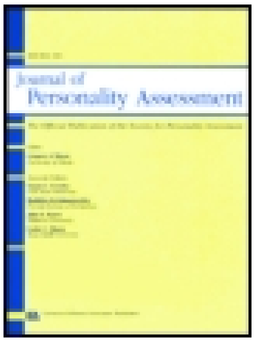

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ABSTRACT

Openness to Experience is a complex trait, the taxonomic structure of which has been widely debated. Previous research has provided greater clarity of its lower order structure by synthesizing facets across several scales related to Openness to Experience. In this study, we take a finer grained approach by investigating the item-level relations of four Openness to Experience inventories (Big Five Aspects Scale, HEXACO–100, NEO PI–3, and Woo et al.'s Openness to Experience Inventory), using a network science approach, which allowed items to form an emergent taxonomy of facets and aspects. Our results ($N =$ 802) identified 10 distinct facets (variety-seeking, aesthetic appreciation, intellectual curiosity, diversity, openness to emotions, fantasy, imaginative, self-assessed intelligence, intellectual interests, and nontraditionalism) that largely replicate previous findings as well as three higher order aspects: two that are commonly found in the literature (intellect and experiencing; i.e., openness), and one novel aspect (open-mindedness). In addition, we demonstrate that each Openness to Experience inventory offers a unique conceptualization of the trait, and that some inventories provide broader coverage of the network space than others. Our findings establish a broader consensus of Openness to Experience at the aspect and facet level, which has important implications for researchers and the Openness to Experience inventories they use.

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Openness to Experience is a broad and complex trait that has gone by many names over the years, such as Openness to Experience, Intellect, Culture, Imagination, and Creativity (Fiske, 1949; Goldberg, 1981; Johnson, 1994; Norman, 1963; Saucier, 1992). Given the trait's breadth and complexity, researchers have identified two aspects of Openness to Experience: Openness to Experience (for clarity, hereafter referred to as Experiencing, following Connelly, Ones, Davies, & Birkland, 2014) from the questionnaire tradition (Costa & McCrae, 1992), and Intellect from the lexical tradition (Goldberg, 1981). The experiencing aspect is characterized by an appreciation for aesthetics, openness to emotions and sensations, absorption in fantasy, and engagement with perceptual and sensory information (DeYoung, Grazioplene, & Peterson, 2012). The intellect aspect is characterized by intellectualism, enjoyment of philosophy, curiosity, and engagement with abstract and semantic information (DeYoung et al., 2012).

Beneath the Experiencing and Intellect aspects, however, are many lower order facets of Openness to Experience. The measurement of these facets has been inconsistent, with some facets being measured in some inventories but not in others. As a result, this has led to variation in the coverage and conceptualization of the Openness to Experience construct. Despite research examining the content and number of facets (Connelly, Ones, Davies, et al., 2014; Woo et al., 2014), there has yet to be an empirical investigation into how the items of different inventories converge (or diverge) on the coverage and content of lower order facets.

Therefore, in this research, we sought to clarify how four commonly used Openness to Experience inventories conceptualize the construct. In addition, we wanted to clarify the number and content of the lower order facets across these inventories. To do so, we applied a computational network science approach to construct a network using the items from these four inventories. From this network, we used a community detection algorithm to identify communities (i.e., facets) in the network. These network-identified facets were then used to examine the conceptual coverage of each inventory—whether items of the inventory were represented in many or a few of the network-identified facets.

Openness to experience taxonomy

Past debates about how the global Openness to Experience trait should be defined has subsided—traditional factor analysis approaches have identified both experiencing and intellect as aspects of the global trait (DeYoung, Quilty, & Peterson, 2007; Woo et al., 2014). Experiencing and intellect are separate but related aspects of Openness to Experience, with differential relations to affective, behavioral, and cognitive outcomes

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(Barford & Smillie, 2016; DeYoung et al., 2012; DeYoung et al., 2014). For example, experiencing is positively related to creative achievement in the arts (Kaufman et al., 2016), implicit learning (Kaufman et al., 2010), and feeling mixed emotions (Barford & Smillie, 2016), whereas intellect is positively related to creative achievement in the sciences (Kaufman et al., 2016), working memory (DeYoung, Shamosh, Green, Braver, & Gray, 2009), and fluid intelligence (DeYoung et al., 2012). As a result, these aspects have been generally agreed on.

Beneath the experiencing and intellect aspects, however, the lower order facet structure of Openness to Experience becomes less clear—depending on which inventory is used, the number of facets included can range from four to nine (Connelly, Ones, & Chernyshenko, 2014). There appears to be some level of agreement on the importance of some facets (e.g., aestheticism, intellectualism) because they are featured in many inventories. Many facets, however, are unique to only one or two inventories (e.g., Feelings, Actions, Curiosity). Additionally, some inventories seem to provide good coverage of the facets in one aspect but have limited coverage of facets in the other. For instance, in the Woo et al. (2014) factor analysis of seven Openness to Experience inventories, facets of the Revised NEO Personality Inventory (NEO PI–R) loaded onto the experiencing aspect well but had relatively low loadings for the intellect aspect. Thus, although several Openness to Experience inventories exist, it appears that they vary substantially in their coverage of the trait's conceptual space.

The special section in the *Journal of Personality Assessment* sought to reach a broader consensus of this lower order taxonomy (Connelly, Ones, & Chernyshenko, 2014). Connelly, Ones, Davies, et al. (2014) undertook the most comprehensive theoretical evaluation of Openness to Experience's lower order facets to date by theoretically sorting and meta-analyzing 85 Openness to Experience–related scales. They identified 11 facets that were theoretically and empirically related to Openness to Experience: Aestheticism, Autonomy, Fantasy, Innovation, Introspection, Nontraditional, Openness to Emotions, Openness to Sensations, Thrill-seeking, Tolerance, and Variety-seeking. Only four of these facets, however, were considered pure (i.e., not related to any other personality trait): aestheticism, openness to sensations, nontraditional, and introspection. Based on Connelly et al.'s sort, these pure facets were placed within the experiencing (aestheticism and openness to sensations) and intellect (nontraditional and introspection) aspects. The other seven facets aligned with Openness to Experience and other personality traits, so they were labeled as trait compounds. For example, fantasy was positively associated with Openness to Experience and negatively with Conscientiousness, whereas innovation, openness to emotions, thrill-seeking, and variety-seeking were positively associated with Openness to Experience and Extraversion. In sum, their extensive analysis of Openness to Experience–related scales provides a general framework for defining which facets are central to the construct.

In the same special section, Woo et al. (2014) empirically evaluated Openness to Experience's lower order structure by factor analyzing a multitude of openness-related scales and assembling a comprehensive inventory. Prior to inventory construction, Woo et al. synthesized several taxonomic approaches to inventory development—questionnaire, lexical, and subject matter experts—to systematically organize their measurement model of Openness to Experience. They used an exploratory factor analysis (EFA) on the existing facets of 36 openness-related scales to uncover two aspects and six facets (Table 1). Subject matter experts reviewed the content (i.e., original facets and their items) of the facets identified in the factor analysis to generate conceptual definitions for these six facets. From these conceptual definitions, a shortened inventory was developed that produced a 54-item Openness to Experience inventory, which was then examined in cross-cultural samples (Woo et al., 2014). In drawing from other inventories, Woo et al. began to establish a more comprehensive lower order facet structure of Openness to Experience.

Connelly, Ones, Davies, et al.'s (2014) and Woo et al.'s (2014) works are the most extensive evaluations of Openness to

Table 1. Descriptions and Rasch reliabilities (R_r) of each facet from each Openness to Experience inventory.

Scale	Facet (R_r)	Description
NEO PI–3 (McCrae, Martin, & Costa, 2005)	Fantasy (.76)	Receptivity to the inner world of imagination
	Aesthetics (.81)	Appreciation of art and beauty
	Feelings (.73)	Openness to inner feelings and emotions
	Actions (.71)	Openness to new experiences on a practical level
	Ideas (.82)	Intellectual curiosity
	Values (.74)	Readiness to reexamine one's own values and those of authority figures
BFAS (DeYoung et al., 2007)	Openness (.80)	Perceptual engagement (perceptual and sensory information), including an interest in art, nature, and sensory experiences
	Intellect (.83)	Intellectual engagement (abstract and semantic information), including an interest in intellectual hobbies and activities as well as intellectual ability
Woo (Woo et al., 2014)	Aesthetics (.84)	Appreciation of various forms of art such as paintings, classical music, buildings, and landscapes
	Depth (.77)	Desire to gain insights into oneself and the world, to self-improve, and to self-actualize
	Tolerance (.69)	Interest in learning about different cultures, preference to immerse self in new customs and traditions when traveling
	Intellectual efficiency (.83)	Efficiency in processing novel intellectual information
	Ingenuity (.82)	Preparedness to create new intellectual knowledge
	Curiosity (.77)	Attraction to novel intellectual ideas
HEXACO (Lee & Ashton, 2004)	Aesthetic appreciation (.67)	Enjoyment of beauty in art and in nature
	Inquisitiveness (.73)	Tendency to seek information about, and experience with, the natural and human world
	Creativity (.73)	Preference for innovation and experimentation
	Unconventionality (.58)	Tendency to accept the unusual

Note. NEO PI–3 = NEO Personality Inventory–3; BFAS = Big Five Aspects Scales.

Experience's lower order taxonomy to date. Undoubtedly, the strength of their assessments was the sheer number of facets that were investigated and synthesized. One limitation of this approach, however, is that the theoretical interpretations of each inventory's facets were taken at face value. For example, Connelly, Ones, Davies, et al. (2014) sorted the theoretical definitions of each facet into a conceptual category. Similarly, Woo et al. (2014) used facets, rather than items, in their factor analyses and subject matter experts used facet descriptions to select items rather than letting the items develop the facets themselves. In this way, their assessments maintained the assumption that the items in each facet unequivocally represented their respective facet. This assumption is practical because facets are designed and validated based on high internal consistency; however, the assumption ignores the underlying covariance between items from other facets that could form new, alternative facets. Thus, by examining the facet structure at the facet level, the rich item-level relationships across all the inventories were obscured.

To examine the item-level relations between different Openness to Experience inventories, we used the network approach, which allows items to covary with one another and emergent facet categorizations to arise. The network approach can be similar to an EFA; however, it provides a representation that allows a visual mapping of how items relate to one another. Therefore, the network approach can offer cleaner distinctions of item classification as opposed to deciphering component loadings, which often have complicated interpretations. Moreover, the graphical representation permits an illustration of each inventory's conceptual coverage of the Openness to Experience construct by depicting where their items appear in relation to items of other inventories.

Psychometric network analysis

Network analysis has become an increasingly popular approach to understand psychopathology and personality phenomena. The network approach treats personality traits as complex systems and items as interacting elements that form emergent properties such as facets and traits (Costantini et al., 2015; Costantini et al., in press; Cramer et al., 2012; Mõttus & Allerhand, in press). In our network, Openness to Experience items will be represented by nodes and their relationships (i.e., correlations between two items) will be represented by edges. From the network perspective, personality traits emerge from the relations that exist between variables (e.g., items; Cramer et al., 2012). Thus, personality variables are not exchangeable—what you measure matters. One item cannot be equally exchanged for another item because the content and interpretation of each item are likely to mean different things. Thus, networks are what you put into them.

Consistent with this perspective, we suggest that Openness to Experience is measured differently depending on which inventory is being used. Moreover, we adopt the view that personality items are valuable and informative in their own right—that is, they are differentially related to affective, behavioral, and cognitive outcomes (McCrae, 2015; Mõttus, 2016). Therefore, exchanging a facet or item for another could alter the conceptualization of the construct and its relations to other items, facets, and outcomes. In this way, the different items and facets in each inventory introduce inconsistencies in how Openness to Experience is conceptualized, and ultimately, these differences lead to variation in Openness to Experience's relationships with outcomes. For example, the intellect aspect of the Big Five Aspects Scales (BFAS) Openness to Experience inventory consistently shows moderately positive relations to working memory (DeYoung et al., 2009; Kaufman et al., 2010). Meanwhile, working memory has shown weak relations (both positive and negative) to the ideas facet (associated with BFAS's intellect aspect) of the NEO Openness to Experience inventory (DeYoung et al., 2009; Smeekens & Kane 2016). The network approach offers a way to clarify these conflicting findings by identifying conceptual similarities and differences between these inventories.

Psychometric network filtering

One key way our network approach differs from previous practices is the way in which we filter the network. Network filtering is an important part of network analysis because it determines the connections and structure of the network. Filtering is necessary to remove spurious connections in the network (i.e., multiple comparisons problem), obtain a parsimonious model, and increase interpretability. In the psychological literature, the standard approach for filtering networks has been the least absolute shrinkage and selection operator (lasso) approach (Epskamp & Fried, in press; van Borkulo et al., 2014).

The lasso approach filters the network by penalizing the inverse covariance matrix, which displays information about the partial correlations between two variables given all other variables in the model (a value of zero between two variables signifies conditional independence). The penalizing term, called the *hyperparameter*, is used in the extended Bayesian information criterion (EBIC; Chen & Chen, 2008), which is used to optimize model selection (Epskamp, 2016; Foygel & Drton, 2010). This penalty parameter shrinks coefficients in the inverse covariance matrix, with some going to zero, implying conditional independence (if variables are related, then they are uniquely related, controlling for all other variables) and creating a sparse model. Although the lasso approach is the current state of the art, there are some limitations (Christensen, Kenett, Aste, Silvia, & Kwapil, 2018). The direct penalization to the inverse covariance matrix, for example, isolates the unique covariation between variables but removes common covariance that is typically considered in latent variable and factor analysis models (but see Golino & Demetriou, 2017; Golino & Epskamp, 2017).

Instead of the lasso approach, we used the information filtering networks (IFN; Barfuss, Massara, Di Matteo, & Aste, 2016; Christensen et al., 2018) approach, which applies a topological (structural) constraint on zero-order correlations. More specifically, the *triangulated maximally filtered graph* (TMFG; Massara, Di Matteo, & Aste, 2016) method of the IFN approach constrains the network to be planar (i.e., edges can be drawn so that no edges cross one another) and retains $3n - 6$ edges (where n equals number of variables), which induces parsimony. In addition, the TMFG network embeds conditional independence within its structure (i.e., the inverse covariance matrix can be associated with the network structure; Barfuss et al., 2016), using zero-order correlations rather than penalizing the inverse covariance matrix directly (Christensen et al., 2018). Thus, despite implying conditional independence, the zero-order correlations retain the common covariance between variables, making it feasible to detect hierarchical information while also reducing measurement error (Forbes, Wright, Markon, & Krueger, 2017).

Another advantage of the TMFG method is that it naturally develops a hierarchy in its construction. This is achieved by building the network from the bottom up: The algorithm begins by connecting four nodes (i.e., items) together, which have the highest sum of correlations to all other nodes, forming a tetrahedron. Then, the algorithm iteratively identifies and adds a node that maximizes the sum of its connections to three of the nodes already included in the network. In this process, a nested hierarchy develops such that the smallest components of the network (*cliques* or sets of connected nodes) are the building blocks of larger components (*communities* or clusters of cliques), which constitute the network (Song, Di Matteo, & Aste, 2011, 2012). Thus, there is an intrinsic hierarchy that is formed from the local connections (between items) to the global structure (the network itself). This feature of the TMFG method is particularly useful for examining personality constructs (Christensen et al., 2018). In short, the TMFG method is a good approach for determining the taxonomic structure of personality traits such as Openness to Experience.

Identifying the hierarchical structure of Openness to Experience

There are several methods that can identify hierarchical structure in networks. Perhaps the most common method is community detection, which identifies how many communities the network can be broken into (for a review, see Fortunato, 2010). In our case, the network's communities are conceptually equivalent to facets; larger collections of communities, in turn, are equivalent to aspects (e.g., experiencing and intellect; Epskamp, Rhemtulla, & Borsboom, 2016; Golino & Epskamp, 2017). The current state of the art in psychometric networks is exploratory graph analysis (EGA; Golino & Epskamp, 2017) via the walktrap algorithm (Pons & Latapy, 2006). The walktrap algorithm uses random walks—random searches through the network starting from each node across edges to other nodes—to detect community boundaries, which are defined by many densely connected surrounding edges and few sparsely connected remote edges.

There are distinct advantages of using the TMFG method combined with the walktrap algorithm over a more traditional approach like EFA. First, because the TMFG method inherently builds a hierarchical structure, the relations between the items form an emergent facet and factor structure from the data, without the direction of the researcher. Conversely, EFA (e.g., principal axis factoring) attempts to maximize the covariance of the first factor, followed by the second factor, and so on, which potentially makes EFA less than ideal for determining lower order structures (e.g., facets). Second, the selection of the number and content of communities (or facets) is relatively deterministic compared to EFA. The researcher does not have to decide—using scree plots, eigenvalues, or component loadings—on how to best categorize the data; instead, the walktrap algorithm determines the size and number of communities based on the structure and connections of the network. Despite the relatively deterministic approach, researchers should still be thorough and inspect the content of the output to ensure that the results fit with theoretical expectations.

Present research

This present research aimed to characterize Openness to Experience's lower order facet structure via the application of network analysis. This was achieved by applying a network approach to the items of four Openness to Experience inventories—BFAS (DeYoung et al., 2007), the HEXACO–100 (Ashton & Lee, 2004; Lee & Ashton, 2004), the NEO Personality Inventory–3 (NEO PI–3; McCrae, Costa, & Martin, 2005), and the Woo et al. (2014) Openness to Experience inventory. The goals of this network construction were twofold. First, we sought to identify facets of Openness to Experience using items from four different inventories (see Table 1). Second, we wanted to examine the network to determine the conceptual coverage of the four inventories.

Notably, our analyses were exploratory, so any a priori hypotheses on the nature and number of facets would be speculative. Based on previous theoretical and empirical findings discussed earlier, however, we expected to find two larger components (i.e., collections of communities) that could be easily identified as the experiencing and intellect aspects. Additionally, we expected several inventory-defined facets to appear (e.g., aestheticism, intellectualism, fantasy), but the degree to which new facets would emerge or the number of facets that would be consistent with previous facet definitions was left as an open question.

Method

Participants

There were three samples used for this study. The first sample was collected during the fall semester of 2015 at the University of North Carolina at Greensboro (UNCG) through the university's psychology research pool. The total sample included 210 participants (58.5% White, 33.5% African American) who were primarily young adults ($M_{age} = 18.95$, $SD_{age} = 3.04$; 76.1% female, 23.3% male).

The second sample was collected during the spring semester of 2017 at UNCG. A total of 140 participants (54.6% White, 31.5% African American) were recruited using the university's psychology research pool and via responding to a flyer recruiting arts majors for psychology research. This sample, who was primarily young adults ($M_{age} = 19.86$, $SD_{age} = 3.70$; 75.9% female), specifically oversampled students majoring in the arts (i.e., music, theater, fine arts) to increase the sample's population of creative domains. If students majoring in the arts were not in a psychology course, then they were compensated $20 for their participation.

The third sample recruited 605 participants from Amazon Mechanical Turk (MTurk), who were compensated $1.75 for their time. This sample (82.4% White, 10.3% African American, 9.4% Asian American) had a broader age range (18–80 years old) and a more equal gender distribution than our college samples ($M_{\text{age}} = 35.37$, $SD_{\text{age}} = 11.22$; 53.5% female, 45.7% male). The study was visible only to people who were native English speakers, over 18 years old, located in the United States, and had completed at least 100 MTurk human intelligence tasks with an approval rating no lower than 80%.

In total, 955 participants were recruited across the three samples—121 of these participants, however, were removed for having elevated scores on items intended to capture inattentive responding (see Maniaci & Rogge, 2014; McKibben & Silvia, 2016, 2017). Thirty-two participants were also removed from the analyses because the network analysis required complete cases. In summary, 802 participants were included in the data analysis.

Lab participants completed a paper consent form and MTurk participants completed an electronic version of the paper consent form via Qualtrics. Participants then completed demographics and the various Openness to Experience inventories. Items were randomized within inventories, and the inventory order was randomized. Psychology participants were compensated with research credits and the students majoring in the arts and MTurk participants were compensated with money. All studies were approved by the university's institutional review board.

Materials

People completed four different measures of Openness to Experience: HEXACO–100, BFAS, NEO PI–3, and Woo et al.'s Openness to Experience Inventory. All responses were given on a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Responses were reverse coded where applicable to provide a positive manifold.

The HEXACO–100 personality inventory's scale of Openness to Experience has four facets—aesthetic appreciation, inquisitiveness, creativity, and unconventionality—with four items per facet (16 items total; Lee & Ashton, 2004).

The BFAS (DeYoung et al., 2007) splits personality traits into two aspects: openness (i.e., experiencing), reflecting perceptual and aesthetic engagement (10 items), and intellect, reflecting engagement in intellectual interests (10 items).

The NEO PI–3 (McCrae et al., 2005) Openness to Experience inventory has eight items per facet—ideas, values, fantasy, action, depth, and aesthetics—for a total of 48 items.

Finally, the Woo et al. (2014) Openness to Experience Inventory contains six facets: aesthetics, curiosity, depth, intellectual efficiency, and tolerance (nine items per facet). Overall, the Openness to Experience Inventory has 54 items and the two aspects—culture (i.e., experiencing) and creative intellect (i.e., intellect)—have 27 items each.

Network construction

Network filtering

In this network, the nodes represent the individual items from the four Openness to Experience inventories and the edges are zero-order Pearson's correlations between items. Pearson's correlations were used to produce a correlation matrix that is most typical of what researchers use when conducting an EFA or confirmatory factor analysis (but see Epskamp & Fried, 2018, for further discussion of nonnormal and ordinal data in network analysis). The TMFG method (Massara et al., 2016) was applied to construct a subnetwork—a smaller network within the full network—that captures the most relevant information between nodes that are embedded in the original network and minimizes spurious associations. The resulting subnetwork is composed of three- and four-node cliques—a set of connected nodes (e.g., a triangle and tetrahedron, respectively)—and it retains a total of $3n - 6$ edges from the original network (i.e., 408 edges).

The TMFG method begins by sorting all edge weights (i.e., the zero-order correlations) in descending order and adds the largest edge weight one by one, based on an iterative construction process of a topologically constrained network (i.e., planar—a network that can be drawn on a sphere without connections crossing each other). In this construction, the algorithm adds a node into three-cliques, based on a "T_2 move" (Massara et al., 2016). The T_2 move inserts a node into any three-clique's center where edges are added to it, forming a tetrahedron and keeping the network planar. When adding these nodes, the algorithm optimizes an objective function that ensures the added node has the maximum increase in the sum of the additional edge weights (see Massara et al., 2016, for more technical details). The TMFG-filtered association matrix was constructed using the *NetworkToolbox* package[1] (Christensen, 2018) in *R* (R Core Team, 2017).

Network analysis

Community detection

After the TMFG method filtered the network, the walktrap algorithm via the *igraph* package (Csardi & Nepusz, 2006) in R was applied to the network to determine the size (i.e., number of items) and number of communities (i.e., facets). The walktrap algorithm begins with a random search from each node to surrounding nodes to satisfy a proportion of high internal edges to surrounding nodes (many dense connections to surrounding nodes) compared to the proportion of edges between the node and more distant nodes (few distant connections to more remote nodes). The proportions provide a measure of similarity between each node and its surrounding nodes, which is then used to identify community membership. The approach is based on the concept that a node's random walks will get "trapped" inside of the densely connected communities to which the node belongs (Pons & Latapy, 2006). Because the algorithm uses random walks, we verified that the results were consistent by setting 10 random seeds in R, which controls the state of R's random number generator. The community results did not change based on the random seeds.

Network visualization

The TMFG-filtered network was visualized using the *qgraph* package (Epskamp, Cramer, Waldorp, Schmittmann, &

[1]The most up-to-date version of the *NetworkToolbox* package can be retrieved from https://github.com/AlexChristensen/NetworkToolbox.

Borsboom, 2012) in R. Notably, the depiction of the networks appears to contradict the property of planarity (a network that can be drawn on a sphere without connections crossing each other). Although depicted with edges crossing, planarity simply means that the network could be depicted in such a way that no edges cross. When drawn in this fashion, however, the figure appears unnecessarily large.

In addition, the distance between the nodes is related to, but not synonymous with, *actual* conceptual distance or strength of relation (Forbes et al., 2017). The layout is based on the Fruchterman and Reingold (1991) algorithm, which has been noted for its stochastic placement process (e.g., a different ordering of variables can dramatically alter the network's visualization). Thus, caution must be taken when interpreting node proximities in the network. Finally, using the communities extracted from the walktrap algorithm, we added labels and colors to each network's visualization.

Core items of Openness to Experience

To determine facet (i.e., community) labels and descriptions, items that were the most central to the Openness to Experience network were identified using a hybrid centrality measure. Centrality measures are network measures that evaluate a node's influence, based on position and connections, in the network. The hybrid centrality measure ranks nodes based on their values across multiple measures of centrality and allows for a singular, continuous measure of overall centrality (Christensen et al., 2018; Pozzi, Di Matteo, & Aste, 2013).

Nodes with high hybrid centrality values are more central in the network; nodes with low hybrid centrality values are more peripheral. Nodes were sorted in descending order of their hybrid centrality values. The top 46 nodes (one third of the nodes) were designated as *core*, the next 46 as *intermediate*, and the last 46 as *peripheral*. These breaks give an even distribution of item classification and have been shown to provide meaningful distinctions for relevant behavioral outcomes for other scales (Christensen et al., 2018). The hybrid centrality measure was computed using the *NetworkToolbox* package in *R*.

Statistical analyses

Facet reliability

Rasch reliability (R_r), the empirical estimate of marginal reliability, for each inventory-defined and network-identified facet were calculated using Winsteps (Linacre, 2017). We used the Rasch rating scale model, which is a polytomous model for data with more than two categories (e.g., a Likert scale). R_r was calculated by $1 - \frac{\sum (Measure\ Standard\ Error)^2 /\ N}{Variance\ of\ Observed\ Measures}$, and has equivalent interpretations to Cronbach's alpha (Cronbach, 1951). In this formula, the mean of the measure standard error (the numerator) is the model's variance divided by the variance of the observed data, which is then subtracted by 1. Typically, R_r is a more conservative measure (i.e., underestimation) of a scale's reliability than Cronbach's alpha because it represents the true lower bound of reliability (Eckes, 2011).

Facet correlations

Prior to correlating the network-identified facets, the items for each network-identified facet were summed and averaged to provide a facet score for each person. Pearson's correlations were calculated for the network-identified facets and a global Openness to Experience variable (the average score of all Openness to Experience items). High correlations with the global Openness to Experience variable would suggest that those network-identified facets are more central to the global trait.

R code and data sharing

All R code to reproduce the analyses are included in the supplementary materials. All data, cleaning procedures, analytic methods, and study materials are available on the Open Science Framework for reproduction and replication purposes <https://osf.io/954a7/>.

Results

Communities of the Openness to Experience network

The walktrap community detection algorithm identified 10 distinct communities (Figure 1), ranging from 7 to 25 items. Through visual inspection, these communities appeared to form two larger components (aspects). Inspection of the identified facets (i.e., communities), however, revealed three distinct aspects: intellect (Communities 1–3), open-mindedness (Communities 4–6), and experiencing (7–10). The descriptions of each community's core items and item composition were used to determine the labels and descriptions for each facet (Table 2). Note that the communities listed here are based on the visual orientation and organization of component relations, not necessarily the actual order that the walktrap algorithm produced.

Community 1

The first community (turquoise in Figure 1) was relatively central in the depiction of the network and included 17 items. The core items of this community reflected interests in discussing philosophy (e.g., "I avoid philosophical discussions"; reversed) and abstract ideas (e.g., "I have never really been interested in science"; reversed). This community was also the most central to the intellect component. Thus, this community was labeled intellectual interests.

Community 2

Extending to the bottom right of the intellectual interests community was a slightly larger community (20 items) related to perceived intellectual ability (violet in Figure 1). Core items in this community denoted quick thinking, fast processing, and an ability to understand difficult ideas. All items in this community emphasize, in one way or another, the person's own assessment of his or her intellectual ability. This self-report of perceived intellectual ability aligns with notions of subjectively assessed intelligence and self-estimates of intelligence (Chamorro-Premuzic & Furnham, 2004). Therefore, this community was identified as self-assessed intelligence.

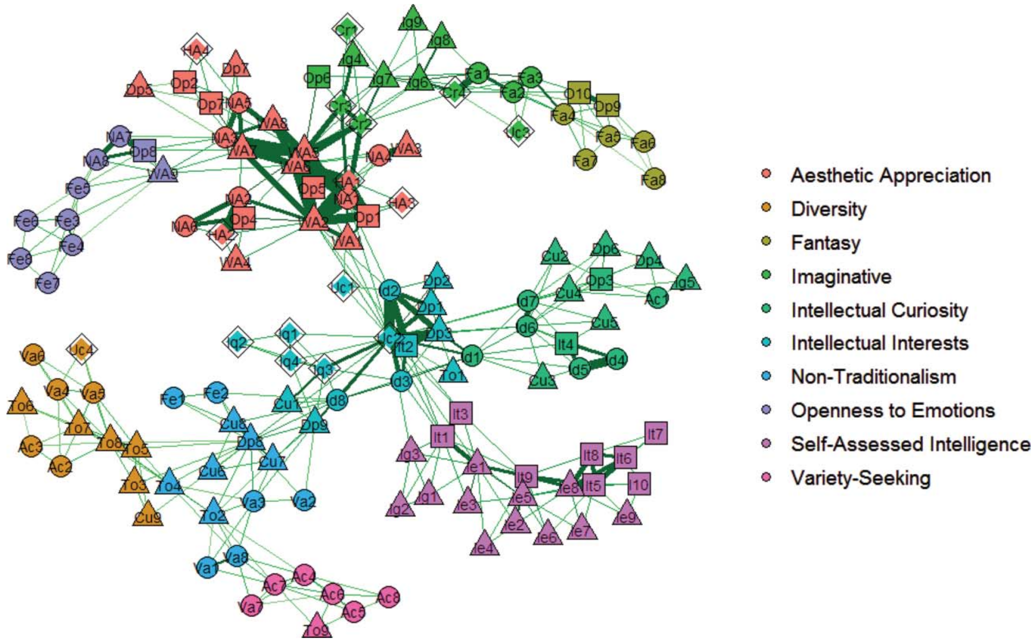

Figure 1. The network of Openness to Experience depicted with all items. The shape of the node indicates the inventory (square = Big Five Aspects Scales [BFAS]; diamond = HEXACO; circle = NEO; triangle = Woo et al.), the color portrays the network-identified facet, and the label represents the inventory-defined facet and the item number of the inventory-defined facet.

Community 3

The last community of the intellect component was located to the right of the intellectual interests community (sea green in Figure 1) and contained 14 items. This community was characterized by items related to reflection (e.g., "I love to reflect on things"), interests in solving complex problems (e.g., "I like to solve complex problems"), and learning new things (e.g., "I try to learn something new every day"). Based on these descriptions, we labeled the community intellectual curiosity.

Community 4

The first community of the open-mindedness component branched to the left of the intellectual interests community (sky blue in Figure 1). The core items of this community described an openness toward beliefs, values, and culture that are different from one's own (e.g., "I think it is rude when others speak in a language I can't understand"; reversed). Overall, the 12 items of this community indicated a general sense of liberalism toward others and opinions, and thus the community was labeled nontraditionalism.

Community 5

Community 5 extended toward the bottom of the network from the nontraditionalism community (pink in Figure 1). This community had seven items that were all reverse coded. This community was slightly harder to define because no items were positively endorsed for people high in the trait. We settled on variety-seeking to be consistent with Connelly, Ones, Davies, et al.'s (2014) findings and because it summarized the opposite characteristics of the items' content in community, which centered on conventional, orthodox, and routine behavioral characteristics. Notably, the facet label is the reverse of the items' content; therefore, items in this facet should also be reversed (as they were in the original inventories). Nonetheless, reversing the items does not ensure that the indicators are the equivalent of their reverse content (van Sonderen, Sanderman, & Coyne, 2013). In addition, this facet might be an artifact of reverse wording rather than evidence for a meaningfully separable facet. Thus, careful consideration is necessary when interpreting this facet.

Community 6

Community 6 was to the left of the nontraditionalism community (orange in Figure 1). This 12-item community was largely related to variety-seeking in environments (e.g., "I enjoy a diverse community"), beliefs (e.g., "I learn a great deal from people with differing beliefs"), and experiences of life (e.g., "I understand that people can have different attitudes toward certain things than I do"). Items that were most central to this community chiefly reflected preference for variety in cultural experiences; thus, we labeled this community diversity.

Community 7

The seventh community was the largest, containing 25 items, and was located above the intellectual interests community (coral in Figure 1). This community was clearly represented by aesthetic interests and appreciation with core items such as, "I have a passion for art" and "I enjoy the beauty of nature," and thus was labeled aesthetic appreciation. Not surprisingly, this community was most centrally located in the experiencing component.

Community 8

The next community included 10 items and branched to the left of the aesthetic appreciation community (slate blue in Figure 1). This community was defined by immersion in emotions and music, with a single core item uniting these two descriptions: "I have been touched emotionally by a great musical performance." Several studies have demonstrated that people high in Openness to Experience,

Table 2. Labels and descriptions of the network-identified facets.

Aspect	Facet	Description
Intellect	Intellectual interests	Engagement in philosophy and discussing abstract, theoretical ideas
	Self-assessed intelligence	Perceived ability to think quickly, solve problems, and process information
	Intellectual curiosity	Enjoyment of learning new things, thinking about complexity, and reflecting on thoughts
Open-mindedness	Nontraditionalism	Receptiveness to new ideas, cultures, and perspectives
	Variety-seeking	Willingness to explore new environments and try new ways of doing things
	Diversity	Embraces a variety of attitudes, beliefs, and lifestyles
Experiencing	Aesthetic appreciation	Engagement in the arts and perceptual experiences
	Openness to emotions	Sensitivity to aesthetic emotions, complex feelings, and strong moods
	Imaginative	Ability to have original thoughts and a desire to create
	Fantasy	Tendency to daydream and mind wander

specifically the experiencing aspect, are more likely to experience complex and subtle emotions related to aesthetic experiences (including music) than people low in Openness to Experience (Cotter, Silvia, & Fayn, in press; McCrae, 2007; Silvia, Fayn, Nusbaum, & Beaty, 2015). For this reason, we labeled this component openness to emotions, with an emphasis on emotions related to aesthetic experiences (Table 2).

Community 9

Stemming to the right of the aesthetic appreciation community was a community of 14 items defined by creativity and imagination (green in Figure 1). Core items were related to having an active imagination and engagement in creativity. The flavor of this community was more related to creativity in the arts, such as "I would enjoy creating a work of art, such as a novel, a song, or a painting," than the sciences. Moreover, the community included some indicators of active daydreaming such as, "letting a fantasy or daydream develop." Therefore, this community was labeled imaginative.

Community 10

The last experiencing community branched off to the right of the imaginative community (seven items; olive in Figure 1). Unlike the active daydreaming indicators of the imaginative community, this community emphasized passive daydreaming like "difficulty letting my mind wander" (reversed). Thus, this community was characterized by daydreaming and mind wandering, so we called it fantasy.

Reliabilities and correlations

Rasch reliabilities

Rasch reliabilities are presented for each inventory-defined facet (Table 1) and each network-identified facet discussed previously (Table 3). In general, most inventory-defined facets had acceptable reliability ($R_r > .70$), with the exception of HEXACO's aesthetic appreciation and unconventionality. The network-identified facets were all satisfactory (R_rs from .75–.92), which was somewhat expected because facets with a larger number of items tended to have larger reliabilities.

Network-identified facet correlations

There are a few network-identified facet correlations that are worth noting (Table 3). First, other than the central experiencing, intellect, and open-mindedness facets (aesthetic appreciation, intellectual interests, and nontraditionalism, respectively), the intellectual curiosity and imaginative facets had the highest correlations with the global Openness to Experience variable. Their high correlations are consistent with their more central positions in the network. Another interesting pattern is the differential relations of the imaginative and fantasy facets to the other facets. For example, the imaginative facet has much larger correlations with the intellectual curiosity, aesthetic appreciation, and self-assessed intelligence facets than the fantasy facet. This suggests that, despite being related ($r = .50$), they are conceptually distinct from one another. Similarly, the diversity and variety-seeking facets have a relatively small correlation ($r = .36$) and have divergent relations with the experiencing aspect's facets, despite having similar relations to nontraditionalism ($r = .50$ and $r = .53$, respectively). Finally, the variety-seeking, openness to emotions, and fantasy facets had relatively small correlations (rs $< .60$) with the global Openness to Experience variable compared to the other facets, which might suggest they are more appropriate as compound traits or

Table 3. Rasch reliabilities (R_r) and correlations of the network-identified Openness to Experience facets.

Network-identified facet	R_r	1	2	3	4	5	6	7	8	9	10
1. Intellectual interests	.89	—									
2. Self-assessed intelligence	.90	**.56**	—								
3. Intellectual curiosity	.88	**.65**	**.61**	—							
4. Nontraditionalism	.80	.65	.44	.46	—						
5. Variety-seeking	.75	.39	.25	.23	**.53**	—					
6. Diversity	.75	.43	.27	.56	**.50**	**.36**	—				
7. Aesthetic appreciation	.92	.63	.35	.54	.50	.32	.48	—			
8. Openness to emotions	.79	.30	.15	.45	.34	.12	.47	**.54**	—		
9. Imaginative	.86	.54	.44	.61	.39	.30	.40	**.68**	**.49**	—	
10. Fantasy	.75	.41	.27	.31	.54	.35	.27	**.40**	**.36**	**.50**	—
Global Openness to Experience	.97	.83	.66	.78	.73	.48	.63	.84	.57	.78	.57

Note. All $p < .001$. Bold values are within-aspect correlations (1–3, intellect; 4–6, open-mindedness; 7–10, experiencing).

peripheral facets of Openness to Experience (Connelly, Ones, Davies, et al., 2014). In sum, each network-identified facet had distinct relations with other facets, which suggests that they are separate but related.

Conceptual coverage

To examine the conceptual coverage of each Openness to Experience inventory, we depicted the network with only the items of the inventory of interest highlighted (Figure 2; see supplemental materials for individual inventories). The number of network-identified facets and the number of items in those facets were used to determine how well (or poorly) each inventory covered each network-identified facet and aspect of Openness to Experience.

BFAS

The BFAS had items in 7 of the 10 network-identified facets (see Figure 2; supplemental materials). The openness aspect had five items in the aesthetic appreciation facet, two in the fantasy facet, and one item in both the openness to emotions and imaginative facets. The intellect aspect was primarily defined by the self-assessed intelligence facet (eight items) with one item reflecting the intellectual interests facet. Both the BFAS openness and intellect aspects had one item in the intellectual curiosity facet. The BFAS inventory adequately covered the experiencing aspect (items in all four experiencing-related facets), whereas the intellect aspect was relatively homogeneous (i.e., mainly self-assessed intelligence). In summary, although the BFAS inventory had sufficient coverage of the experiencing aspect, it had narrow coverage of the intellect aspect and no coverage of the open-mindedness aspect.

HEXACO

The HEXACO–100 inventory had the narrowest coverage of the Openness to Experience network (items in only 4 of 10 facets; see Figure 2, supplemental materials). HEXACO's inquisitiveness, aesthetic appreciation, and creativity facets were relatively homogeneous: All four items for each subscale were in the intellectual interests, aesthetic appreciation, and imaginative facets of the network, respectively. In contrast, its unconventionality facet was sparsely spread out in the network, with two items in the intellectual interests facet, one item in the diversity facet, and one item in the imaginative facet. Overall, the HEXACO–100 inventory had adequate coverage of the network-identified experiencing and intellect aspects but little coverage of the open-mindedness aspect (one item).

NEO PI–3

The NEO PI–3 had items in every network-identified facet except for the self-assessed intelligence facet (see Figure 2, and the online supplemental materials). The NEO PI–3′s feelings facet spanned both the openness to emotions (six items) and nontraditionalism (two items) facets. The inventory's aesthetics facet was primarily contained within the network's aesthetic appreciation facet (six items), with its remaining two items in the openness to emotions facet. The NEO PI–3′s actions facet was spread out in the network: Most items fell within the network's variety-seeking facet (five items) with its remaining items falling into the diversity (two items) and intellectual curiosity (one item) facets. The inventory's values facet was also spread across the network, with four items in the nontraditionalism facet, three items in the diversity facet, and one item in the variety-seeking facet. The fantasy facet of NEO PI–3 made up most of the items in the network-identified fantasy facet

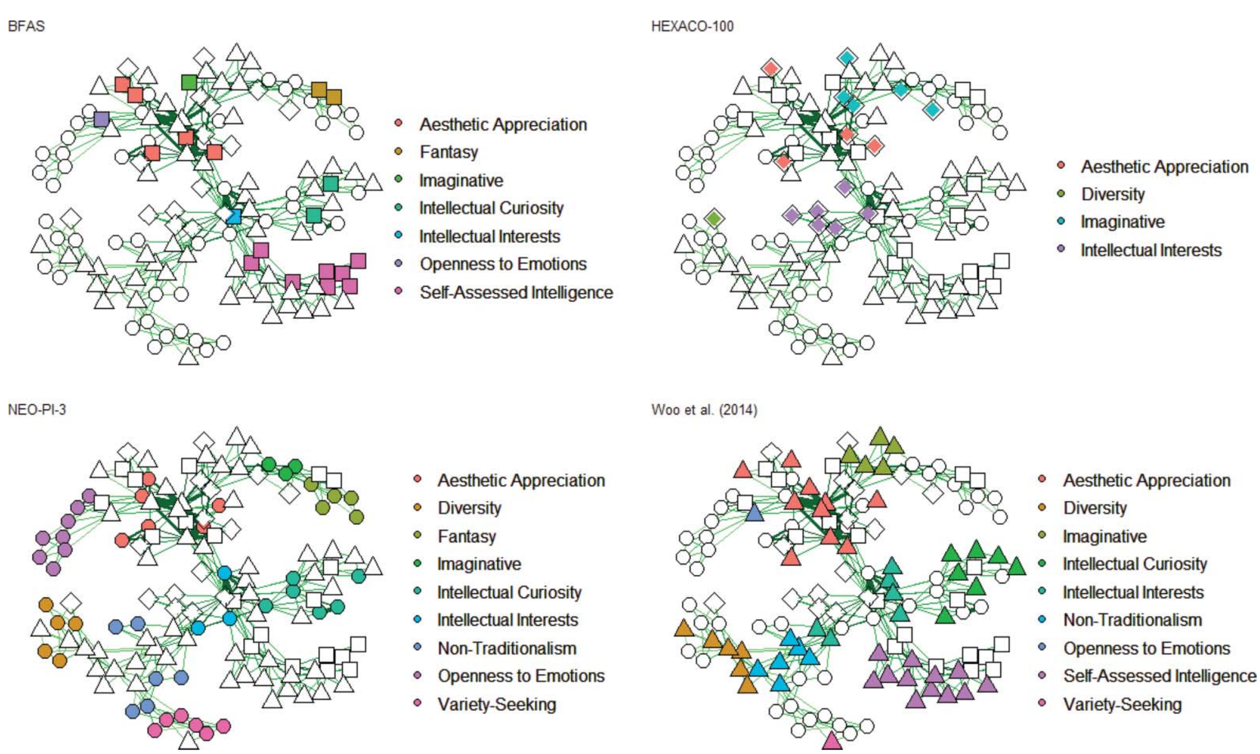

Figure 2. The networks depict the item coverage based on the network-identified facets of each Openness to Experience inventory. Colored nodes represent items in the respective inventory and network-identified facet and white nodes indicate items of other inventories. For full view of each inventory see supplementary materials. BFAS = Big Five Aspects Scales; NEO Personality Inventory–3 (NEO PI–3).

(five of seven items) and had some items in the imaginative (three items) facet. Finally, NEO PI–3′s ideas facet was equally spread between the intellectual interests (four items) and intellectual curiosity (four items) facets. In terms of the coverage of the network-identified aspects, experiencing and open-mindedness were evenly covered (with some of NEO PI–3′s facets being the primary measurement of a few of the network-identified facets), and the intellect aspect was adequately covered.

Woo et al.'s Inventory

Like the NEO PI–3, Woo et al.'s inventory had items in every network-identified facet except one (fantasy; see Figure 2, supplemental materials). Woo et al.'s intellectual efficiency facet only appeared in the self-assessed intelligence facet (all nine items). Similarly, the inventory's aesthetics facet had eight of its nine items in the aesthetic appreciation facet. The other aesthetics item was the inventory's lone representative in the openness to emotions facet. The tolerance facet of Woo et al.'s inventory was spread across four facets: diversity (five items), nontraditionalism (two items), variety-seeking (one item), and intellectual interests (one item). Likewise, Woo et al.'s curiosity facet appeared in four facets: intellectual curiosity (four items), nontraditionalism (three items), diversity (one item), and intellectual interests (one item). The ingenuity facet's items were mainly found in the imaginative facet (five items), and the remaining items were in the self-assessed intelligence (three items) and intellectual curiosity (one item) facets. Finally, the depth facet had the most diverse coverage in four facets that spanned the three network-identified aspects: intellectual interests (four items), aesthetic appreciation (two items), intellectual curiosity (two items), and nontraditionalism (one item). In summary, Woo et al.'s Openness to Experience inventory had considerable coverage of all of the aspects.

Discussion

This study investigated the taxonomic structure of Openness to Experience and the conceptual coverage of four commonly used Openness to Experience inventories by applying network analysis to all inventories' items. Using the walktrap community detection algorithm, we found 10 facets—variety-seeking, aesthetic appreciation, intellectual curiosity, diversity, openness to emotions, fantasy, imaginative, self-assessed intelligence, intellectual interests, and nontraditionalism—that formed three higher order aspects: two commonly found in the literature (experiencing and intellect) and one novel aspect (open-mindedness).

The correlational patterns of the 10 network-identified facets suggest that each facet is distinct and has dissociable relations, despite some having seemingly similar descriptions. Moreover, network-identified facets that were closer to the center of the network had higher correlations with a global Openness to Experience variable, suggesting that facets more central in the network are defining features of Openness to Experience. Finally, based on the network representation, we were able to determine the conceptual coverage of each inventory. These findings provide researchers with a clearer picture of the construct that each inventory measures. Researchers should take these results into consideration when evaluating how Openness to Experience relates to affective, behavioral, and cognitive outcomes.

Taxonomic structure of Openness to Experience

The larger components of the network seemed to suggest that three aspects of Openness to Experience might better define the global trait than two. We labeled this third aspect open-mindedness because it was largely defined by a receptiveness toward others' ideas, values, beliefs, lifestyles, and culture. Notably, this aspect was almost entirely defined by items from the two larger inventories (i.e., NEO PI–3 and Woo et al.'s Openness to Experience Inventory), which highlights that they might have a broader conceptualization of Openness to Experience than the smaller inventories. In terms of open-mindedness's position in the network, it was more peripherally located than the other two aspects. This suggests that open-mindedness might be a compound aspect with another trait (e.g., Agreeableness) rather than a pure Openness to Experience aspect. Future research is necessary to replicate this finding and to investigate the potential of open-mindedness as a compound aspect. Nonetheless, our results demonstrate that a third aspect of Openness to Experience might exist and is currently captured by popular inventories.

Below the three aspects, the network-identified facets were consistent with many of the previous categorizations provided by Connelly, Ones, Davies, et al. (2014). Many facets were identical in their label and description (Connelly et al.'s in parentheses): aesthetic appreciation (aestheticism), openness to emotions (openness to emotions), fantasy (fantasy), variety-seeking (variety-seeking), diversity (tolerance), and nontraditionalism (nontraditional). This intersection is unsurprising considering that several inventories included in Connelly, Ones, Davies, et al.'s theoretical sort were also used in this study, yet it is notable given the very different analytic approaches that these studies used.

Some network-identified facets, like intellectual interests and intellectual curiosity, were harder to relate to Connelly, Ones, Davies, et al.'s (2014) categories. For example, the intellectual interests and intellectual curiosity facets appear to fall under their global Openness to Experience category, which was defined by an openness to ideas, complexity, and curiosity. This interpretation seems appropriate given that intellectual interests and intellectual curiosity had two of the highest correlations with our global Openness to Experience variable. Our imaginative facet, however, was much less clear and seemed to be a blend of their innovation (is creative and inventive; likes to come up with new ideas) and fantasy (has an overactive imagination) facets. Connelly, Ones, Davies, et al. seemed to treat imagination and fantasy as synonymous in their description of their fantasy facet. Our correlational findings, however, suggest that the imaginative and fantasy facets have different relations with other facets in the Openness to Experience network (e.g., intellectual curiosity, aesthetic appreciation, and self-assessed intelligence facets). Finally, there were a few facets that did not overlap. For example, we found a self-assessed intelligence facet whereas they did not, and Connelly, Ones, Davies, et al. found a few facets that we did not (e.g., openness to sensations, autonomy, and thrill-seeking). These differences are likely due to the different scales and inventories that were investigated in each study rather than differences in analytical approaches.

More important, the central facets—based on position and their correlations with the global Openness to Experience variables—of our network (intellectual interests, aesthetic appreciation, and intellectual curiosity) perfectly align with Connelly, Ones, Davies, et al.'s (2014) description of global Openness to Experience: wanting to think and understand problems, having artistic or scientific interests, and being introspective and curious. Moreover, the most central open-mindedness facet, nontraditionalism, fit with additional descriptors of Connelly, Ones, Davies, et al.'s global Openness to Experience category (liberal and independent minded).

Similarly, our most peripheral facets (fantasy, variety-seeking, and openness to emotions) aligned with Connelly, Ones, Davies, et al.'s (2014) Openness to Experience trait compounds. This seems to confirm their position as peripheral facets and that they are probably associated with other traits. Finally, the diversity and self-assessed intelligence facets were neither central nor peripheral, but might also reflect trait compounds. Diversity, for instance, is likely related to agreeableness, whereas self-assessed intelligence is likely related to conscientiousness and psychometric intelligence (although the facet purely refers to self-reported intellectual ability; Chamorro-Premuzic, Furnham, & Moutafi, 2004).

In summary, our network largely reproduces Connelly, Ones, Davies, et al.'s (2014) theoretical sort. These results are encouraging because the lower order facet structure seems to be appropriately measured when using all four inventories. In most research practices, however, it's not practical to administer all four inventories. Time constraints and the redundancy of questions across inventories mean that researchers should try to use inventories that are most appropriate for the outcomes they are measuring.

Conceptual coverage of Openness to Experience

Woo et al.'s (2014) Openness to Experience Inventory had the broadest coverage of Openness to Experience. Notably, the inventory had the most items of the inventories considered in this study. In terms of the intellect, experiencing, and open-mindedness aspects, Woo et al.'s inventory appeared to be well balanced across all three. Our network revealed a notable difference in the categorization of one inventory-defined facet: tolerance. In the original scale design, the tolerance facet was part of Woo et al.'s culture (experiencing) aspect. In contrast, our results reveal that the tolerance facet strongly characterized the open-mindedness aspect. Although this facet could be consistent with both factors, Connelly, Ones, Davies, et al.'s (2014) meta-analytic correlations show that it is more likely that it is influenced by another trait (agreeableness), which means it might be best conceptualized as a compound trait. In general, Woo et al.'s Openness to Experience Inventory provides the most comprehensive coverage of the Openness to Experience construct.

The NEO PI–3 also had a large number of items, many of which were in peripheral facets and sparsely spread out in the network. There were a few facets that were primarily described by the NEO PI–3 compared to other inventories (variety-seeking, openness to emotions, and fantasy). These facets were also the most peripheral in the network and had the lowest correlations with the global Openness to Experience variable. Thus, although there are many items in the NEO PI–3, it seems that nearly half of them cover fringe characteristics of Openness to Experience. Indeed, these facets are likely to be considered compound traits (e.g., variety-seeking with Extraversion, openness to emotions with Extraversion and Neuroticism, and fantasy with low Conscientiousness; Connelly, Ones, Davies, et al., 2014). In terms of the coverage of the experiencing, intellect, and open-mindedness aspects, the inventory seemed to favor experiencing and open-mindedness, which is consistent with Connelly, Ones, Davies, et al.'s (2014) suggestion and Woo et al.'s (2014) factor analytic findings. Indeed, the self-assessed intelligence facet contained no NEO items, which should be considered when researchers are evaluating the NEO PI–3 with cognitive outcomes; that is, it is less likely to be related to cognitive outcomes compared to the other inventories.

For the smaller inventories, the HEXACO–100 inventory measured fewer facets (four) than the BFAS inventory (seven), suggesting that it covers a narrow spectrum of Openness to Experience. The HEXACO inventory mainly measured the central facets of Openness to Experience (aesthetic appreciation and intellectual interests). Interestingly, the unconventionality facet of the HEXACO inventory had items in three different network-identified facets (intellectual interests, diversity, and imaginative), despite being composed of four items. This could explain why the unconventionality facet had the lowest reliability across all Openness to Experience inventory-defined facets. In terms of aspect coverage, the HEXACO inventory was evenly distributed between the experiencing and intellect, but had only one item in the open-mindedness aspect, suggesting limited coverage of the broader Openness to Experience construct.

Similarly, the items in the BFAS inventory were evenly distributed between the experiencing and intellect aspects but did not have any items in the open-mindedness aspect. Our network revealed that the BFAS's intellect aspect primarily covered the self-assessed intelligence facet, which had the lowest correlations (*r*s from .15–.44) with the experiencing aspect's facets. This finding could explain why there tends to be only moderate correlations between its openness and intellect aspects (*r*s usually between .30–.40). Thus, we expect that the experiencing and intellect aspects in other inventories would have stronger relations. Furthermore, our results could account for why the NEO PI–3 inventory has relatively weak (positive and negative) findings with working memory, whereas the BFAS inventory finds consistent moderately positive associations (DeYoung et al., 2009; Kaufman et al., 2010; Smeekens et al., 2016). Because the NEO PI–3 lacks coverage of the self-assessed intelligence facet and BFAS intellect is mainly self-assessed intelligence, it is likely that relationships with cognitive attributes will vary depending on which scale is used. In general, the BFAS covers both the experiencing and intellect aspects, but tends to favor the specific facets of aesthetic appreciation and self-assessed intelligence, respectively.

In summary of the larger two inventories, researchers interested in measuring the most comprehensive coverage of Openness to Experience should consider using Woo et al.'s (2014) inventory. The NEO PI–3, when contrasted to Woo et al.'s scale, appears to measure conceptually distinct regions of the Openness to Experience construct. This contrast seems to suggest that Woo et al.'s inventory has the broadest coverage of the Openness to Experience network not simply because it has the most items (the NEO PI–3 has only six fewer items), but because it has a greater diversity of items that were also related to items in the other inventories included in our study. The smaller inventories covered the experiencing and intellect aspects adequately but neither covered the open-mindedness aspect. Moreover, the intellect aspect of the BFAS seemed to strongly favor the self-assessed intelligence facet, whereas the HEXACO inventory only covered the intellectual interests facet. These findings suggest that researchers should take consideration in which inventories they use because it could affect how Openness to Experience relates to other outcomes.

Limitations

Several possible limitations of this study warrant consideration. First, the data are suitable for a wide range of analytic methods, such as EFA and clustering methods. One important limitation is that no comparison was made between our network analysis and more traditional methods, so it is unclear if our network approach would produce notably different results than EFA or any other factor finding methods. Previous network analysis studies have evaluated the lasso approach's ability to uncover factor structure via EGA (Golino & Demetriou, 2017; Golino & Epskamp, 2017). Golino and Epskamp (2017) demonstrated, in a simulation study, that EGA performs at least as well as other factor finding approaches, such as parallel analysis and the minimum average partial procedure. Therefore, future work should emulate their simulation studies to determine if the approach used in this study performs comparable or favorably compared to other more traditional methods.

Another important consideration is the detection and interpretation of communities. Whereas the walktrap algorithm deterministically decides on the number and size (i.e., number of items) of the communities, the interpretation of the communities is ultimately up to the researcher (similar to EFA). The fantasy and imaginative facets, for example, were determined to be separable communities based on the algorithm, and we also interpreted these communities as separable. From a theoretical standpoint, however, a researcher might instead interpret these two communities as one facet. In addition, our aspects (intellect, experiencing, and open-mindedness) were our interpretation of how the communities were clustered and were not derived from the algorithm at all. Therefore, researchers might ultimately disagree with our conclusions.

Another possible limitation is that different samples (college and MTurk participants) were pooled together. Post-hoc multivariate analyses of variance and Box's M test revealed some significant differences in the means and covariances of the items (see supplemental materials). Thus, although the diversity of participants beyond young college adults strengthens the generalizability of the findings to the larger population, there might be instances of differential item functioning that are obscured by pooling the samples in the network approach, which could influence the relations between items. Other network methods, such as the fused graphical lasso (Costantini et al., 2017; Danaher, Wang, & Witten, 2014) or the Ising model (Marsman et al., 2018; van Borkulo et al., 2014), might be able to extract such information. Future work, however, should examine the implications of pooling different samples and the effects this has on the pooled versus individual samples' network structure.

In addition, sample size is likely to have a large effect on the reliability and estimates of parameters in the model (Epskamp, Borsboom, & Fried, 2017). In our study, for example, there were 9,453 possible parameters and 408 parameters in the network model. This means that, despite our sample of 802 people, there were just under 2 people per estimated parameter. Some of this could be ameliorated by including missing data (e.g., full information maximum likelihood), which was removed by our analyses. Even so, having a few more people would not change the fact that only having a few people per parameter renders any attempts of cross-validation, such as split-half sampling, unreliable. Moreover, this makes it relatively difficult to estimate the reliability of the community structures. Future developments should try to overcome the limitation of sample size by including missing data and harnessing bootstrapping (Epskamp et al., 2017; Golino & Demetriou, 2017) or permutation (van Borkulo et al., 2018) techniques.

In consideration of the sample size, some of the estimated relations between variables and variables' inclusion in one facet rather than another might be unreliable.[2] In the intellectual curiosity facet, for example, there is an item referring to "broad intellectual interests" that, in a larger sample, might be more likely to belong to the intellectual interests facet. Other than sample size, there could be other explanations for this result. One explanation could be that the intellectual curiosity facet is not specifically measured by any inventory included in the study. Therefore, if there were more items with content related to the intellectual curiosity facet, then the item (and others) might align more with the intellectual interests facet. Notably, this limitation is not unique to this approach but also applies to EFA component loadings and clustering analysis. Thus, like EFA, researchers should use considerable caution when applying these methods and evaluate the results in light of theory and past research.

Where do we go from here?

Openness to Experience is a broad, complex trait that is difficult to pin down. As demonstrated by this research, prominent personality inventories, although generally agreeing on the higher order aspects of experiencing and intellect, inconsistently assess a variety of fine-grained facets. The most immediate implication of this research is that researchers might not be measuring the Openness to Experience they believe they are measuring. Each inventory examined here demonstrated

[2]In general, the reliability of network estimates is a critical concern in the developing field of psychological networks, and has stirred recent debate (see Borsboom et al., 2017; Forbes, Wright, Markon, & Krueger, 2017; Steinley et al., 2017). The approach used in this study was not discussed in the debate; however, recent research has compared the approach used in this study to the current state-of-the-art lasso (Christensen, Kenett, Aste, Silvia, & Kwapil, 2018).

differential coverage of the trait and its two aspects. Moreover, we suggest a third aspect—open-mindedness—also exists in Openness to Experience's taxonomy and should be considered in the development of future Openness to Experience inventories. Overall, this means that researchers should carefully consider their outcome measures and select the inventory or inventories that best assess the facets that are of greatest theoretical interest.

Future work should broaden the network to include more inventories of Openness to Experience to replicate our aspect and facet findings in the current network but also to determine whether any additional aspects or facets should be included. With this consideration, networks reflect their inputs—that is, the network is constrained by what the researcher puts into it. Our network, for example, is limited to the elements within these inventories, and might not reflect all possible facets. Indeed, subject matter experts might disagree with some of the facets (e.g., self-assessed intelligence), and others might disagree with how the content aligns within each facet (e.g., intellectual curiosity and intellectual interests). Adding additional inventories will ultimately alter the structure of the network but could clarify, add, or reduce the number of facets identified in this study. Additional work that moves beyond preexisting inventories might also aid in the formation of new developments and conceptualizations (DeYoung et al., 2012). For example, including outcome measures in the network—such as apophenia and intelligence, as DeYoung et al. (2012) suggested—might further clarify the structure of lower order facets. Costantini and Perugini (2016) already embraced this approach by constructing a network of Conscientiousness and related outcome variables. Although they used only self-report measures, their findings have enhanced the understanding of the Conscientiousness trait continuum.

Another avenue would be to broaden the content of the items within the facets that are at the core of Openness to Experience (e.g., intellectual interest, aesthetic appreciation, nontraditionalism, imaginative, and intellectual curiosity). In an inspection of the intellectual interests facet, for instance, there is a large redundancy of items related to philosophy. It is obvious that intellectual interests should be much broader than philosophical interests and that the inventories investigated in this study severely limit the breadth of this facet. Mussel (2013), for instance, already took a step in this direction by developing a lower order framework of BFAS's intellect that broke into a two-dimensional structure (seek and conquer) with three operations (think, learn, and create). Mussel's framework develops a finer grained view that provides meaningful differentiations within one aspect of Openness to Experience.

This approach echoes McCrae (2015), who suggested researchers should try to increase the breadth of facets rather than scale reliability. HEXACO's unconventionality facet might be the best example of this perspective. Although its reliability was relatively poor, it covered three different network-identified facets within the Openness to Experience network. Taking this idea one step further, facets could be inventories in their own right. For example, the imaginative facet could easily be a full-fledged inventory for the investigation of imagination. Another step in this direction would be to evaluate facets (rather than traits) with outcome variables, and remove items that have implied relations to the outcome within the item's description (e.g., "I believe in the importance of art" in relation to the outcome of drawing as a hobby; Mõttus, 2016). In this way, facets could be further refined by their relations to outcomes rather than their internal consistency.

Conclusion

In summary, our study builds on previous work that examined the lower order facet structure of Openness to Experience by constructing a network from items in four commonly used Openness to Experience inventories. Our results were in line with previous theoretical investigations of the lower order facet structure of Openness to Experience. In addition, our network model suggests that an additional aspect of open-mindedness should be considered. We also show that each inventory covers different conceptual space of the Openness to Experience construct, with some covering narrow regions and others covering most of it. The choice of inventory will thus influence how Openness to Experience relates to outcome variables. The findings reported here can aid researchers seeking to select items and inventories, and to refine and develop additional assessment tools for Openness to Experience, a complex and intriguing trait.

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