecting the affective component of trait aggression. The hostility facet refers to a cynical distrust of and disdain for others alongside a biased perception of ambiguous social stimuli as threats, constituting the cognitive component of trait aggression. This four-factor model of trait aggression has been replicated in violent offender populations and across various languages and cultures (e.g., Spanish, Chinese, Japanese, Portuguese) indicating the utility of this model and the generalizability of trait aggression as a construct (e.g., Ando et al., 1999; Diamond et al., 2005; Gallagher & Ashford 2016; García-León et al., 2002; Maxwell, 2007; Pechorro et al., 2016). Despite the wide acceptance of and supporting evidence for the Buss-Perry model of trait aggression, little work has sought to examine where trait aggression may reside within higher-order models of personality. The FFM provides a clear framework by which to rectify this gap in the literature by examining the nomological, psychometric network surrounding trait aggression.

The Five Factor Model and Trait Aggression

The FFM of personality contains five traits: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (Digman, 1990). This model posits that all lower-order personality constructs (e.g., trait aggression) can be appropriately situated under one or more of the five domains (e.g., Lynam & Miller, 2015). Recent empirical work has provided clear evidence that the FFM serves as a clear taxonomy by which lower-order traits (e.g., trait aggression) can be organized (Bainbridge et al., 2021). The traits of the FFM are bipolar in nature, such that a low score on any given personality trait does not simply reflect an absence of that factor, but rather reflects *high* levels of that trait's opposing end of the spectrum. Specifically, low agreeableness scores reflect high antagonism, low neuroticism scores indicate less negative emotion[1], low extraversion scores indicate higher levels of introversion, low levels of openness reflect high levels of close-mindedness, and low levels of conscientiousness indicates disinhibition (John & Srivastava, 1999).

Application of the FFM to trait aggression has yielded a wealth of evidence indicating that trait aggression has some degree of association with each of the FFM traits. Meta-analytic work indicates that agreeableness, conscientiousness, extraversion, low neuroticism, and openness are each negatively associated with dispositional and behavioral forms of aggression (Jones et al., 2011). Of these associations, agreeableness, neuroticism, and conscientiousness yield the strongest (Barlett & Anderson, 2012; Jones et al., 2011). However, variance in trait aggression is best explained by low agreeableness (i.e., high antagonism; Chester & West, 2020). The pattern of domain-level associations between trait aggression and the FFM obscure a more

[1]Recent work suggests that neuroticism may be better defined as one's disposition toward the experience of negative emotions rather than the traditional emotional stability conceptualization (Kalokerinos et al., 2020).

nuanced array of associations that exist at the lower-order, *facet level* of personality.

The physical and verbal aggression facets of trait aggression are most linked to agreeableness, whereas the hostility and anger facets of trait aggression are most linked to neuroticism (Tremblay & Ewart, 2005). However, research also evinces neuroticism and agreeableness yielding similarly-sized associations with physical and verbal aggression (Ode et al., 2008). As such, it remains unclear if the lower-order facets of trait aggression are most appropriately situated below a single FFM trait or a combination of them. The lower-order facets of the FFM traits themselves share unique variance across a blend of higher-order FFM domains. For example, the compliance facet of agreeableness shares substantial variance with both agreeableness and neuroticism (Schwaba et al., 2020). It thus stands to reason that the facets of trait aggression may be best accounted for by a blend of two or more of the FFM traits. Yet other lower-order personality traits that are linked with aggression (e.g., psychopathy) may obscure the appropriate placement of trait aggression within the FFM hierarchy of personality.

The so-called 'dark' tetrad (DT) of personality contains four malevolent traits: psychopathy, Machiavellianism, narcissism, and Sadism (Međedović & Petrović, 2015; Paulhus, 2014). Like trait aggression, each component of the DT is positively associated with neuroticism, and negatively associated with the remaining FFM traits (e.g., Fernández-del-Río et al., 2020; Miller et al., 2018). However, antagonism (i.e., low agreeableness) has been identified as a major core component of the DT (Paulhus, 2014). Further, trait aggression demonstrates positive associations with each of the DT traits (e.g., Neumann et al., 2020). Due to the conceptual and empirical overlap of these traits, an analytic approach that allows for the simultaneous examination of trait associations while controlling for other relationships among a constellation of traits is necessary. One analytic framework that may address such questions is psychometric network analysis.

Psychometric Network Analysis

Network analysis was initially developed to understand dynamic relations among groups of people (Scott, 1988). This analytic framework has been adapted for psychometric purposes, such as examining the structure of personality traits and symptoms of psychopathology (e.g., Armour et al., 2017; Constantini et al., 2015). In traditional social network analyses, each *node* within a network represents a single person, whereas in psychometric networks nodes represent a single variable. Such nodes may represent measures' overall scores, domain scores, more specific facet-level scores, or even scores of individual items. *Edges* refer to the paths that connect any given pair of nodes in a network. Such networks are typically weighted and undirected, such that edges visually reflect the association (e.g., bivariate partial correlations) between any two nodes in the network (Epskamp & Fried, 2018). Advancements in computational approaches to network estimation (e.g., machine learning) allow researchers to find a set of partial associations that best fits the data (Epskamp & Fried, 2018). Networks of cross-sectional trait data reflect exploratory associative structures that can be used to develop confirmatory hypotheses. Yet such cross-sectional networks cannot establish causal influences between traits and their constituent facets and items. Psychometric network analyses also provide information about the importance of a given node to the flow of information in a specified network (i.e., centrality).

The expected influence and functionality of nodes is commonly examined in terms of the degree of centrality they exhibit within a network. *Strength centrality* is a commonly-used index of centrality and indicates the overall influence of a node within a network. Strength centrality is ideal for examining personality networks at the domain and facet levels because it provides a direct estimate of the importance of a specific trait to the structure of the network. Networks may also contain communities which comprise a collection of traits or individual scale items. Another class of centrality statistics is required to examine the centrality of nodes that bridge such communities.

Recently developed measures of bridge centrality are ideal for understanding the connections among different network communities. *Bridge centrality* provides information regarding the extent to which a given node links together node communities. Such communities can be identified automatically by applying an algorithm or by imposing a chosen theoretical model (Jones et al., 2019). At the facet-level trait scores may be placed in communities based on the higher-order trait they are couched within. In this application bridges are conceptualized as the traits that connect higher-order constructs. In the context of item-level personality data, a community may be identified as a collection of scale items measuring the same construct and the bridges represent the nodes that interconnect these communities. The identification of such bridges uniquely allows for the identification of lower-order traits that may be best explained by a blend of higher-order traits. For example, if an item connects a 'trait anger' community to a 'trait neuroticism' community, then this item may reflect a mixture of these two trait constructs. The item content of bridge nodes can then be examined to identify the core themes comprising the associations observed among node communities to produce insight about the core nature of such associations. Such insights can then be applied towards improvement of the psychometric properties of a given measure. Psychometric network analysis thus provides an ideal analytic framework for examining the connections among trait aggression and the FFM of personality.

The Present Research

Due to the lack of clarity regarding the structure of trait aggression and its connections to the FFM traits, we present an initial effort to examine this structure by applying network analytic procedures. To do so, we used three datasets that implemented combinations of different instruments to measure the FFM traits and trait aggression to estimate networks at three conceptual levels: the domain-level, the facet-level, and the item-level. Our domain-level analyses focused on trait aggression (as a unitary trait) and its links to the five FFM domains. We then estimated facet-level networks that focused on the five FFM domains and the four facets of trait aggression (i.e., physical aggression, verbal aggression, anger, and hostility). Subsequent analyses focused on the facets of the two most important FFM domains for trait aggression: agreeableness and neuroticism. We then estimated an item-level network that examined the items most responsible for the patterns of associations found in the previous networks (i.e., bridge nodes). We also examined trait aggression's connections with other antisocial traits (e.g., psychopathy) in a 'malevolent' traits network.

Methods

Participants

Participants were acquired from three existing samples (Table 1). Samples 1 and 2 comprised undergraduate students recruited from introductory psychology subject pools at an American university who were compensated with partial course credit. Sample 3 was acquired from a public data repository (https://osf.io/yv65h/; Delhove & Greitemeyer, 2020) after completing a brief search for datasets on the Open Science Framework using the terms "trait aggression" and "Big Five". We ended our search after acquiring Sample 3 as the size of Sample 3 allowed us to construct a stable item-level network (Network 9). Sample 3 comprised participants who were recruited from various online video game forums for entry into a lottery to win one of ten $40/€40 prizes. In Sample 3, 385 participants were under the age of 18 and were subsequently excluded from our analyses. Sample 3 was collected by researchers in Austria, yet data collection was completed online and thus participants in this sample could reasonably be from anywhere in the world. However, neither the publicly available dataset nor the original publication using it contain ethnicity estimates of their participants and thus we are unable to present them here (Delhove & Greitemeyer, 2020).

Table 1

Sample characteristics.

Sample	*N*	% Female	Age *M* (*SD*)	% White	Age Range	Networks
1	620	71.10	19.03 (1.89)	67.70%	18-41	1, 4, 8
2	367	68.10	18.65 (0.98)	74.10%	18-26	2, 5, 7
3	1,940	11.00	24.27 (5.34)	-	18-55	3, 6, 9, 10

Note. Ethnicity data is not available for Sample 3.

Measures

Buss-Perry Aggression Questionnaire. We used the 29-item BPAQ to measure trait aggression in Samples 1 and 3 (Buss & Perry, 1992). The BPAQ included four facet-level subscales: physical aggression (9 items), verbal aggression (5 items), anger (7 items) and hostility (8 items). Sample 2 used an abbreviated version of the BPAQ, the 12-item Brief Aggression Questionnaire (BAQ; Webster et al., 2014), which measured the facets of trait aggression with three items each.

Big Five Inventory. The BFI was used to measure each of the FFM domains in Samples 1 and 3 (John et al., 1991; John et al., 2008): openness (10 items), conscientiousness (9 items), extraversion (8 items), agreeableness (9 items), and neuroticism (8 items).

Comprehensive Assessment of Sadistic Tendencies. The CAST was used to measure trait Sadism in Sample 3 (Buckles & Paulhus, 2014). Sadism was measured as a singular trait comprising all 18 items from the CAST.

Dirty Dozen. The traits of psychopathy, Machiavellianism, and Narcissism were measured in Sample 3 using the Dirty Dozen questionnaire (DD; Jonason & Webster, 2010). The DD measured each of the dark triad traits using four items per trait.

IPIP-NEO-120. In Sample 2, the FFM traits were measured using the 120-item International Personality Item Pool version of the NEO Personality Inventory (Goldberg et al., 2006). The IPIP-NEO measured each of the FFM traits using 24 items.

Procedures

Sample 1. Participants in Sample 1 arrived at the laboratory individually or in groups of two to four. They were then randomly assigned to consume a pill capsule containing 1000mg of acetaminophen, a placebo (corn starch), or no pill at all as part of a broader study examining the role of physical pain in decision-making (e.g., DeWall et al., 2015). Prior to the acetaminophen becoming psychoactive, participants then completed a questionnaire battery that included the BFI and BPAQ. Following this, participants completed a series of decision-making tasks prior to being debriefed and dismissed from the laboratory.

Sample 2. Participants in Sample 2 arrived at the laboratory individually or in groups of two to four (see Chester et al., 2017). They were randomly assigned[2] to experience social exclusion or inclusion using the Cyberball task (Williams et al., 2000). Then, participants completed a series of behavioral tasks (e.g., a Go/No-Go task) and then completed a questionnaire battery containing the BAQ and IPIP-NEO-120 prior to being debriefed and dismissed from the laboratory.

[2]One of our reviewers requested that we explore whether the means and variability of the constructs measured in Sample 2 different because of this manipulation. We performed independent-samples *t*-tests for all Sample 2 variables and found that A) none of the variables from Sample 2 differed on average across conditions and B) only one of these variables had differential variability across conditions per Levene's test (i.e., the Depression facet of neuroticism). The results of these analyses are available in Supplemental Document 1.

Sample 3. Participants in Sample 3 were recruited via internet forums for an online study as part of a broader project examining potential personality differences across video game playing styles (Delhove & Greitemeyer, 2020). After providing informed consent, participants completed a demographics questionnaire and a survey of their in-game habits and behaviors. Following this, participants completed a questionnaire battery that included the BFI and BPAQ.

Analytic Approach

All analyses were conducted using R version 4.0.2 (R Core Team, 2020). Prior to estimation of each network, we tested each set of variables for redundant nodes using the *goldbricker* function from the networktools package (Jones, 2017). We reduced (i.e., combined) redundant nodes identified using the *net_reduce* function of the networktools package as networks containing redundant nodes yield artificially inflated centrality values (Jones, 2017).

All networks were estimated using the *estimateNetwork* function from the bootnet package in R (Epskamp et al., 2018). We used the adaptive least absolute shrinkage and selection operator (LASSO) for network estimation. The adaptive LASSO attempts to find a network model that is balanced between a network free from spurious edges and a network that allows for discovery of weaker (but potentially important) edges (Epskamp & Fried, 2018). To accomplish this the LASSO attempts to reduce smaller edges to zero, yielding networks with sparse connections and few spurious edges (Epskamp et al., 2018). Missing data were treated using full information maximum likelihood (FIML) estimation. All networks were visualized using the *plot* function from the qgraph package (Epskamp et al., 2012). Network topography was determined by the Fruchterman Reingold algorithm. Networks containing the same nodes (i.e., Networks 1-3 and Networks 4-6) were given the same topography by using the averageLayout function from the *qgraph* package for ease of visual comparison.

We focused on two forms of centrality for our networks: strength centrality for our domain and facet level networks and bridge centrality for our item-level network. Strength centrality was computed as the combined absolute value of all edges directly connected to any given node using the *centrality_auto* function from the qgraph package. Expected influence (EI) can be estimated as a one-step index that considers the value of all edges connected to a given node outside of the node's respective community or as a two-step index that additionally accounts for indirect influence that a bridge node may exert in other communities. Given that we were interested in the degree of intercommunity influence, we relied on two-step EI for our index of bridge centrality (Jones et al., 2019). Bridge centrality was estimated using the *bridge* function from the networktools package.

Each network was also subjected to two 5,000 sample bootstrap procedures via the *bootnet* function from the bootnet package: a non-parametric bootstrap and a case-dropping bootstrap. The non-parametric bootstrap allowed us to test for differences between edge weights and to examine the accuracy of our networks (Epskamp & Fried, 2018). The case-dropping bootstrap was used to estimate the stability of centrality and edge weight estimates of each network. This procedure yields a correlation stability (*CS*) coefficient for edge weights and indices of centrality. Each *CS* represents the proportion of cases that could be dropped from the sample while maintaining a correlation of at least 0.70 between the empirical and bootstrapped network edge weight and centrality estimates. Any estimate of stability must be above .25 and ideally above .50 to consider a given estimate stable and thus interpretable (Epskamp et al., 2018). Estimation of network stability takes the place of traditional power analyses in network analysis because researchers have no way of knowing how many parameters will be retained in any given model, thus rendering *a priori* power analyses impossible.

Results

Descriptive Statistics

Descriptive and reliability statistics of all variables used in our networks are available in Supplemental Document 2 (Tables S2-S5). Zero-order correlations from all variables included in our networks are also available in Supplemental Document 2 (Figures S1-S8).

Domain-level Networks

Pre-estimation. We estimated domain-level networks containing total trait aggression, agreeableness, neuroticism, openness, conscientiousness, and extraversion for each of our three samples. Prior to the estimation of these networks, we conducted a redundancy analysis. We found no redundant nodes in our domain-level networks (i.e., Networks 1-3) and thus we proceeded with the estimation procedure. No variables in the facet-level networks exhibited significant skew or kurtosis (i.e., beyond +/- 2.00).

Network estimation. Stability estimates for edge weights (*CSs* > .67) were ideal for Networks 1-3. Strength centrality *CS* values however ranged from questionable (Network 2 *CS* = .28) to ideal (Network 3 *CS* = .75). See Supplemental Document 3 (Table S6) for all correlation stability coefficient values for Networks 1-3.

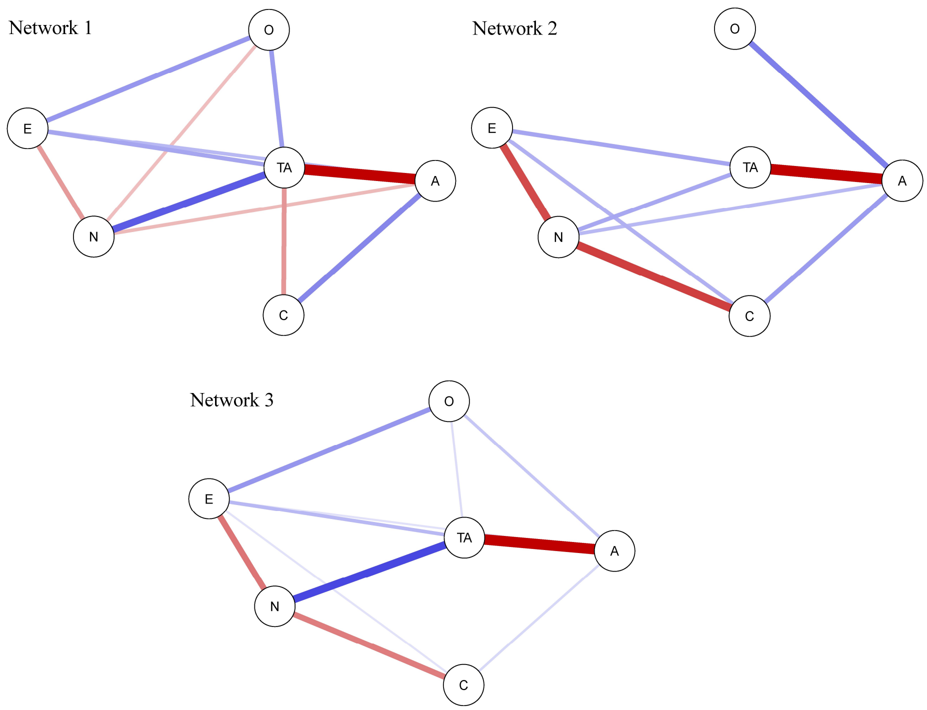

Figure 1. The three domain-level networks, (Network 1 = Sample 1, Network 2 = Sample 2, Network 3 = Sample 3). Blue edges represent positive associations, red edges represent negative associations. Edge width and depth of color indicate association strength. N = neuroticism, C = conscientiousness, A = agreeableness, E = extraversion, O = openness, and TA = trait aggression. Interactive versions of these networks are available – Network 1: https://aggressionnet1.netlify.app/, Network 2: https://aggressionnet2.netlify.app/, Network 3: https://aggressionnet3.netlify.app/.

Network edges. Complete edge weight estimates for all networks are presented in Supplemental Document 3 (Table S7 – Table S9). Neuroticism demonstrated moderate (Networks 1 & 3) to weak (Network 2) positive edges with trait aggression. Conscientiousness demonstrated a weak negative edge with trait aggression (Network 1) or no edge at all (Networks 2-3). Openness to experience demonstrated weak positive edges with trait aggression in Networks 1-3. Extraversion also demonstrated weak positive edges with trait aggression in

Networks 1-3. Finally, agreeableness shared relatively strong negative edges with trait aggression in Networks 1-3. Supporting our general expectations, agreeableness demonstrated a significantly stronger edge with total trait aggression than any other FFM trait in all three networks (Supplemental Document 4).

Centrality estimates. Total trait aggression emerged as highly central to Networks 1-3 due to the edges it shared with the FFM traits (Table 2). Of the FFM traits, agreeableness and neuroticism were also highly central to Networks 1-3, underscoring their relatively strong edges with trait aggression. Extraversion exhibited relatively high in centrality in Networks 2-3 because it shared moderate-to-strong edges with other FFM traits.

Table 2

Node Strength Estimates from the Domain-Level Networks

	Network 1	Network 2	Network 3
Agreeableness	0.79	1.06	0.74
Conscientiousness	0.35	0.70	0.39
Extraversion	0.56	0.67	0.73
Neuroticism	0.62	1.01	0.88
Openness	0.41	0.37	0.38
Trait Aggression	1.10	0.94	1.06

Network replicability. Spearman's rank-order correlations between each network's edge weights revealed that our domain-level networks largely replicated across all three samples: Networks 1 and 2, $rs(13) = .56$, $p = .031$; Networks 1 and 3, $rs(13) = .86$, $p < .001$; and Networks 2 and 3, $rs(13) = .76$, $p < .001$.

Facet-Level Networks: Modeling Trait Aggression Facets Alongside FFM Domains

Pre-estimation. Networks 4-6 each included all the FFM traits and the four facets of trait aggression (i.e., physical aggression, verbal aggression, anger, and hostility). We observed no redundant nodes in Networks 4-6 and thus proceeded with estimation. No variables in Networks 4-6 exhibited significant skew or kurtosis (i.e., beyond +/- 2.00).

Network estimation. Networks 4-6 (Figure 2) yielded sufficient stability coefficients for edge weights (*CSs* > .52). Stability values for strength centrality ranged from low (Network 5 *CS* = .36) to ideal (Network 6 *CS* = .75; see Supplemental Document 3, Table S10 for full *CS* values).

Network edges. Networks 4-6 each contained negative edges between agreeableness and the trait aggression facets of verbal aggression and anger. Network 4 contained no edges between agreeableness and physical aggression or hostility, though Networks 5-6 contained negative edges between agreeableness and all four facets of trait aggression. All three networks revealed strong positive edges among neuroticism and the anger and hostility facets of trait aggression. However, neuroticism either yielded no edges (Network 5) or negative edges with physical (Networks 4 & 6) and verbal (Network 6) aggression. Of the extraversion—trait aggression edges, the most consistent was the positive extraversion—verbal aggression edge which appeared in Networks 4-6. Extraversion also demonstrated modest positive edges with anger in Networks 4 & 6. One of our preregistrations contained hypotheses regarding the comparison of certain edges in Networks 4-6. However, some of the anticipated edges did not emerge in Networks 4-6 making such comparisons impossible. As such, we abandoned these hypotheses marking a deviation from our preregistration.

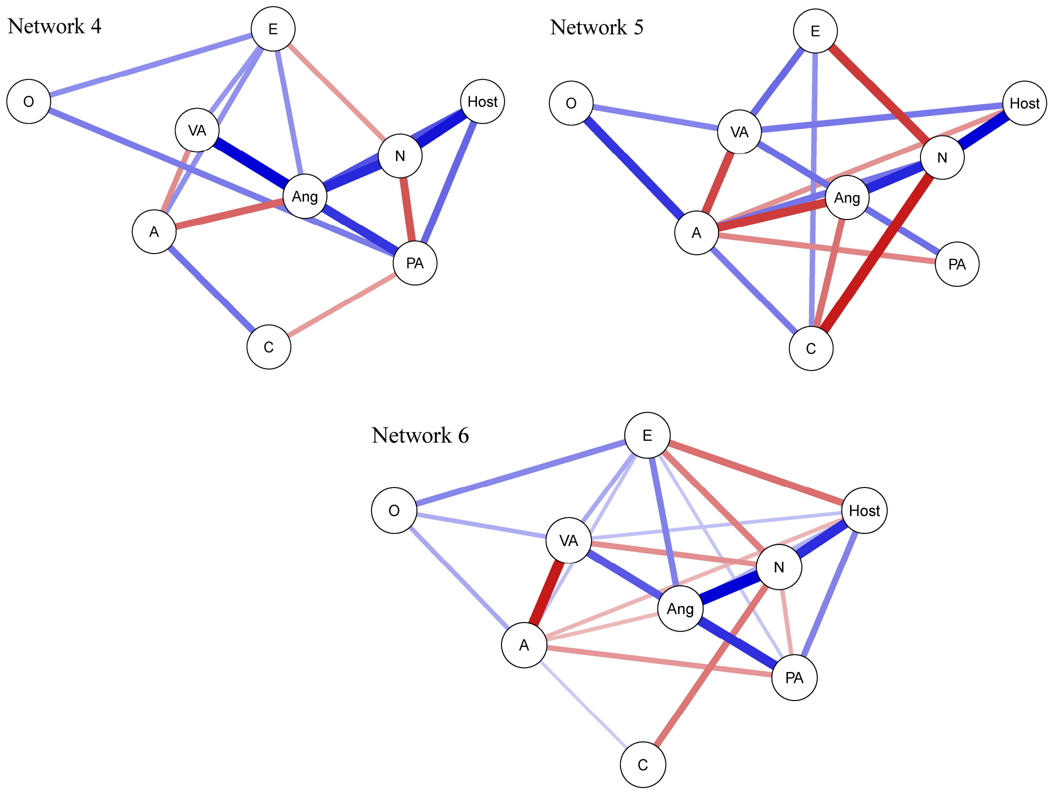

Figure 2. Visualization of Networks 4-6 (Network 4 = Sample 1, Network 5 = Sample 2, Network 6 = Sample 3). Blue edges represent positive associations, red edges represent negative associations. Edge width and depth of color indicate association strength. N = neuroticism, C = conscientiousness, A = agreeableness, E = extraversion, O = openness, PA = physical aggression, VA = verbal aggression, Ang = anger, Host = hostility. Interactive versions of these networks are available – Network 4: https://aggressionnet4.netlify.app/, Network 5: https://aggressionnet5.netlify.app/, Network 6: https://aggressionnet6.netlify.app/.

Centrality estimates. Estimates of strength centrality indicated agreeableness and neuroticism were highly central to Networks 4-6 (Table 3). Extraversion also yielded relatively high strength centrality values in Networks 4 & 6. This appears to be due to extraversion's dense connections in each network, as it demonstrates edges with each of the FFM traits (excepting conscientiousness in Networks 4 & 6) and edges with some of the trait aggression facets.

Comparison of the strength centrality estimates from Networks 4 & 6 with those from Network 5 revealed some curious differences. For example, extraversion was a relatively central node in Networks 4 & 6 but not Network 5. Similarly, conscientiousness was the least central node in Networks 4 & 6 but yielded a relatively higher centrality value in Network 5. These differences may be due to the different measures used in this sample. However, because Network 5 utilized a different measure of the FFM traits (IPIP-NEO) and trait aggression (BAQ) than did Networks 4 & 6, it is unclear which of these measures may account for such differences. Finally, anger appeared to be a highly important aspect of trait aggression as it served as a connective hub among the trait aggression facets in Networks 4-6.

Table 3

Strength Centrality Estimates from Networks 4-6.

	Network 4	Network 5	Network 6
Agreeableness	0.69	1.44	1.04
Anger	1.47	1.06	1.38
Conscientiousness	0.32	0.80	0.29
Extraversion	0.72	0.59	1.10
Hostility	0.74	0.68	1.06
Neuroticism	0.96	1.51	1.40
Openness	0.33	0.45	0.44
Physical Aggression	1.16	0.59	0.87
Verbal Aggression	0.78	1.13	1.12

Network replicability. Our facet-level networks produced highly similar structures and associations across all three samples: Networks 4 and 5, $rs(34) = .56$, $p < .001$, Networks 4 and 6, $rs(34) = .76$, $p < .001$, and Networks 5 and 6, $rs(34) = .70$, $p < .001$.

Facet-Level Network: Modeling Trait Aggression Facets Alongside Facets of Agreeableness and Neuroticism

To better understand which facets of agreeableness and neuroticism were most important to the facet-level structure of trait aggression, we estimated another facet-level network (i.e., Network 7) that included the four facets of trait aggression alongside the six facets of agreeableness and the six facets of neuroticism measured by the IPIP-NEO-120. Such networks were not estimated for Samples 1 and 3, as the majority of the BFI's facets yielded poor internal consistency (e.g., the compliance facet of agreeableness; $\omega = .52$). Full internal consistency information is presented in Supplemental Document 2, Tables S2 and S4.

Pre-estimation. We observed no redundant nodes in Network 7 excepting the anger facets from neuroticism and trait aggression. Given this redundancy, these two nodes were reduced to a single composite node using a principal components analysis per our preregistered analysis plan. No nodes in Network 7 demonstrated significant skew or kurtosis (i.e., +/- 2.00).

Network estimation. Network 7 demonstrated acceptable stability coefficients for edge weights ($CS = .44$), but questionable stability for strength centrality estimates ($CS = .28$). The resultant network contained relatively few edges, yet revealed some interesting features regarding trait aggression's connections to agreeableness and neuroticism.

Network edges. Most striking in Network 7 (Figure 3) was that physical aggression was only directly connected to a single node: the cooperation facet of agreeableness. All other nodes were indirectly connected to physical aggression and thus passed through the cooperation node first. Cooperation also shared direct negative edges with the verbal aggression and composite anger nodes. The composite anger node also shared a positive edge with the vulnerability facet of neuroticism. Verbal aggression further shared a negative edge with the self-consciousness facet of neuroticism. Finally, hostility shared positive edges with the depression and anxiety facets of neuroticism and a negative edge with the trust facet of agreeableness.

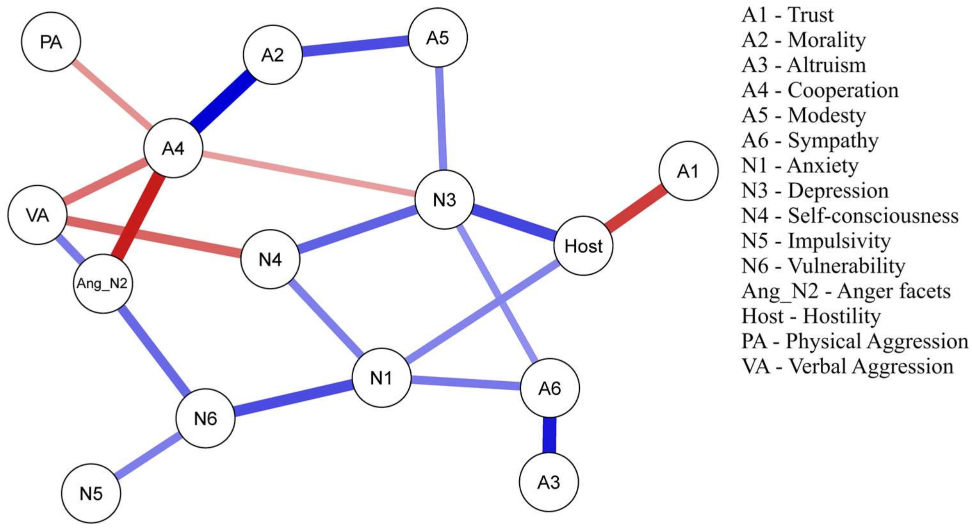

Figure 3. Visualization of Network 7 (Sample 2). Blue edges represent positive associations, red edges represent negative associations. Edge width and depth of color indicate association strength. An interactive version of this network is available at https://aggressionnet7.netlify.app/.

Centrality estimates. Inspection of the centrality estimates from Network 7 indicated that the cooperation facet of agreeableness and the depression facet of neuroticism were highly central to the network due to their connections to the trait aggression facets (Table 4). Interestingly, the impulsivity facet of neuroticism was not connected to any of the trait aggression nodes and was the second-least central node in the network. However, we note that because the *CS* coefficient for Network 7's strength estimates was near the lower cutoff (i.e., .25) that these estimates must be interpreted with caution.

Table 4

Strength Centrality Estimates from Network 7

	Network 7
Altruism (A3)	0.32
Anger (N2 + BAQ)	0.71
Anxiety (N1)	0.79
Cooperation (A4)	1.16

Depression (N3)	0.95
Hostility	0.71
Impulsivity (N5)	0.18
Modesty (A5)	0.42
Morality (A2)	0.61
Physical Aggression	0.15
Self-consciousness (N4)	0.62
Sympathy (A6)	0.67
Trust (A1)	0.27
Verbal Aggression	0.60
Vulnerability (N6)	0.64

Note. A = agreeableness facet , BAQ = brief aggression questionnaire, N = neuroticism facet.

Item-level Networks: Identifying Bridges

To examine the core manifest content underlying the edges observed in Networks 1-7 we estimated item-level networks using Samples 1 and 3. Because agreeableness and neuroticism appeared to be the most important of the FFM traits to trait aggression in Networks 1-6, we included all items from each of these scales along with all the items from the BPAQ. Sample 2 data was not used to estimate an item-level network because the IPIP-NEO implements nearly three times as many items to measure each trait and such a network would demand more statistical power than that afforded by Sample 2. We also applied a hierarchical exploratory factor analysis to the data from Network 9 to contrast the results from this different analytic approach with our item-level network. Specifically, we conducted a single-factor EFA using principal axis factoring with no rotation and then extracted two factors from the same variables using a promax rotation (as described in Crowe et al., 2018). We utilized a factor loading cutoff of |0.30| and items that loaded onto multiple factors were not included in the final factor solution. These analyses were conducted using the fa function from the *psych* package in R (Revelle, 2019). We note that our item-level networks and EFAs were not a part of our preregistered analysis plans.

Pre-estimation. Prior to network estimation, we coded node communities based on the FFM domain or trait aggression facet that each respective item belonged to in order to estimate bridge centrality. Items 1 and 4 from the BPAQ exhibited substantial skew in both samples (Supplemental Document 2, Table S5). Because such violations of normality are more problematic for nodes with restricted variance (i.e., individual scale items with an ordinal response scale) we applied the nonparanormal (NPN) transformation to these items using the *huge.npn* function from the huge package for R (Zhao et al., 2012). Because the NPN transformation and bridge centrality functions are not tolerant of missing values (i.e., do not allow for the use of FIML), four cases from Sample 1 were excluded from these analyses.

Data combination. Network 8 presented with unconnected nodes and poor stability for two-step EI estimates (*CSs* = .28; Supplemental Document 3, Table S15). These features taken together suggest insufficient statistical power for the number of nodes in the network (Epskamp et al., 2018). We thus standardized and then combined the data from Sample 1 and Sample 3, resulting in a final dataset of 2,556 participants.

Network estimation. Network 9 had ideal stability for interpreting edge weights (*CS* = 0.75) and two-step EI (*CS* = 0.75) bridge centrality estimates (Figure 4).

Network edges. Visual inspection of Network 9 suggested that BFI agreeableness item 12 served as a bridge connecting agreeableness with the physical aggression, verbal aggression, and anger facets of trait aggression. Agreeableness items 2 and 37 also appeared to serve as bridges between agreeableness and verbal aggression. Agreeableness items 22 and 27 served as bridge nodes between hostility and agreeableness. However, no direct connections between the hostility node community and the remaining aggression facet communities were observed.

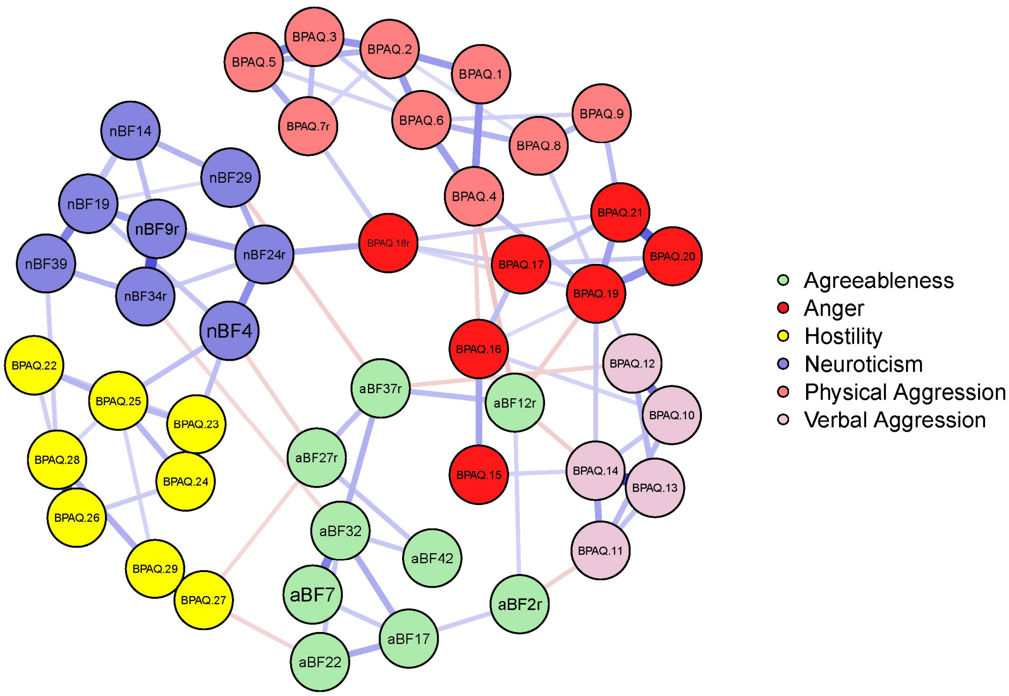

Figure 4. Network 9 (Samples 1 and 3). Blue edges represent positive associations, red edges represent negative associations. Edge width and depth of color indicate association strength. An interactive version of this network is available at https://aggressionnet9.netlify.app/.

The neuroticism community contained bridges to the anger and hostility facets. Neuroticism items 4 and 39 served as bridges between neuroticism and the hostility community. BPAQ item 18 from the anger subscale served as a bridge among neuroticism, anger, and physical aggression. However, no direct connections between the neuroticism node community and the verbal or physical aggression communities were observed. Lastly, neuroticism items 4, 29, and 34 appeared to serve as bridges between neuroticism and agreeableness.

Centrality estimates. Bridge centrality estimates supported our visual inspection of the network, as agreeableness item 12 and BPAQ item 18 demonstrated the greatest two-step EI and estimates in the network due to their connections to multiple node communities (Table 5). Because many nodes served as bridges among the item communities, we only report and interpret the five strongest bridges between the trait aggression facets, neuroticism, and agreeableness here. Complete bridge centrality estimates for Network 9 can be found in Supplemental Document 3 (Table S17).

Table 5

Five Greatest Bridge Estimates and Item Content from Network 9

Item	2EI	Connections	Item Content
BFI 12a	-0.64	BP 4p, 14v, 19an	Starts quarrels with others
BP 18an	0.51	BP 7p, 24n	I am an even-tempered person
BFI 4n	0.40	BP 23h, BP 25h, BFI 27a	Is depressed, blue
BFI 37a	-0.39	BP 12v; BFI 29n	Is sometimes rude to others
BFI 27a	-0.32	BP 27h; BFI 4n, 34n	Can be cold and aloof

Note. Lower-case suffixes following item numbers indicate which domain or subscale that item is from in its respective measure. a = agreeableness items, an = anger items, BFI = Big Five Inventory, BP = Buss-Perry Aggression Questionnaire, h = hostility items, n = neuroticism items, p = physical aggression items, 2EI = two-step expected influence bridge centrality, v = verbal aggression items.

Bridge content. We examined the item content of nodes connected to each of the strongest bridges in the network for common themes which were determined based on the subjective interpretations of the authors. This approach yielded some distinct themes, illuminating the core nature of the connections between communities. Specifically, agreeableness item 12 (“Starts quarrels with others”), was connected to each of the trait aggression communities excepting hostility. The content of the anger item connected to this bridge (BPAQ item 19, “Some of my friends think I’m a hothead”) reflected the expression of anger as a component of one’s identity. The content of the verbal and physical aggression items (BPAQ item 4, “I get into fights a little more than the average person”; BPAQ item 14, “My friends say I’m somewhat argumentative”) connected to agreeableness item 12 reflected the frequency of engaging in such behaviors. Agreeableness item 37 (“Is sometimes rude to others”) also served as a bridge among agreeableness and verbal aggression via its edge with BPAQ item 12 (“When people annoy me, I may tell them what I think of them,”), reflecting an explicit recognition of antagonistic tendencies. As such, agreeableness, physical aggression, verbal aggression, and anger appear to be linked together by the *intent to initiate* aggressive altercations.

Anger's bridge to neuroticism, BPAQ item 18 ("I am an even-tempered person"), shared a relatively strong edge with neuroticism item 24 ("Is emotionally stable, not easily upset"). The content of these two nodes reflected dysregulated experiences of anger. Thus, neuroticism appears to be connected to anger by *affective resiliency*. Neuroticism's strongest bridge, item 4 ("Is depressed, blue"), was connected to two nodes in the hostility community. Inspection of the content of these items (BPAQ item 23, "At times I feel I have gotten a raw deal out of life"; BPAQ item 25, "I wonder why sometimes I feel so bitter about things") revealed a theme of *depressive contemplation* as connecting hostility and neuroticism. Agreeableness also yielded multiple bridges to hostility, as BFI items 22 ("Is generally trusting,") and 27 ("Can be cold and aloof,") both connected to a single hostility node (BP 27, "I am suspicious of overly friendly strangers"). The content of these items reflected *interpersonal suspicion* as the link between agreeableness and hostility.

Hierarchical EFA

Our findings from these analyses (see Supplemental Document 5 for full results) revealed that the two-factor model was generally a better fit to the data and explained more variance than the single factor solution (21% vs 29%, respectively). In our two-factor model, the majority of trait aggression items (16/29) and agreeableness items (6/9) loaded onto the first factor which comprised a general *antagonistic aggression* factor. The second factor comprised the neuroticism items (7/8), and some remaining trait aggression items (7/29) six of which were from the hostility subscale, and one was from the anger subscale, thus comprising a *neurotic hostility* factor. Further, six of the BPAQ items failed to yield simple structure as they loaded onto both factors. These findings are consistent with Network 9, such that the EFA procedure was unable to separate trait aggression from agreeableness excepting the single trait anger and six trait hostility items that loaded onto the neurotic hostility factor.

Malevolent Traits Network

To examine the specificity of trait aggression in relation to other traits that are closely linked with low agreeableness we estimated a final ‘malevolent traits’ network containing agreeableness, the four trait aggression facets, and the four DT facets. Specifically, our aim was to examine whether the variance shared between trait aggression and antagonism was redundant with that of other antagonistic traits, or if the observed associations and centrality from our previous networks were unique to trait aggression.

Pre-estimation. To better understand the possible connections among the facets of trait aggression and the DT traits we again estimated bridge centrality as two-step EI. To this end we coded three node communities: the DT community (psychopathy, Narcissism, Machiavellianism and Sadism nodes), the trait aggression community (the four facets of trait aggression), and agreeableness.

Network estimation. The estimation procedure revealed a relatively well-connected network such that all nodes had four or more edges. Network 10 was stable, such that edges (*CS* = .75), strength centrality (*CS* = .67), and two-step EI (*CS* = .75) had sufficient stability.

Network edges. Agreeableness again shared edges with all four facets of trait aggression despite the inclusion of the DT traits. The psychopathy node was relatively well-connected, but only shared a direct edge with the hostility facet of trait aggression. The DT structure appeared to emerge in the network, as the DT traits were relatively well-connected within their node community. However, the psychopathy—Narcissism edge was negative rather than positive. Sadism shared positive edges with all the trait aggression facets excepting anger. Sadism's strong positive edge with physical aggression marked the only direct connection from the DT community to this facet of trait aggression.

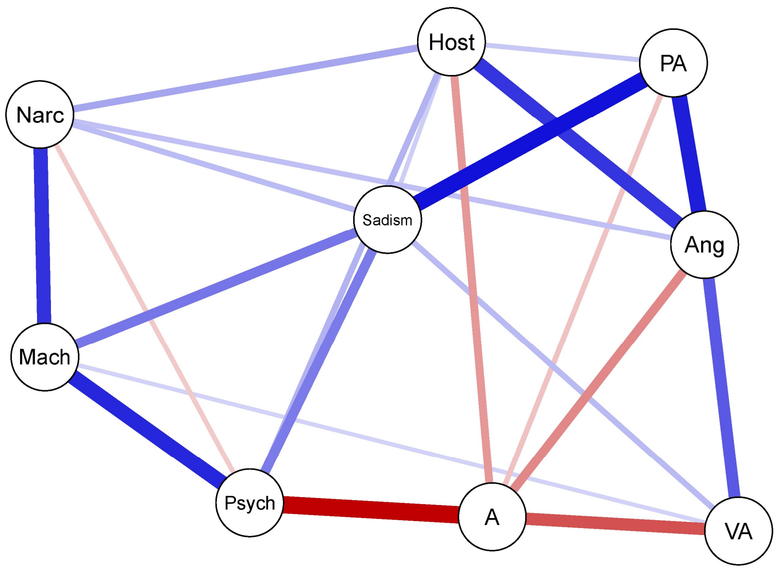

Figure 5. Network 10, the 'malevolent' traits network (Sample 3). Blue edges represent positive associations, red edges represent negative associations. Edge width and depth of color indicate association strength. A = agreeableness, Ang = anger, Host = hostility, Mach = Machiavellianism, Narc = Narcissism, PA = physical aggression, Psych = psychopathy, VA = verbal aggression. An interactive version of this network is available at https://aggressionnet10.netlify.app/.

Centrality estimates. Inspection of the strength centrality estimates (Table 6) revealed that psychopathy, anger, agreeableness, and Sadism were highly central to Network 10. Inspection of the bridge centrality estimates (Table 6) revealed that agreeableness yielded the greatest two-step EI of any node in Network 10, though this value was somewhat inflated due to it being the only node in its community. Agreeableness shared weak to moderate negative edges with all four facets of trait aggression and a relatively strong negative edge with psychopathy, it thus appears that agreeableness serves as a bridge between the DT and trait aggression. Sadism yielded the second greatest bridge centrality in the network and appeared to serve as a crucial bridge between the DT and trait aggression.

Table 6

Bridge and Strength Centrality Estimates from Network 10.

	2EI	Strength
Agreeableness	-1.48	0.92
Anger	0.11	1.00
Hostility	0.25	0.74
Machiavellianism	0.15	0.78
Narcissism	0.33	0.62
Physical Aggression	0.38	0.75
Psychopathy	0.15	1.04
Sadism	0.56	0.90
Verbal Aggression	0.15	0.68

Notes. 2EI = two-step expected influence bridge centrality.

Discussion

People vary in their dispositional aggression. This individual difference has been recognized by psychologists as one of crucial importance since the beginning of our science. Contemporary theories have made great strides in understanding the nature of aggression, yet they remain largely silent on the place of trait aggression and its facets among the greater constellation of human personality traits. In the present research, we employed psychometric network analyses to identify the complex array of associations between trait aggression and the FFM of personality.

Trait Aggression is a Lower-Order Facet of Agreeableness

Across our three levels of analysis (domains, facets, and items), we found evidence that trait aggression is most appropriately situated in the FFM as a lower-order facet of agreeableness. Specifically, in Networks 1-3 we found that agreeableness yielded significantly stronger edges with total trait aggression than any other FFM trait. We also found that agreeableness was highly central to Networks 1-3. These findings are consistent with work demonstrating that agreeableness yields stronger associations with aggression than the other FFM traits (e.g., Barlett & Anderson, 2012; Jones et al., 2011) and that trait aggression is a lower-order facet of agreeableness (Chester & West, 2020).

This importance of agreeableness for trait aggression was further reflected in the facet-level networks, in which we found that agreeableness shared negative edges with all four facets of trait aggression (Networks 5-6) and ranged from moderate (Network 4) to high (Networks 5-6) in network centrality. Network 7 revealed the cooperation facet of agreeableness served as the only direct connection to physical aggression with extensions to both verbal aggression and anger. These findings are consistent with work indicating that the cooperation facet of agreeableness shares more variance with dispositional and behavioral aggression than any other FFM facet (e.g., Jones et al., 2011). Network 7 also revealed that the trust facet of agreeableness shared a negative edge with hostility. In Network 9 the agreeableness items served as crucial bridges among agreeableness, neuroticism, and the trait aggression facets. Our hierarchical EFA of the Network 9 data was largely unable to separate the trait aggression construct from agreeableness, which is consistent with prior work utilizing similar methods (Chester & West, 2020). Finally, in Network 10 we found that even after adding other malevolent traits, agreeableness was one of the most central nodes in the network and was connected to all four facets of trait aggression but only one DT trait - psychopathy. Indeed, despite the high centrality of trait psychopathy in Network 10, it yielded no direct edges with physical aggression, verbal aggression, or anger and only a weak positive edge with hostility. However, psychopathy did share a relatively strong negative edge with agreeableness, which is consistent with the argument that trait antagonism is the core of lower-order malevolent traits (Lynam & Miller, 2019). We further observed that Sadism was the only malevolent trait that shared a direct edge with physical aggression, consistent with literature indicating that overt aggression is an intrinsically rewarding experience to some (Chester, 2017; West et al., 2021). Our analyses also provided some evidence that neuroticism may also have links to trait aggression.

Neuroticism and Trait Aggression

At the domain-level (Networks 1-3), neuroticism shared weak-to-moderate positive edges with total trait aggression, consistent with work indicating that neuroticism is positively associated with aggression (e.g., Vize et al., 2018). At the facet-level (Networks 4-6), neuroticism shared strong positive edges with the anger and hostility facets of trait aggression. These findings support the conceptual overlap of neuroticism with the affective and cognitive components of trait aggression, as opposed to the overt behavioral facets (Buss & Perry, 1992). Interestingly, once the shared variance among neuroticism, anger, and hostility was accounted for, neuroticism was negatively associated with physical (Networks 4 & 6) and verbal (Network 6) aggression. These findings were unexpected and suggest that research demonstrating a positive association between neuroticism and these facets of aggression may be evincing an association between neuroticism and the variance that anger and hostility share with the overt aggression facets (e.g., Vize et al., 2018). In Network 7 hostility was the only facet of trait aggression that shared a positive edge with any of the neuroticism facets. This is consistent with work demonstrating that neuroticism at greater levels is associated with biased, hostile perceptions (Svärd et al., 2012). In Network 9 we found that the neuroticism item community yielded direct connections to the hostility and anger trait aggression communities. Our hierarchical EFAs also revealed six hostility items and a single anger item (the same Neuroticism-Aggression bridge found in Network 9; BPAQ 18) loaded onto the neurotic hostility factor. As such, neuroticism was not linked with verbal and physical aggression directly and had to pass through agreeableness or anger first.

Bridges from Trait Aggression to Agreeableness and Neuroticism

In Network 9 we found that a single item from the agreeableness measure of the BFI (item 12, “Starts quarrels with others”) served as a crucial bridge among physical aggression, verbal aggression, anger, and agreeableness. Inspection of the content of the items connected to this bridge revealed a common theme of the intent to initiate aggressive encounters. In our hierarchical EFA we found that each of these items loaded relatively strongly onto the antagonistic aggression factor. The bridge items among neuroticism, anger, and hostility also revealed distinct themes that unified these node communities. Anger was linked to neuroticism via affective resiliency and hostility was linked to neuroticism via depressive contemplation. These findings indicate that the hostility measured by the BPAQ/BAQ is not solely a cognitive facet as described by Buss and Perry (1992), but also includes affective content. Agreeableness was also linked to hostility by a theme of interpersonal suspicion in Network 9. As such, it appears that agreeableness may account for the cognitive component of hostility whereas neuroticism accounts for the affective component. This interpretation is consistent with recent work indicating that neuroticism is better defined as high levels of negative emotion rather than emotional instability (Kalokerionos et al., 2020). Taken together, these findings indicate that the most direct route among the FFM traits to overt forms of trait aggression is through low agreeableness (i.e., antagonism), but that the anger and hostility facets can be directly accessed through agreeableness or neuroticism.

Neuroticism’s most-direct path to overt forms of aggression in Network 9 was through a single anger node. Despite neuroticism and agreeableness both evincing multiple bridges to hostility, the hostility nodes yielded no direct edges with the other trait aggression communities. Agreeableness was able to access physical and verbal aggression through anger, but was also shared direct edges with physical and verbal aggression. Our findings thus suggest that neurotic aggression may require anger, but antagonistic aggression does not. These findings support the notion that trait aggression is primarily a facet of agreeableness, but the affect-laden components of trait aggression may be accessed via neuroticism. It appears then that trait aggression is a blend of agreeableness and neuroticism, but that agreeableness accounts for the lion’s share of this construct whereas neuroticism only accounts for specific components of anger and hostility.

Implications for Trait Aggression

Our findings also hold important implications for trait aggression as a construct. In Networks 4 and 6 anger yielded high strength centrality values. These values appear to be due to the role of anger in trait aggression, as all three networks contained relatively strong positive edges between anger and the other three facets of trait aggression. Further, the anger item nodes in Network 9 were highly interconnected with the physical and verbal aggression node communities. It thus appears that of the four facets, anger is the common bond that holds trait aggression together. This finding appears to be consistent with functional accounts of anger as a means of motivating aggressive behaviors when others do not sufficiently value our well-being (Sell, 2011). However, our findings call into question the inclusion of hostility as an inherent component of trait aggression.

In Network 7 hostility was connected to facets of agreeableness and neuroticism but not the facets of trait aggression. In Network 9 the hostility nodes shared no direct edges with the anger, physical or verbal aggression node communities. It was only through a series of indirect connections that hostility was linked to the other facets of trait aggression in these networks. The most-direct path from the hostility community to any of the other trait aggression communities in Network 9 required it pass through at least three other nodes first. Despite this, the structure of the hostility community in Network 9 suggested that hostility as measured by the BPAQ is a well-defined construct itself, as its node community contained dense intraconnectivity. These findings considered together suggest that it may be inappropriate to include hostility in computations of ‘total’ trait aggression scores.

Our findings also carry implications for the measurement of trait aggression. Our examination of the bridge items from Network 9 indicated that an *intent to initiate* aggressive encounters is the common core linking together antagonism (i.e., low agreeableness) and trait aggression. We thus argue that this component should be more clearly reflected in measures of trait aggression, such as the items that comprise the BPAQ. Many of the BPAQ items not only lack the component of intent, but provide exogenous justifications for aggression. This is evident in many of the physical (e.g., “If I have to resort to violence to protect my rights, I will,”) and verbal (e.g., “I can’t help getting into arguments when people disagree with me.”) aggression items. In the few BPAQ items that do appear to consider intention, it is only implied (e.g., “I have threatened people I know”). As such, we recommend updating the language in the BPAQ and other trait aggression measures to better reflect the intention component of trait aggression and to use more contemporary language. For example, the first item in the BPAQ “Once in a while I can’t control the urge to strike another person,” could be rewritten as “Sometimes I start fights with people”. The former places the inability to control an urge at the center of the item content, where the latter emphasizes the intent to initiate the altercation.

Limitations

Although the current work yielded novel insights into the nomological network surrounding trait aggression it is not without limitations. First, Sample 3 was collected as part of a broader study of those who regularly play videogames and included an 89% male sample. However, considering that our findings from our other samples either compliment or directly replicate those from Sample 3, we argue that this major difference in sample characteristics poses little problem to our interpretations. Next, in Samples 1 and 3 we relied on the BFI as our measure of the FFM traits, which yielded facets with unacceptable internal consistency. This prevented us from estimating the more granular facet networks as we did in Network 7 using these measures. Similarly, Sample 2 was not large enough to compute an item-level network using the IPIP-NEO-120. Further, we relied on Spearman's rank-order correlation coefficients for estimating the extent to which our networks replicated across samples. However, this approach only provides a rough approximation in contrast to more formal invariance testing such as that provided by the NetworkComparisonTest (NCT) package in R.

We used this approach for several reasons. First, the NCT was developed to test invariance between groups within the same sample (i.e., differences between populations) whereas we had no reason to expect our three samples marked different populations. Second, networks that are relatively dense in their structure yield poorer statistical power for the NCT with densities beyond .30 requiring both networks to contain large (e.g., $N > 1{,}000$) samples for predictive accuracy (van Borkulo et al., 2017). Given that Networks 1-6 each presented density values greater than .50 and ranged widely in sample size ($N = 367 – 1940$), the results of NCT comparisons would have been underpowered. Although the most crucial elements of our networks were reliably found across our samples, instruments, and analyses, other features of our networks were not. Some work indicates that this may be due to an inherent instability (i.e., limited ability to replicate) among network models of psychopathology (Forbes et al., 2017; Steinley et al., 2017). However, more recent work has indicated that such instability is not an inherent feature of network analyses but rather is a feature of sampling variability (Jones, Williams, & McNally, 2021). A recent effort to provide guidelines for selecting the most appropriate network estimator compared the EBICglasso estimator (i.e., the estimator we used in our networks) to latent network estimation in various contexts, as latent networks may provide greater stability (Epskamp et al., 2017; Ivsoranu & Epskamp, 2021). One such context was using personality trait data from the BFI at different sample sizes. In our case (i.e., networks including BFI personality data at samples of $N = 300$, $N = 600$, and $N = 2500$) the EBICglasso-estimated networks provided greater specificity and precision and were more likely to correctly replicate edges in smaller samples (i.e., $N = 300$, 600) and were similar to the latent model in larger samples (i.e., $N = 2500$). Further, the ongoing debate around the instability of network analyses has been almost entirely in reference to networks of psychopathology (i.e., individual symptoms) rather than personality. The literature examining the replicability of personality networks indicates they are not likely to suffer from the instability issues found with psychopathology networks (e.g., Obert & Miller, 2021). Given that our latent variable (i.e., our hierarchical EFAs) analyses agreed with our network-derived conclusions, and our networks had substantial stability coefficients, we hold that it is not likely that our networks suffered from such instability.

Future work should seek to replicate our findings using different measures of these traits and theoretical models of personality. Our analyses were constrained to a specific set of measures and future research is needed to examine how well our networks replicate using other psychometric instruments of trait aggression and the Big Five traits. Further, many of our most specific analyses (e.g., item-level analyses) must be replicated in independent samples before they are considered truly reliable. For example, the HEXACO model of personality includes agreeableness but also includes the additional trait of honesty-humility, which is also associated with trait aggression (e.g., Međedović, 2017). Finally, although our item-level analyses revealed several striking findings with clear theoretical implications, some of these associations were likely due, in part, to similarities in item content. Items with similar meanings will tend to share strong bonds. Future work should examine whether our findings replicate using broader item pools with more, semantically dissimilar items.

Conclusions

The current work provided evidence that trait aggression is a lower-order facet of agreeableness with some secondary connections to neuroticism. Our findings also revealed that the core component that links aggression to agreeableness is the intent to initiate aggressive encounters. Future research should examine the suggestions made in this work to improve the measurement and understanding of trait aggression by validating an updated version of the BPAQ and examining the structure of trait aggression in networks that also include measures of aggressive behavior. Such advances will further build on the foundation provided by the findings in the current work and stand to improve not only our understanding of trait aggression, but all aggressive actions within the context of individual differences.

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