Scale Development via Network Analysis:
A Comprehensive and Concise Measure of Openness to Experience

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Abstract

Psychometric network analysis is an emerging tool to investigate psychological constructs. Most of the psychometric network literature has emphasized the formation of constructs. In the present study, we explored whether network analysis could be used as a tool for scale development. To do so, we used previously published data (*N* = 794) of four Openness to Experience measures and network analysis, including two novel network measures, to develop a comprehensive yet concise measure of the Openness to Experience construct. We then compared the network-derived measure to measures that were developed using classical test theory (CTT) and item response theory (IRT). Our results demonstrate that the network-derived measure was comparable to those developed using CTT and IRT and had better coverage of the full measure's conceptual content. In short, the network approach is a promising tool for scale development, providing an alternative perspective for the formation and assessment of constructs.

Key words: psychometrics, network analysis, scale development, openness to experience, assessment

Scale Development via Network Analysis:

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Psychometrics is concerned with the measurement of psychological traits, and the construction and validation of assessment instruments. The most recent addition to the field is psychometric network analysis, which conceptualizes traits as the mutualistic interactions between variables (Epskamp, Maris, Waldorp, & Borsboom, 2018; Marsman et al., 2018). The psychometric network literature has emphasized a novel perspective in the formation of traits (e.g., Cramer et al., 2012), while the application of network methods for constructing assessment instruments has not received much attention. Indeed, the scope of network analysis as a construction and validation method has been limited to dimension reduction methods (Golino & Epskamp, 2017).

So far, the results in this area appear promising and suggest that network analysis has potential as a method for constructing psychometric assessments. Recently, researchers demonstrated that certain network models are mathematically similar to models already used for the construction and validation of psychometric assessments (Epskamp et al., 2018; Marsman et al., 2018). To date, however, research has yet to examine whether network analysis can be used as a tool for the construction of a psychometrically reliable and valid assessment. Therefore, in the present study, we demonstrate how network analysis can be used to construct a questionnaire measure and introduce two novel network measures to assist researchers in their own scale development using network analysis.

Our application used the construct of Openness to Experience. This construct is ideal because it is popular, being one of the major higher-order factors of personality, but also contentious (Connelly, Ones, Davies, & Birkland, 2014; McCrae & Costa, 1985). Many models of its facet structure have been proposed, typically identifying four to ten facets (Connelly et al., 2014). Although there is some agreement on which facets are important, there is substantial variability in each model's coverage of the construct (Christensen, Cotter, & Silvia, 2018). The diversity and heterogeneity of current Openness to Experience models makes an interesting context for examining network methods as a tool for scale development. Therefore, our goal was to develop a comprehensive yet concise measure of Openness to Experience that encompasses the breadth of current models.

Network Analysis in Psychometrics

The psychometric network approach suggests that constructs (e.g., Openness to Experience) arise from causal, mutualistic interactions between their constituent elements (e.g., facets and items; Costantini & Perugini, 2016; Cramer et al., 2012). Conversely, traditional psychometric approaches suggest that constructs are an underlying common cause (i.e., latent variable) of their constituent elements (Edwards & Bagozzi, 2000). Although these frameworks are not mutually exclusive, their theoretical interpretations differ (Kruis & Maris, 2016). Items in the common cause framework, for example, are considered *exchangeable*—that is, each item is an equivalent indicator of the construct (Edwards & Bagozzi, 2000). In contrast, the psychometric network approach represents the reciprocal affect framework, where the interactions between items form emergent variables (e.g., facets, aspects, factors); thus, exchanging one item for another alters the essence of the emergent construct (Kruis & Maris, 2016).

The basic units of networks are called *nodes*, which represent psychological variables (e.g., self-report items). The connections between nodes are called *edges*, which represent the relationships between nodes (e.g., correlations). From these connections, clusters (sets of connected nodes) often emerge, forming communities that are equivalent to latent factors (Golino & Epskamp, 2017). Recently, Exploratory Graph Analysis (EGA; Golino & Epskamp, 2017) was developed to identify these communities in the network. EGA first constructs a network and then applies a community detection algorithm, which deterministically decides the number of communities and the number of nodes that belong to those communities. So far, simulation studies and real-world data have demonstrated that EGA has comparable or better accuracy in determining the number of dimensions than more traditional methods (e.g., parallel analysis; Christensen, Gross, Golino, Silvia, & Kwapil, 2018; Golino & Epskamp, 2017), particularly when the dimensions are highly correlated (Forkmann et al., 2017; Golino & Demetriou, 2017). Thus, network analysis has demonstrated that it can be a useful method for determining how many dimensions exist within a construct.

Taxonomic Structure of Openness to Experience

A recent study applied EGA to four different Openness to Experience measures to uncover its lower-order facet structure (Christensen, Cotter, & Silvia, 2018). The trait—defined by the engagement in novel experiences, ideas, and perspectives—is notoriously broad and complex, with a taxonomy that has been debated over the years (Connelly et al., 2014; McCrae & Costa, 1985). In Christensen, Cotter, and Silvia's study (2018), EGA identified 10 facets (aesthetic appreciation, openness to emotions, imaginative, fantasy, intellectual interests, intellectual curiosity, self-assessed intelligence, non-traditionalism, diversity, and variety-seeking) that corroborated a theoretical facet structure reached by subject matter experts (Connelly et al., 2014).

A novel finding from the study was that three aspects (i.e., meso-facets) were identified in the network. Two of the three replicated previous findings (Openness and Intellect; DeYoung, Quilty, & Peterson, 2007), but the third (Open-Mindedness) was previously unidentified. Openness (hereafter referred to as Experiencing; Connelly et al., 2014) included the facets of aesthetic appreciation, openness to emotions, imaginative, and fantasy, reflecting perceptual engagement (DeYoung, Grazioplene, & Peterson, 2012). Intellect included the facets of intellectual interests, intellectual curiosity, and self-assessed intelligence, reflecting intellectual engagement (DeYoung et al., 2012). Open-Mindedness included the facets of non-traditionalism, diversity, and variety-seeking, reflecting cultural engagement.

The authors also took advantage of the visual representation of the network by examining each measure's coverage of the network (i.e., the conceptual space), which revealed that none of the measures adequately covered all aspects and facets of Openness to Experience. Although measures with more items covered more of the conceptual space, each measure missed measuring some aspect or facet of Openness to Experience. Thus, there is a need for a consensus measure that comprehensively captures all aspects and facets, without the necessity to administer all four measures. Therefore, we employed network analysis and several network measures, including two novel measures, to construct a comprehensive yet concise measure of Openness to Experience.

A Roadmap for Scale Development using Network Analysis

As with traditional scale development methods, we followed DeVellis's (2017) scale development guidelines. The first guideline is defining trait specifications—that is, clearly defining the desired dimensions of the construct (DeVellis, 2017). Our trait specifications were guided by the facets and aspects identified by EGA. Our main objective was to construct a comprehensive Openness to Experience measure that covered all aspects and facets. Another aim was for the measure to be concise so that it could easily be administered within most experimental time constraints. Finally, we wanted to avoid shortcomings of other short assessment instruments, namely, providing proportional representation of each facet in each aspect (Smith, McCarthy, & Anderson, 2000).

Many personality measures treat each personality characteristic as an equivalent manifestation of the overall trait; however, this assumption represents a more traditional approach to measurement—that is, items and facets are exchangeable (Schmittmann et al., 2013). From the network perspective, this may be problematic because some characteristics are “purer” assessments (or more core conceptualizations) of the construct (e.g., aesthetic appreciation) than others (e.g., variety-seeking; Christensen, Cotter, & Silvia, 2018; Connelly et al., 2014). Thus, identifying more central facets (i.e., communities) could potentially provide a more conceptually valid approach to scale development by allowing proportional representation of each facet.

Community Closeness Centrality

In the psychometric network literature, some attention has been given to community-level (i.e., facet-level) measures, which tend to emphasize each node’s influence at the community-level (Blanken et al., 2018; Guimera & Amaral, 2005). Few measures, however, have been developed to examine the relative position of communities in the network (Bell & Vaughn, 2018; Everett & Borgatti, 1999; Giscard & Wilson, 2018). Some researchers have taken the mean or sum of node-wise (i.e., node-level) centrality measures (Bell & Vaughn, 2018; Everett & Borgatti, 1999), which may not perform as well as community-based measures (Giscard & Wilson, 2018). Others have relied on visual inspection to identify the “centralness” of communities in the network (Christensen, Cotter, & Silvia, 2018), which is qualitative and potentially prone to misrepresentation (e.g., positioning of nodes is stochastic and may not be related to *actual* centrality; Forbes et al., 2017). Therefore, we developed a novel measure called *community closeness centrality* to objectively assess communities' positions in the network.

The community closeness centrality is based on the node-wise closeness centrality measure. Node-wise closeness centrality is the reciprocal of each node's *average shortest path length* ($ASPL_i$; the mean number of edges from the reference node to all other nodes). Similarly, the community closeness centrality is the reciprocal of the community's average shortest path length. Instead of a single node, each node's ASPL_i in the community is obtained, and then the mean is computed and its reciprocal taken. Thus, a larger value of the community closeness centrality suggests that a community is more central than other communities in the network and should be better represented in the measurement instrument than less central communities. The number of items to include from each community should be determined based on the researcher's objectives (e.g., desired factor structure, scale length).

Moving forward with DeVellis's (2017) scale development guidelines, the next steps are to generate candidate items, have experts and non-experts review these items, and administrator the candidate items (with evaluation, modification, and dropping of items) to large and diverse samples. Because our item pool was derived from Openness to Experience measures that have been repeatedly evaluated and validated in diverse samples by other researchers, we skipped this step and continued to item selection.

Hybrid Centrality

Currently, there are few network measures that appear to be applicable for item selection. In traditional psychometric approaches, item selection is typically determined by item-scale correlations and factor analysis loadings in classical test theory (CTT), and by item difficulty, item discrimination, and item information parameters in item response theory (IRT; Kleka & Soroko, 2018). In psychometric network analysis, the most common measure of an item's relationship to the overall construct is node centrality, which measures the influence of each node based on its relative position to other nodes in the network. Although traditional measures such as item-scale correlations have yet to be directly compared to node centrality measures, it's likely these measures are related. In general, more central nodes should be more related to other nodes in the network, thus suggesting a stronger relationship with the overall construct (i.e., the network).

One node centrality measure that could be potentially useful for this application is the hybrid centrality measure (Pozzi et al., 2013). The hybrid centrality measure ranks nodes across several different node centrality measures, providing a single overall measure of a node's centrality. In one study, the hybrid centrality meaningfully differentiated schizotypy items: more central items were related to interview-rated schizophrenia-spectrum symptoms above and beyond intermediate and peripheral items (Christensen, Kenett, Aste, Silvia, & Kwapil, 2018). This suggests that nodes with higher hybrid centrality values had greater criterion-related validity. Therefore, the hybrid centrality seems to be a suitable measure for item selection.

Although the item selection process could be automatic (i.e., simply taking the most central items), we wanted a measure with broad coverage of Openness to Experience, its aspects, and its facets. Hence, we chose the most central items whose item content was not redundant with an item's content that was already selected (priority being given to nodes with higher hybrid centrality values).

Network Coverage

Assessment of conceptual coverage of an abbreviated assessment instrument in traditional psychometric methods is often based on the researcher's theoretical knowledge (Smith et al., 2000). There are few measures available that directly assess how well an abbreviated assessment instrument captures the full instrument. Typically, the correlation between the abbreviated and full measure is used to demonstrate that the abbreviated measure captures the same construct as the full measure. A complementary approach is to examine the correlation patterns of both measures with outcome variables. These options, however, indirectly inform the researcher about whether the abbreviated instrument adequately captures the conceptual space of the full instrument.

To provide a direct measure, we developed a novel measure called *network coverage*. Network coverage quantifies the average minimum distance from a specified subset of nodes (e.g., the abbreviated measure) to all other nodes in the network (e.g., the full measure). First, the distance (i.e., number of links) is computed from each node in the subset to all nodes in the network. Then, for each node in the network, the minimum distance to be reached from the subset is derived and the mean across all nodes is computed. In terms of conceptual space, good coverage would suggest that all nodes are, on average, within a couple edges' reach from the specified subset of nodes. Poor coverage would mean that many nodes of the subset are clustered in one area of the network with few connections to nodes further away in the network, suggesting greater minimum distances, on average. Notably, this measure penalizes conceptually similar nodes because they are more likely to have stronger relations and thus be closer to one another, spanning less network space.

Present Study

The main goal of the study is to demonstrate that psychometric network analysis can be used as a tool for the development of assessment instruments. Using the guidelines provided above, we constructed a 30-item measure of Openness to Experience using network analysis. For a comparison, we constructed three different measures of equivalent length based on CTT (item-scale correlations), IRT (item information), and random selection. These measures and the network-derived measure were compared using brief-to-full measure correlations (the full measure being all four published Openness to Experience measures), Spearman-Brown's prophecy formula, and the network coverage measure.

A secondary goal of the study was to demonstrate criterion-related validity. Therefore, we compared the consistency of the network-derived measure and the full measure's relationships with outcome measures of the HEXACO-100 personality inventory (HEXACO-100-PI; Lee & Ashton, 2004) and political conservatism. Based on previous evidence, we expected to find that the Intellect and Experiencing aspects would be differentially related to Extraversion (larger, positive effect size for Intellect), Emotionality (i.e., Neuroticism in the Five Factor Model; negatively and positively related, respectively), and Conscientiousness (positively and neutrally related, respectively; DeYoung et al., 2007). In addition, based on previous theoretical suggestions, we expected the Open-Mindedness aspect to be positively related to the HEXACO-100-PI factors linked to agreeableness (i.e., Agreeableness and Honesty-Humility; Christensen, Cotter, & Silvia, 2018; Connelly et al., 2014).

A measure of political conservatism was selected to examine the criterion-related validity of the Open-Mindedness aspect, which has yet to be empirically differentiated from the Intellect and Experiencing aspects. We expected that political conservatism would be negatively correlated with all aspects of Openness to Experience but that the Open-Mindedness aspect would have the largest effect size. Additionally, we expected Experiencing to be slightly more related (negatively) to political conservatism than Intellect because of its stronger association with political liberalism (Hirsh, DeYoung, Xu, & Peterson, 2010).

Methods

Participants

The sample used in this study was the same sample used to examine the lower-order facet structure of Openness to Experience (Christensen, Cotter, & Silvia, 2018). In total, 955 participants were recruited from the University of North Carolina at Greensboro (UNCG) and Amazon's Mechanical Turk (MTurk) across three different studies. Demographic and methodological information can be found in Christensen, Cotter, and Silvia (2018). One-hundred and fifty-three participants were removed due to high scores on inattentive responding measures (Maniaci & Rogge, 2014; McKibben & Silvia, 2017), missing data, or both. An additional eight participants were removed because their response patterns showed obvious signs of repetitive, inattentive responding (e.g., a single response value for all items in one or more measures). The final sample for data analysis consisted of 794 participants.

Materials

Openness to experience. Four different measures of Openness to Experience—HEXACO-100-PI (Lee & Ashton, 2004), BFAS (DeYoung et al., 2007), NEO-PI-3 (McCrae, Martin, & Costa, 2005), and Woo et al.'s Openness to Experience Inventory (Woo et al., 2014)—were completed by all participants. All responses were on a 5-point Likert scale ranging from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*), with responses reverse coded, where applicable. Across the four measures, 3 aspects (Experiencing, Intellect, and Open-Mindedness) and 10 facets (aesthetic appreciation, openness to emotions, imaginative, fantasy, intellectual interests, intellectual curiosity, self-assessed intelligence, non-traditionalism, diversity, and variety-seeking) were identified using EGA (Christensen, Cotter, & Silvia, 2018). Each aspect and facet were composed of a various number of items ranging from 32 to 57 items and from 7 to 27 items, respectively.

Personality measurement. All three samples (*n* = 794) completed the Emotionality and Openness to Experience measure in the HEXACO-100-PI (Lee & Ashton, 2004). Two of the three samples (*n* = 689) completed the full HEXACO-100-PI. The HEXACO-100-PI measures six major personality factors Honesty-Humility, Emotionality, Extraversion, Agreeableness, Conscientiousness, and Openness to Experience. The 100-item inventory contains 16 items per factor, which are defined by four facets (4 items per facet). The inventory also includes a 4-item scale of altruism, which loads on to multiple factors (Honesty-Humility, Emotionality, and Agreeableness; Lee & Ashton, 2018). All items were on a 5-point Likert scale ranging from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*) and items were reverse coded, where applicable. In general, the factors have good reliability and are relevant across cultures (Lee & Ashton, 2018).

Political conservatism. One of the two samples that completed the full HEXACO-100-PI (*n* = 175) also completed the brief measure of the Right-Wing Authoritarianism scale (RWA; Zakrisson, 2005). The RWA brief form was designed to capture right-wing political views with less extreme wording, fewer confounding items (e.g., "country" was replaced with "society" to avoid ambiguity with nationalism), and fewer references to specific groups (e.g., homosexuals) than the full measure. The scale contains 15 items that were responded to on a 7-point Likert scale from 1 (*Strongly Disagree*) to 7 (*Strongly Agree*). The RWA has been shown to have acceptable reliability and convergent validity (Zakrisson, 2005).

Procedure

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, the various Openness to Experience inventories (about 25 min.), the rest of the HEXACO-100-PI (about 8 min.), and the RWA (about 2 min.). Openness to Experience items were randomized within measures, and the Openness to Experience measure order was randomized. All studies were approved by the UNCG Institutional Review Board.

Scale Construction

Exploratory graph analysis. As in Christensen, Cotter, and Silvia (2018), EGA, using the Triangulated Maximally Filtered Graph (TMFG; Massara, Di Matteo, & Aste, 2016) network construction method (EGAtmfg; Golino, Garrido, Christensen, & Shi, 2018), was applied to identify the communities in the network. The same 10 communities were identified and examined in this study. The network visualization was produced using the *qgraph* package (Epskamp et al., 2012) in R.

Community closeness centrality. To identify the "centralness" of the EGA communities (i.e., facets) in the network, we computed community closeness centrality (C_{LC}). C_{LC} was computed using the *NetworkToolbox* package (Christensen, 2018) in R.

Using the community closeness centrality, the proportion of the number of items to include from each community was determined. For the purposes of our network-derived measure, we decided a priori to include 10 items per aspect (30 items in total). This was based on a previous aspect scale of Openness to Experience, the Big Five Aspects Scale (DeYoung et al., 2007), which measured the Experiencing and Intellect aspects (10 items each and 20 items in total).

The number of items per facet were agreed upon a priori (based on their centrality ordering within their respective aspect). To this end, the Experiencing aspect had 4 facets, so we selected 3 items for the two most central facets (aesthetic appreciation, C_{LC} = .27; imaginative, C_{LC} = .24) and 2 items for the two more peripheral facets (openness to emotions, C_{LC} = .21; fantasy, C_{LC} = .17). For the Intellect aspect, there were 3 facets, so we selected 4 items for the most central facet (intellectual interests, $C_{LC} = .28$) and 3 items for the two more peripheral facets (intellectual curiosity, $C_{LC} = .25$; self-assessed intelligence, $C_{LC} = .19$). Similarly, for the Open-Mindedness aspect, there were 3 facets, so we selected 4 items for the most central facet (non-traditionalism, $C_{LC} = .27$) and 3 items for the two more peripheral facets (diversity, $C_{LC} = .22$; variety-seeking, $C_{LC} = .19$).

Hybrid centrality. The hybrid centrality measure was computed for each node in the full network (see Christensen, Kenett et al., 2018 and Pozzi et al., 2013 for a more detailed explanation). For each facet, items with the highest hybrid centrality were selected unless an item was conceptually redundant with an already selected item (according to two subject matter experts' agreements). The hybrid centrality was computed using the *NetworkToolbox* package in R. Additionally, we assessed the stability of the hybrid centrality using the *bootnet* package (Epskamp, Borsboom, & Fried, 2018) in R. The description of this method and detailed results can be found in the supplementary materials (SI 1). In short, the hybrid centrality had strong stability: *CS*(cor = .70) = .733 (Epskamp, Borsboom, & Fried, 2018).

Comparison forms. ***CTT and IRT short forms*.** The ten items with the largest item-scale correlations (CTT) and item information values from a graded response model (IRT; Samejima, 1969) for each aspect were selected (30 items total) and used as comparison forms. Similar to the network-derived short form, conceptually redundant items were agreed on by two subject matter experts and excluded. The item-scale correlations were computed using the *CTT* package (Willse, 2018) in R and the graded response models were computed using the *ltm* package (Rizopoulos, 2006) in R.

***Random short form*.** To investigate whether the network-derived measure was better than random, we randomly selected 10 items per aspect from each aspect's item pool. On the one hand, random items have the potential to be redundant, which should increase the reliability of an aspect's measurement due to increased shared variance. On the other hand, random items could be relatively incoherent, producing lower estimates of reliability. In general, the items in this study were derived from psychometrically validated measures, so they should have reasonably sound psychometric properties despite being randomly selected.

Statistical Analyses

Reliability. Omega and Cronbach's alpha (Cronbach, 1951) were computed for the full, network, and comparison forms of each aspect. Omega is an alternative measure of reliability, which does not assume that the item covariances with the common factor are equal, but its interpretation is identical to alpha (DeVellis, 2017). Omega performs as well as alpha when alpha's assumptions are met and outperforms alpha when alpha's assumptions are violated (which often occurs in psychological constructs; Dunn, Baguley, & Brunsden, 2014; McDonald, 1999). For both measures of reliability, we defined acceptable reliability as greater than .70, good reliability as greater than .80, and excellent reliability as greater than .90 (DeVellis, 2017).

To assess the relative reliability of each aspect in the abbreviated measures to the full measure, we computed the Spearman-Brown prophecy formula using the Cronbach's alpha values. The Spearman-Brown prophecy formula provides the predicted test length of a new measure given a specified reliability (i.e., the reliability of an aspect in the abbreviated measure) and the reliability of the original measure (i.e., the reliability of the same aspect in the full measure; Brown, 1910; Spearman, 1910). This was used to examine how many items from the full aspect measure would be necessary to achieve the reliability of the abbreviated aspect measure. Thus, if more than 10 items are necessary to achieve the reliability of an abbreviated measure, then this suggests the average item quality in the abbreviated measure is higher than the average item quality in the full measure.

Omega and Cronbach's alpha (including confidence intervals) were computed using the *userfriendlyscience* package (Peters, 2014) in R and the Spearman-Brown prophecy formula was computed using the *CTT* package in R.

Brief-full correlations. The participant's mean score of each aspect for each abbreviated measure was computed and then correlated with the participant's mean score of each aspect in the full measure.

Network coverage. To examine how well the network-derived measure and comparison measures covered the conceptual space of the network, we computed network coverage. In addition, we examined each Openness to Experience measure to provide quantitative evidence of their network coverage. In general, smaller values indicate better coverage of the network, with the lowest possible value being 1. While more nodes make greater coverage more likely, this is not necessarily the case if they are not well spread across the network (i.e., the nodes are all clustered together). The network coverage measure was computed using the *NetworkToolbox* package in R.

Outcomes measures. The aspects of the network-derived measure were correlated with each other and their effect sizes were compared with the effect sizes of the aspects correlations of the full measure. This was done to investigate the similarity of the aspect relations within the network-derived measure.

The network-derived measure and full measure's aspects were correlated with the HEXACO-100-PI and RWA to examine the criterion-related validity of each aspect. Notably, the outcome measures had different sample sizes. Because the likelihood of finding a significant result increases with sample size, we adjusted the alpha significance level to be consistent between the samples following Pérez and Pericchi's (2014, p. 23) formula (Lakens et al., 2018):

$$\alpha_{adj} = \frac{\alpha \times \sqrt{n_0 \times (\log(n_0 + \chi^2_\alpha(1))}}{\sqrt{n^* \times (\log(n^*) + \chi^2_\alpha(1))}}. \tag{1}$$

In the formula, α is the original significance-level, n_0 is the reference sample, and n^* is the experimental sample. It's necessary to select a reference sample size, n_0, when adjusting alpha. For both samples, we determined the size of this reference sample based on a power of .80, a medium effect size (r = .3), and a significance level of .05, which yielded a reference sample size of 84. The original significance level (α = .05) was then adjusted according to the same reference sample (n_0 = 84), providing a consistent significance level. For n^* = 794, the alpha was adjusted to .014, for n^* = 689, the alpha was adjusted to .016, and for n^* = 175, the alpha was adjusted to .033. The adapted alpha values were computed using the *NetworkToolbox* package in R.

R code and data sharing. All data, cleaning procedures, and study materials are available on the Open Science Framework for reproduction and replication purposes: osf.io/954a7/. R code to reproduce all analyses is available here: osf.io/nv4yh/.

Results

Descriptive statistics, omega and alpha reliabilities, the Spearman-Brown prophecy estimates, and brief-full correlations for all measures are presented in Table 1.

Reliabilities

Across all measures, omega and alpha reliability estimates were acceptable, ranging from .78 to .91 for omega and from .72 to .89 for alpha. In general, the CTT-based and IRT-based measures had slightly higher reliabilities than the network-derived and random measures, suggesting these measures had more homogeneous constructs for each aspect. The Spearman-Brown prophecy analysis predicted that all measures except the random Open-Mindedness measure had larger reliabilities than would be expected for 10 items. This suggests that the average item quality of the items in these measures are generally higher than the average item quality in the full measure.

Conceptual Coverage of the Full Measure

The network-derived measure had comparable correlations to the CTT-based and IRT-based measures with full measure for each aspect (Table 1). In general, the numerical differences of effect sizes were small, suggesting that all measures adequately captured the full measure. Table 2 presents the descriptive statistics for the network coverage measure. The network-derived measure had the smallest average minimum distance value compared to all other comparison measures and all Openness to Experience inventories[1] (Figure 1). Although this metric is relative, this suggests that the network-derived measure had the best conceptual coverage of the full measure.

Outcomes Measures

Table 3 displays the correlations between the network-derived measure's aspects as well as the correlations between the full measure's aspects. The correlations of the network-derived and full measure mostly mirror one another. In general, the correlations suggest separate but related aspects.

Table 4 displays the correlations between the outcome measures with the network-derived and full measure. As expected, the Intellect aspect had larger, positive correlations with Extraversion and Conscientiousness than the Experiencing aspect. Similarly, there was no

[1] This result might seem unsurprising given the network-derived short form was developed based on a similar measure (i.e., the hybrid centrality). However, analyses of the 10 largest hybrid centrality values for each aspect produces network coverage with a mean of 1.36 (*SD* = .65) and a range of 1 to 3. Similarly, the CTT-based and IRT-based forms, based on the 10 largest values per aspect, demonstrate a similar result (*M* = 1.38, *SD* = .72, range = 1-4 and *M* = 1.41, *SD* = .75, range = 1-4, respectively). Thus, they perform equivalent to the random form and suggest that conceptual coverage is less than would be expected when excluding redundant items (i.e., diversifying the conceptual content).

correlation between Intellect and Emotionality and a significant positive correlation between Experiencing and Emotionality. These results support previous aspect findings (DeYoung et al., 2007) and suggest the network-derived measure performs equivalently to the full measure. Also consistent with our predictions, the Open-Mindedness aspect had larger effect sizes than the other aspects for outcome measures associated with agreeableness (i.e., HEXACO-Agreeableness and Honesty-Humility), supporting previous suggestions (Christensen, Cotter, & Silvia, 2018; Connelly et al., 2014). Similarly, the Open-Mindedness aspect had a large, significant negative correlation with political conservatism, with an effect size larger than the Intellect and Experiencing aspects. Finally, the Open-Mindedness aspect's correlations with Emotionality fell between the Intellect and Experiencing aspects.

Discussion

This study presents the first development of an assessment instrument using network analysis. First, we introduced three network measures, including two novel measures, and described how they could be used by researchers in their own scale development using network analysis. Next, we demonstrated that the network-derived measure produces a reliable scale whose reliability is comparable to measures developed using CTT and IRT. Then, using the newly developed network coverage measure, we showed that the network-derived measure had comparable or better conceptual coverage of the Openness to Experience construct than the comparison measures (random, CTT-based, and IRT-based) and established measures of Openness to Experience (HEXACO-100, BFAS, NEO-PI-3, and Woo et al.'s Openness to Experience inventory). Finally, we validated the network-derived measure by showing that it produces similar relations between aspects and outcome measures (personality traits and political conservatism) as the full measure.

Network Measures for Scale Development

Two novel network measures introduced in this study represent new tools for the psychometrician's toolbox. The first network measure introduced in this study was the community closeness centrality. The community closeness centrality demonstrated that it could be an effective tool for objectively measuring the "centralness" of communities in the network. This provides an advantage over more traditional approaches in that it allows researchers to evaluate the structure of the construct's hierarchy and determine how to emphasize certain facets of the construct (Kleka & Soroko, 2018). In addition, the measure closely resembles the closeness centrality index of node centrality, making the interpretation intuitive with measures that researchers using network analysis are already familiar with.

This resemblance lends some credibility to the idea that other node centrality measures could potentially generalize to the community-level (Bell & Vaughn, 2018). Node strength, for example, could translate into community strength, which may simply be the sum of all connections of nodes within the community (conceptually similar to the *stabilizing* measure introduced by Blanken et al., 2018). Indeed, there have been developments in other areas of network science that demonstrate that the eigenvector centrality could be used in a similar fashion (Giscard & Wilson, 2018). Therefore, future studies should attempt to develop additional community-based measures of centrality that may be useful beyond scale development.

The other novel measure introduced in this study was network coverage. This measure was specifically designed to assess how a subset of nodes is arranged in the network, providing a direct measure of their coverage (or spread) in a network. The network-derived measure had the best network coverage (i.e., the smallest minimum average distance value) compared to all other measures investigated in this study. This finding appeared to be supported by the network-derived measure's aspects having slightly smaller reliabilities than the other forms (except for the random measure) but comparable correlations with the full measure of each aspect. One reason why the network-derived measure may have had better coverage than the CTT- and IRT-based measures is because the network-derived measure benefited from a more balanced selection of items across the facets, which was based on the centrality of the communities.

More generally, we found quantitative evidence to support Christensen, Cotter, and Silvia's (2018) suggestion that Woo et al.'s Openness to Experience measure has the most comprehensive coverage of the Openness to Experience construct in the extant measures. Surprisingly, the network-derived, CTT-based, and IRT-based measures had comparable or better coverage than Woo et al.'s Openness to Experience inventory, which had 24 more items, thus demonstrating that similar content coverage could be achieved with few items. Notably, the random measure and NEO-PI-3 had comparable coverage of the network, despite the NEO-PI-3 having 18 more items.

We show that the network coverage measure provides an additional approach for researchers to evaluate how consistent the conceptual content of their abbreviated measure is with the full measure. This information could be used to strike a balance between keeping the content coverage of the full measure and retaining the reliability in the abbreviated measure. In the future, there is potential for the item selection process to become more automated based on increasing conceptual coverage of the full measure (i.e., optimizing network coverage) while maintaining high item quality (i.e., high hybrid centrality).

Outcomes Measures

The network-derived measure had remarkably similar relations as the full measure with the outcome measures of HEXACO-100-PI's personality traits and the political conservatism measure. All correlations were comparable in size and direction, with the most discriminant differences between aspects appearing in both the network-derived and full measures. Notably, the correlations between the network-derived measure's aspects were lower than the correlations for the full measure's aspects. We suspect that these lower correlations are due to the diversity of item content in the network-derived measure's aspects, thereby decreasing the shared variance that might have been inflated due to content redundancy in the full measure. Overall, the lower correlations between aspects may be more desirable because it suggests that the aspects are better differentiated, minimizing the issue of multicollinearity when used as separable predictors in regression analyses.

Our results also demonstrate the first evidence of criterion-related validity for the Open-Mindedness aspect, specifically for its relations to HEXACO-Agreeableness, Honesty-Humility, and political conservatism (Christensen, Cotter, & Silvia, 2018; Connelly et al., 2014). We also extend previous evidence of Openness to Experience being negatively related to political conservatism by showing this relationship is most strongly related to items in the Open-Mindedness aspect of Openness to Experience (Sibley, Osborne, & Duckitt, 2012; Lee et al., 2010, 2018). Thus, future work examining political orientation may consider investigating the Open-Mindedness aspect to see if the strength of this relationship holds across political constructs.

Limitations

It's worth noting that the facet and aspect structure of Openness to Experience was based on network analytic detection of dimensionality (i.e., EGA). It's possible that the more traditional psychometric approaches would have elicited a different dimensional structure than the one that formed the basis of the development of our measures. Notably, networks have already been shown to be an improvement over more traditional psychometric approaches to dimension reduction (Golino & Demetriou, 2017; Golino & Epskamp, 2017); therefore, it could be argued that the comparison of the psychometric approaches was based on a more equal footing (i.e., the same dimensional structure). In either case, we take this as evidence that network analysis can be used for scale development while potentially offering other advantages (e.g., identifying more central facets and illuminating conceptual coverage of the full measure). Another limitation is that we developed our network-derived measure based on four different measures of Openness to Experience that had already undergone extensive psychometric evaluation and validation (using CTT-based measures). Therefore, it's unclear how well network analysis can be used to develop a measure from scratch and whether instruments developed from the network perspective would lead to drastically different measures. Nevertheless, our study provides a proof-of-concept and suggests that there is no reason to think that network analysis couldn't be used as a tool to construct reliable and valid assessment instruments. More research in this area is necessary to further flesh out potential problems and identify new measures that might lead to advancements in this area of network psychometrics.

Conclusions

In short, our study demonstrates that network analysis is a feasible approach to developing a comprehensive measure. We provide novel tools to assist researchers in their own scale development using network analysis and offer our study as an example for other researchers to follow. Moreover, we show that network analysis offers distinct advantages over more traditional psychometric approaches, such as the consideration of the centrality of facets and the measurement of conceptual coverage of constructs, which have the potential to improve scale development methods. Although more robust assessments are needed, we suggest that the network approach is a promising tool for the psychometrician’s toolbox.

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Table 1. Descriptive statistics and reliabilities of the full, network, and comparison forms of Openness to Experience.

Aspect	Form	*M* (*SD*)	Brief-Full Correlation (*r*)	Omega (95% CI)	Cronbach's α (95% CI)	Spearman-Brown
Intellect	Random	3.65 (.61)	.93	.86 [.85, .87]	.82 [.80, .84]	11.75
	Network	3.62 (.69)	**.95**	.89 [.87, .90]	.85 [.84, .87]	14.72
	CTT-based	3.60 (.74)	.94	**.90 [.89, .91]**	**.87 [.86, .89]**	**17.51**
	IRT-based	3.68 (.68)	.94	**.90 [.89, .91]**	.87 [.85, .88]	16.41
	Full	3.57 (.56)	—	.96 [.96, .97]	.95 [.95, .96]	49
Experiencing	Random	3.59 (.71)	.92	.86 [.85, .87]	.83 [.81, .85]	12.90
	Network	3.66 (.69)	**.94**	.87 [.85, .88]	.83 [.82, .85]	13.43
	CTT-based	3.65 (.79)	.93	**.91 [.90, .92]**	**.89 [.87, .90]**	**20.62**
	IRT-based	3.73 (.76)	**.94**	**.91 [.90, .92]**	.88 [.87, .89]	19.81
	Full	3.60 (.58)	—	.96 [.96, .97]	.96 [.95, .96]	57
Open-Mindedness	Random	3.64 (.51)	.90	.73 [.70, .75]	.65 [.62, .69]	7.26
	Network	3.63 (.55)	**.93**	.82 [.80, .84]	.78 [.76, .81]	13.50
	CTT-based	3.81 (.62)	**.93**	.86 [.84, .87]	**.79 [.77, .82]**	**17.22**
	IRT-based	3.94 (.56)	.90	**.86 [.85, .88]**	**.82 [.80, .84]**	17.04
	Full	3.61 (.48)	—	.92 [.91, .93]	.89 [.88, .90]	32
Openness to Experience	Random	3.63 (.50)	.96	.91 [.90, .92]	.88 [.87, .90]	29.97
	Network	3.64 (.53)	**.97**	.92 [.92, .93]	.90 [.89, .91]	37.16
	CTT-based	3.69 (.59)	**.97**	**.94 [.93, .95]**	**.92 [.91, .93]**	46.38
	IRT-based	3.78 (.56)	**.97**	**.94 [.93, .95]**	**.92 [.91, .93]**	46.14
	Full	3.59 (.48)	—	.98 [.98, .98]	.97 [.97, .98]	138

Note. The Spearman-Brown values represent the number of items that would need to be retained from the full measure to achieve the Cronbach's α of the short form. The full measure's Spearman-Brown values are the number of items in the full measure. Better values are bolded.

Table 2. Descriptive statistics for network coverage of the network and comparison short forms as well as each Openness to Experience inventory

		Network Coverage		
Inventory	**# of Items**	*M*	*SD*	Range
HEXACO-100-PI	16	2.04	1.04	1 - 5
BFAS	20	1.80	1.10	1 - 5
Random	30	1.32	.55	1 - 3
Network	30	**1.04**	**.19**	**1 - 2**
CTT-based	30	1.21	.41	**1 - 2**
IRT-based	30	1.24	.49	1 - 3
NEO-PI-3	48	1.32	.63	1 - 4
Woo et al.	54	1.22	.48	1 - 3

Note. Lower values are bolded.

Table 3. Correlations between the aspects of the network-derived short form and full measure

	Intellect	**Experiencing**	**Open-Mindedness**
Intellect	—	.62	.61
Experiencing	.52	—	.61
Open-Mindedness	.54	.52	—

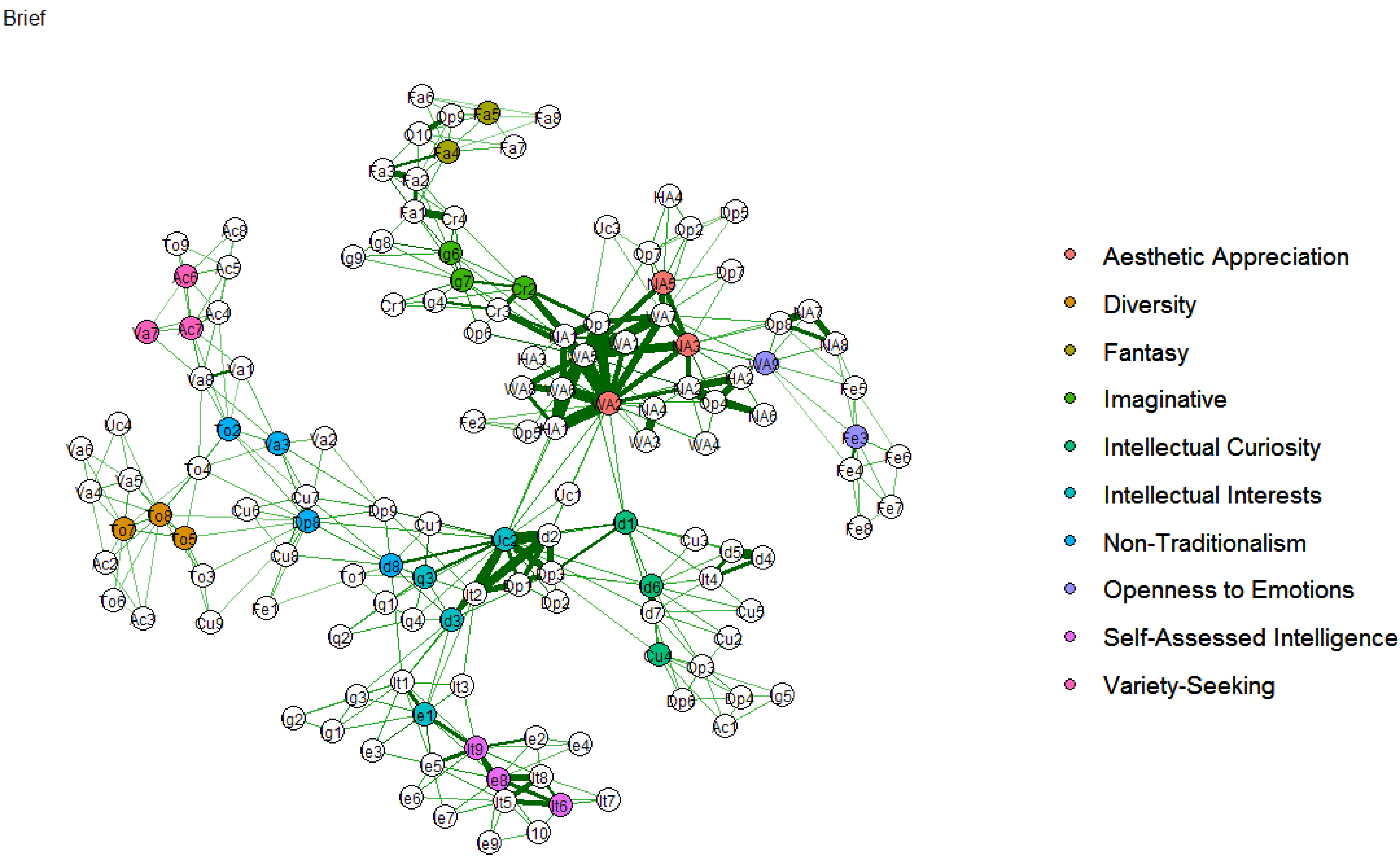
Note. The bottom diagonal represents the correlations between the network-derived short form and the top diagonal represents the correlations between the full measure. All *p*'s < .001.

Table 4. The network-derived short form and full measure's correlations with outcome measures

	Aspects					
	Intellect		Experiencing		Open-Mindedness	
Outcome Measures	Short	Full	Short	Full	Short	Full
Honesty-Humility (*n* = 689)	**.11**	**.11**	*.09*	**.14**	**.21**	**.22**
Emotionality (*n* = 794)	-.04	-.01	**.29**	**.33**	**.09**	**.10**
Extraversion (*n* = 689)	**.24**	**.28**	*.08*	**.14**	**.13**	**.14**
Conscientiousness (*n* = 689)	**.45**	**.48**	**.15**	**.23**	**.23**	**.24**
Openness to Experience (*n* = 794)	**.73**	**.76**	**.79**	**.85**	**.60**	**.66**
Agreeableness (*n* = 689)	**.17**	**.19**	*.08*	**.15**	**.25**	**.24**
Altruism (*n* = 689)	**.25**	**.28**	**.30**	**.38**	**.38**	**.39**
Political Conservatism (*n* = 175)	**-.16**	**-.16**	**-.32**	**-.33**	**-.56**	**-.61**

Note. Bolded values are significant with the adjusted alpha of .05 for the sample size of 794 ($|r| \geq .09$, $p < .014$), 694 ($|r| \geq .09$, $p < .016$), and 175 ($|r| \geq .16$, $p < .033$). Italicized values are significant with an unadjusted alpha of .05 ($n = 794$, $|r| \geq .07$; $n = 694$, $|r| \geq .07$; $n = 175$, $|r| \geq .15$).

Figure 1. A network depicting the network-derived short form’s item coverage



Appendix

Network-derived Short Form

Item Key: Description (Openness to Experience inventory; network facet, network node label, reversed)

Intellect

1. enjoys playing with theories (NEO-PI-3[2]; Intellectual Curiosity, Id1)

2. loses interest when talking about abstract matters (NEO-PI-3; Intellectual Interests, Id3, reversed)

3. a lot of curiosity (NEO-PI-3; Intellectual Curiosity, Id6)

4. I am very quick at processing information (Woo et al.; Self-Assessed Intelligence, Ie8)

5. I can handle a lot of information (BFAS; Self-Assessed Intelligence, It6)

6. I learn things slowly (BFAS; Self-Assessed Intelligence, It9, reversed)

7. I would be very bored by a book about the history of science and technology (HEXACO-100-PI; Intellectual Interests, Iq3, reversed)

8. I find it boring to discuss philosophy (HEXACO-100-PI; Intellectual Interests, Uc2, reversed)

9. Tasks that require a lot of thinking confuse me easily (Woo et al.; Intellectual Interests, Ie1, reversed)

10. I continually strive to uncover information about topics that are new to me (Woo et al.; Intellectual Curiosity, Cu4)

[2] NEO-PI-3 items are shortened and obscured

Experiencing

1. range of emotions (NEO-PI-3; Openness to Emotions, Fe3)

2. keep thoughts realistic (NEO-PI-3; Fantasy, Fa5, reversed)

3. read poetry and feel chills (NEO-PI-3; Aesthetic Appreciation, NA3)

4. intrigued by art and nature (NEO-PI-3; Aesthetic Appreciation, NA5)

5. don't waste time daydreaming (NEO-PI-3; Fantasy, Fa4, reversed)

6. I would enjoy creating a work of art, such as a novel, song, or a painting (HEXACO-100-PI; Imaginative, Cr2)

7. I like coming up with imaginative plans (Woo et al.; Imaginative, Ig6)

8. I would rather have a job that involves creativity than one that doesn't (Woo et al.; Imaginative, Ig7)

9. Art bores me (Woo et al.; Aesthetic Appreciation, WA2, reversed)

10. I have been touched by a great musical performance (Woo et al.; Openness to Emotions, WA9)

Open-Mindedness

1. prefer familiar surroundings (NEO-PI-3; Variety-Seeking, Ac6, reversed)

2. better to stick to principles (NEO-PI-3; Variety-Seeking, Va7, reversed)

3. likes old-fashioned methods (NEO-PI-3; Variety-Seeking, Ac7, reversed)

4. hearing controversial speakers confuses and misleads (NEO-PI-3; Non-traditionalism, Va3, reversed)

5. I think it is rude when others speak in a language I can’t understand (Woo et al.; Non-traditionalism, To2, reversed)

6. Like most people, I am open to listening to what others have to say (Woo et al.; Diversity, To5)

7. I learn a great deal from people with differing beliefs (Woo et al.; Diversity, To7)

8. I enjoy diversity in the community (Woo et al.; Diversity, To8)

9. I believe in-depth discussions are a complete waste of time (Woo et al.; Non-traditionalism, Dp8, reversed)

10. little interest in speculating on the human condition (NEO-PI-3; Non-traditionalism, Id8, reversed)