Mapping the Creative Personality: A Psychometric Network Analysis of Highly Creative Artists and Scientists

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Conflict of interest

None of the authors have potential conflicts of interest to be disclosed.

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Abstract

Existing research has consistently supported a relationship between creative achievement and specific personality traits (e.g., openness to experience). However, such work has largely focused on univariate associations, potentially obscuring complex interactions among multiple personality factors, rendering an incomplete picture of the creative personality. We applied a psychometric network approach to characterize the multidimensional personality structure of highly creative individuals in the arts ("artists") and sciences ("scientists"), using data from three samples (N=4,015): college students, a representative adult sample, and the Big-C project of eminent creative professionals. Replicating past work, we found that artists showed reliably higher levels of openness to experience compared to scientists and a control group of less creative people. Psychometric network analysis revealed that artists were characterized by higher connectivity (i.e., co-occurrence) with other personality traits for openness, indicating that openness may be more heterogeneous in how it co-occurs with other personality traits in highly creative people. Across all three samples, we found that the scientists' personality network structure was more cohesive than the personality network of artists and the control group, indicating greater homogeneity in the personality characteristics of scientists. Our findings uncover a constellation of traits that give rise to creative achievement in the arts and sciences.

Keywords: psychometric networks, openness to experience, scientific creativity, artistic creativity, creative achievement

Introduction

Personality psychology has been a major avenue to addressing long-standing questions on the characteristics that distinguish highly creative individuals. Existing empirical and meta-analytic research has consistently supported a positive relationship between specific personality traits (e.g., openness to experience) and both creative ability (e.g., divergent thinking) and real-world achievement (Japardi et al., 2018; Karwowski & Lebuda, 2016; Kaufman et al., 2016; Lebuda et al., 2021b; McCrae, 1987; Puryear et al., 2017; Silvia et al., 2009; Zabelina et al. 2020). Many studies have also found that highly creative individuals in different domains (e.g., artists and scientists) show distinct and common personality characteristics. For instance, artists and scientists tend to be more open, flexible, and imaginative than less creative people, while artists show more variable affective traits than scientists, such as anxiety and sensitivity (Feist, 1998).

Although these investigations have provided important insights into the creative personality, such work has exclusively focused on correlating discrete personality traits with creative achievements, potentially obscuring complex, and multivariate interactions among multiple personality factors. Personality itself is a complex construct, characterized by multiple traits and mutual relationships among them (DeYoung, 2006; McCrae & Costa, 2008). This view has given rise to a network perspective of personality, providing higher resolution into the nature of and relations between multiple personality traits (Beck & Jackson, 2019, 2020; Christensen et al., 2020; Cramer et al., 2012; Wright et al., 2019). In the present research, we applied new methods in psychometric network analysis to map the constellation of personality traits, with a particular focus on creativity in the arts and sciences. We examined several samples of people ranging in creative achievement, from students to well-known creative professionals (e.g., award-winning musicians and prolific researchers), using network science to comprehensively characterize the personality profiles of high-achieving artists and scientists.

Decades of behavioral research have demonstrated that personality traits reliably predict present and future creative performance (Feist & Barron, 2003; Soldz & Vaillant, 1999). The most robust predictor of creativity—assessed as a cognitive ability (e.g., divergent thinking) and behavioral outcome (e.g., creative achievement)—is openness to experience (Oleynick et al., 2017). Open people are characterized by having flexible boundaries between beliefs, concepts, emotions, perceptions, and experiences (Rogers, 1954). Highly open people are more likely to pursue creative hobbies and report higher levels of creative achievement (Kaufman et al., 2016; Lebuda et al., 2021b; Silvia et al., 2014), and they show consistently better performance on creative thinking tasks (Beaty & Silvia, 2013; Prabhakaran et al., 2014; Silvia et al., 2008). In addition to openness, extraversion also relates to individual differences in creative performance. According to the Big Two framework of personality (DeYoung, 2006; Digman, 1997), *plasticity* (extraversion and openness) has a stronger association with creativity than *stability* (neuroticism, agreeableness, and conscientiousness; Feist, 2019; Karwowski & Lebuda, 2016; Puryear et al., 2017). More specifically, a combination of high plasticity and low stability showed the strongest prediction of creative cognition and achievement (Feist, 2019). Similar findings were found in a person-centered study which found that resilient people—with low neuroticism and high extraversion, openness, and conscientiousness—had significantly higher creative achievement than the ove-rcontrolled and under-controlled types (Lebuda et al., 2021a).

Personality predictors of creativity can also vary as a function of creative domain. For instance, although artists and scientists both exhibit higher levels of openness compared to less creative people, artists tend to show higher levels of affective traits than scientists (e.g., anxiety and aesthetic sensitivity), whereas scientists typically exhibit higher conscientiousness compared to non-scientists (Feist, 1998). In a recent study, linguistic analysis was used to estimate the personality profiles of Nobel Prize winners (N = 255) in the fields of art (i.e., literature) and science, and results revealed that artists (i.e., literary prize winners) exhibited greater openness, neuroticism, and less conscientiousness than scientists (Lebuda & Karwowski, 2021). Several studies investigated the independent predictive validity of the personality trait openness/intellect from the Big Five personality model for artistic and scientific creative achievement and consistently found that while openness (including affective engagement and aesthetic engagement) predicts creative achievement in the arts, intellect (including explicit cognitive ability and intellectual engagement) predicts creative achievement in the sciences (Kaufman, 2013; Kaufman et al., 2016; Lebuda et al., 2021b). These studies suggest that artistic and scientific creativity should be influenced by distinct personality structures.

The past few decades have thus yielded key discoveries about the personality correlates of creativity. However, a critical limitation of past work has been a strong reliance on univariate approaches to testing the relationship between a single personality trait and creativity, e.g., correlating a personality trait with a measure of creative performance. It is increasingly acknowledged that these approaches provide an incomplete picture of the human personality, which is complex and multivariate in nature (Gerlach et al., 2018). Moreover, constraining personality to broad traits has limited our understanding of what more specific characteristics may be more relevant for different outcomes (such as creative achievement; Mõttus, 2016; Revelle, Dworak, & Condon, 2021). Network science provides a powerful approach to characterizing the structure and function of complex systems such as personality (Costantini et al., 2018; Schmittmann et al., 2013). Networks have been widely studied in various disciplines, ranging from genetic and cellular networks to human cognitive and brain networks to sociological systems (Barabási, 2016; Siew et al., 2019; Sporns, 2011; Stam, 2014; Strogatz, 2001).

Recently, network science methods have been applied to the study of personality, providing a novel approach to quantifying interactive relationships among psychological variables (Beck & Jackson, 2019, 2020; Wright et al., 2019). In a network of psychological variables, *nodes* represent observed variables (e.g., items, traits, or factors of measure) and *edges* represent associations (correlations) between pairs of observed variables (Christensen et al., 2018; Cramer et al., 2012; Epskamp et al., 2018). This approach is based on applying network science methods to analyze psychometric questionnaires, allowing us to quantify the structure and dynamics of multidimensional psychological constructs such as personality (Beck & Jackson, 2019).

Psychometric network analysis is increasingly used to quantify the complex relationships among personality traits and psychiatric symptoms (Beck & Jackson, 2020; Borsboom, 2017; Borsboom & Cramer, 2013; McNally, 2016). We view personality as a complex system, where components interact and mutually reinforce one another (Cramer et al., 2012; Costantini et al., 2018). From this perspective, personality traits are emergent properties that summarize the covariation between unique personality components (i.e., characteristics that have unique causes; Christensen, Golino, & Silvia, 2020). For example, Costantini and Perugini (2016) reported that all conscientiousness facets seemed to be characterized by two shared features, self-control (e.g., industriousness and impulse-control) and the orientation towards the future (e.g., the consideration of future consequences) by means of network analysis, indicating that these two facets may be particularly important in the emergence of conscientiousness. Psychometric network analysis has also been applied to study the so-called “Dark Triad” of personality, demonstrating that interpersonal manipulation and callousness occupied central positions among a set of dark personality traits (Marcus et al., 2018). In sum, network science tools not only capture the most central traits among sets of psychological variables, but also offer insight into how and why personality changes over time (Costantini et al., 2019; McNally et al., 2015).

Here, we leverage psychometric network analysis to quantitatively characterize the personality structure of highly creative individuals in the arts and sciences. We aim to identify the core characteristics of the “creative personality” as well as distinct personality profiles of artists and scientists. This latter aim extends beyond between-person personality into assessing “archetypes” or kinds of people where group characteristics may diverge from the traditional population personality structure (e.g., the five-factor model). First, across three samples, we applied clustering analyses to classify individuals into three groups: high-achieving artists (hereafter, “artists”), high-achieving scientists (hereafter, “scientists”), and a less creative group (hereafter, the “control group”)—based on participants’ self-reported creative achievement in the arts and sciences. Next, we sought to replicate past work reporting differences among the three groups on the Big-Five personality dimensions (e.g., Feist, 1998; McCrae, 1987; Lebuda & Karwowski, 2021) hypothesizing that artists would be higher in openness and extraversion compared to scientists and the control group, whereas scientists would be higher in conscientiousness compared to artists and the control group, and higher in openness than the control group. We then conducted a series of psychometric network analyses to model and compare the personality networks among the three groups. Specifically, we used network percolation analysis (removal of edges from a personality network with an increasing threshold) to examine the extent to which the networks remained a cohesive personality system, providing evidence for the homogeneity of the personality characteristics in the groups’ networks. Recent studies demonstrate that percolation analysis is a powerful way to quantitatively examine cognitive phenomena, such as memory structure in Alzheimer’s disease patients (Borge-Holthoefer et al., 2011) and the semantic memory networks of low and high creative individuals (Kenett et al., 2018). In addition, we used graph analysis to quantify the interaction between dimensions. Our analyses leveraged diverse samples with varying levels of creative accomplishment which included over 4,000 individuals completing both personality and creative achievement questionnaires. The whole sample consisted of two representative adult samples and a sample of renowned creative professionals (e.g., award-winning artists and eminent scientists).

Methods

Participants

The characteristics of the three samples included in this study are depicted in Table 1. The first sample (Sample 1) came from the Southwest University (SWU), which consists of data from healthy young adults who participated in one of the following projects: the SWU Longitudinal Imaging Multimodal project (Liu et al., 2017), the Gene-Brain-Behavior project (Chen et al., 2019; Zhuang et al., 2021), and the Behavioral Brain Research Project of Chinese Personality (He et al., 2021). This sample consisted of 2554 participants (1699 females, age = 19.04 ±1.41) who completed assessments related to creative achievement and personality.

The second sample (Sample 2) is a publicly available data consisting of 1344 participants (https://osf.io/aymje; Sutu et al., 2019), in which 1315 participants (888 females, age = 22.74± 6.37) completed both creative achievement and personality measurements, and a set of demographic questions including race, social-economic stage, parental education attainment, and general cognitive ability (measured by SAT-math and SAT-writing). Previous studies report that individual creative achievement is influenced by several extraneous factors, including family environment (e.g., social-economic stage, educational attainment (Piffer & Hur, 2014) and intelligence (Benedek et al., 2014). In Sample 2, we performed clustering analyses after adjusting for several confounding variables, including sex, age, race, social-economic stage, parental education attainment, and general cognitive ability (measured by SAT-math and SAT-writing), which may have influenced the pattern of results reported in Sample 1. Sample 2 is somewhat more representative of the general population compared to Sample 1 in terms of age distribution (Sample 1 was college students).

The third sample (Sample 3) was provided by the Big-C Project (Japardi et al., 2018; Knudsen et al., 2019) consisting of 117 participants (51 females, age range: 21-60). The Big-C Project includes internationally renowned individuals with high levels of creative achievement in the arts and sciences. Artists (N = 37) included individuals renowned for their achievements in the visual arts and music; scientists (N = 38) included researchers with multiple high-quality publications, inventions, or both. All Big-C artists and scientists additionally were identified by other experts in their domains as demonstrating novel contributions (Japardi et al., 2018). In addition, 42 individuals formed a “smart comparison group” (hereafter, the “control group”), matched to the high-achieving artists and scientists on parental educational attainment and estimated intelligence.

Table 1 Overview of samples and measures

		Sample 1	Sample 2	Sample 3
Size		2554	1315	117
Sex	Male	855	427	66
	Female	1699	888	51
Age	Mean	19.04±1.41	22.74± 6.37	40.5
Test	Creativity	CAQ	CAQ	CAQ
	Personality	NEO-PI-R[1]	BFI[2]	IPIP-NEO[3]

Note: [1]The Revised NEO Personality Inventory (240 items; Costa & McCrae, 1992); [2]Big Five Inventory (44 items; John & Srivastava, 1999); [3]International Personality Item Pool Representation of the NEO PI-

R (120 items; Goldberg et al., 2006).

Materials

Creativity Assessment. Across all three samples, the Creative Achievement Questionnaire (CAQ; Carson et al., 2005) was used to assess individual creative accomplishments in multiple domains. The CAQ is a production-based and well-validated measurement (Silvia et al., 2012), consisting of 96 items divided into three parts. In part one, participants are asked to indicate which areas they have greater self-perceived talent than the average person in 13 specified domains. Part two assessed individual creative accomplishments in 10 specified domains: visual arts, music, dance, architectural design, creative writing, humor, inventions, scientific discovery, theater, and culinary arts. Each domain (e.g., creative writing) contains eight items in which different achievement statements were described from “no accomplishment” (e.g., “I do not have training or recognized talent in creative writing”) to “top accomplishment” (e.g., “my work has been reviewed in national publications”). Participants were required to report which items corresponded to their accomplishments. For several of the items, participants were instructed to indicate how many times this accomplishment had been achieved if it was endorsed (e.g., number of publications). Part three asked participants to indicate any other domains (not listed in part two) in which they had accomplishments.

In the present study, we focused on data from part two of the CAQ, consistent with past work. For each domain, a domain achievement score was derived by summing the eight items. Then, a total (domain-general) CAQ score was derived by summing across all eight domains. Notably, the CAQ commonly yields a highly skewed distribution as only a small number of people have high-level achievements (Carson et al., 2005; Silvia et al., 2009). We divided creative achievements into two domains—artistic and scientific creativity—consistent with the original CAQ principal components analysis (Carson et al., 2005). Artistic creativity included drama, dance, humor, music, visual arts, and creative writing; scientific creativity included invention, scientific discovery, and culinary (Carson et al., 2005). To mitigate the skewed distribution in creative achievements, we applied natural logarithmic conversion *[ln(x+1)]* (Silvia et al., 2012).

Personality Assessment. Sample 1 used the Revised NEO Personality Inventory (NEO-PI-R) to assess individual personality, which is a widely used measure of the Five-Factor Model (FFM). The NEO-PI-R was developed through lexical and factor-analytic methods and is comprised of 240 self-report items with responses using a 5-point Likert scale, ranging from 1 (*disagree strongly*) to 5 (*agree strongly* (Costa & McCrae, 1992). The five domains of the NEO-PI-R are neuroticism, extraversion, openness, agreeableness, and conscientiousness. Each domain includes six facet-level traits assessed with eight items. Here we used the Chinese version of the NEO-PI-R, revised by Yang et al. (1999), which has good reliability and validity among the Chinese population.

In sample 2, personality was assessed with the 44-item Big Five Inventory (BFI-44; (John & Srivastava, 1999), a brief measure of the Big-Five, with 8-10 items per dimension. Like the NEO-PI-R, the BFI-44 is a self-report questionnaire with a 5-point Likert scale, ranging from 1 (*disagree strongly*) to 5 (*agree strongly*). The BFI-44 has suitable validity and high convergent validity with other self-report scales (John & Srivastava, 1999).

In sample 3, personality was assessed with the 120-item IPIP-NEO-PI-R (Maples et al., 2014), a Five-Factor Model inventory with five dimensions and thirty facets from the NEO Personality Inventory (Costa & McCrae, 1992). The 120-item IPIP-NEO-PI-R has demonstrated good internal consistency and convergence with the full-scale NEO. For each of the 120 items, participants were asked to rate themselves “as you generally are now” using a 5-point Likert scale, ranging from 1 (*very inaccurate*) to 5 (*very accurate*).

Classifying participants into groups

We classified individuals in our samples into three groups—artists, scientists, and control group—based on the z-score values of their CAQ art and science scores. This was achieved using the Affinity Propagation (AP; Frey & Dueck, 2007) clustering algorithm to discover latent creative achievement groups with the *apcluster* package in R (Bodenhofer et al., 2011). AP is a non-hierarchical clustering method that uses a message-passing algorithm recently introduced for applications to psychological research. It has several advantages over common clustering methods (e.g., k-means clustering), such as (1) applying to multiple types of data; (2) using the algorithm to determine the number of clusters in the data; and (3) high computational efficiency. During the AP clustering process, a similarity matrix is used as input, which is defined as the negative of the Euclidean distance between the data points. In our study, the pairwise similarities were estimated by any two participants based on their art and science scores, resulting in a symmetric similarity matrix. Next, the AP algorithm iterated through the similarity matrix by alternating between data points to compute availability and responsibility matrices, and finally, a set of exemplars and corresponding clusters was determined using the minimum similarity as a constraint. Briefly, AP clustering determines the number of clusters without an a priori number of clusters, thus yielding a data-driven set of clusters. Subsequently, quartile deviation was calculated to obtain a low-creative achievement group (lower 3st quartile) and a high-creative achievement group (upper or equal to 3st quartile); to separate clusters from the AP clustering, we used a z-score cutoff of .5, which is between the low and high creative achievement groups, resulting in four groups. We also excluded the rare group with high art and science achievement in the following analysis because this group was not consistently identified in all datasets. This group was particularly underrepresented in the Big-C dataset, which recruited prominent artists and scientists (but not both).

Psychometric network analysis

Network construction. The polychoric correlation was used to estimate different group-based personality networks, where nodes represent the individual items in the personality assessment questionnaire (e.g., NEO-PI-R), and edges represent endorsement associations between items. Given that most of the edges will have noise (e.g., weak correlation value) and thus possible spurious associations, we applied the Triangulated Maximally Filtered Graph (TMFG; Christensen, 2018; Massara et al., 2016) using the *NetworkToolbox* package in R (Christensen, 2018) to minimize the these connections and capture the most relevant information. The TMFG algorithm firstly constructs a tetrahedron (i.e., a subnetwork) by connecting the four nodes which have the highest sum of correlations to all other nodes in the personality network. Next, the algorithm identifies a new node and adds it into the seminal tetrahedron by maximizing its sum of correlations to other nodes already in the subnetwork. Last, every node is gradually added to the network through iteration. The resulting network is a fully connected network with a certain number of edges (3n–6, where n is the number of nodes) that could be determined such that no edges are crossing (Tumminello et al., 2005). Thus, the TMFG algorithm avoids the confound of personality network structures being due to the same number of edges between different groups (Christensen, 2018; van Wijk et al., 2010). Furthermore, one property of these networks is that they form a "nested hierarchy" such that its constituent elements (3-node cliques) form sub-networks in the overall network (Song et al., 2012). TMFG is increasingly applied to psychometric network literature because it is computationally efficient and statistically robust, with several studies showing that TMFG is an appropriate choice for modeling interrelationships between psychological constructs, such as personality traits and semantic memory (Cosgrove et al., 2021; Christensen et al., 2019; Golino et al., 2022; Li et al., 2021).

Network visualization. The layout of the network for visualization was based on the Fruchterman-Reingold algorithm (Fruchterman & Reingold, 1991) using the *qgraph* R package (Epskamp et al., 2012). In these networks, the nodes with stronger connections are located at the center of the graph, and the nodes with weak connections are located at the periphery. For edges, thicker connections represented a stronger relationship, whereas thinner connections represented a weaker relationship.

***Interaction between the theoretical dimensions*.** To assess the interactive characteristics of the theoretical personality dimensions in the empirical networks, we calculated (for each item) the "out-module degree"—the number of edges connected to a given node with other nodes in other dimensions. Higher out-module degree indicates more interaction of one personality trait with others. In this way, we measure the heterogeneity for each traditional dimension in each group, and the interactive characterization between different dimensions. Moreover, we created 1000 random personality networks from the filtered personality network in each group with preserved weight and degree distributions using the function 'null_model_und_sign' of the Brain Connectivity Toolbox (Rubinov & Sporns, 2010; http://www.brain-connectivity-toolbox.net/), yielding a distribution of difference values between two groups for out-module degree in each dimension. In this way, significant differences between-groups were defined as only 5% of the randomly-produced value that exceeded the real difference value for each dimension.

***Network Percolation Analysis*.** The network percolation analysis was used to measure the process in which the structure of the network “breaks apart”, by removing links in the network with an increasing threshold (Borge-Holthoefer et al., 2011; Kenett et al., 2018; Cosgrove et al., 2021). This approach could be seen as a simulated attack to the personality network by applying a threshold from 0 (i.e., the smallest weight) to 1 (the largest weight) with a step of 0.1, in which the number of connected components will decrease with the increasing threshold. Here, the smallest possible connected component would consist of at least three nodes (Derényi et al., 2005); otherwise, nodes within the component would be seen as disconnected. In this way, we can compute the change in the number of nodes of connected components with an increasing threshold. The area under the curve (AUC) of the percolation process was used to measure network stability, representing how quickly the personality networks break apart. For example, a personality network with a higher AUC will have a more stable personality structure than a network with a lower AUC. To examine the robustness of the percolation integral, we randomly removed links between pairs of 10% nodes in the three groups (independently) and reiterated this process 1000 times. In each iteration, we calculated the percolation integral for each personality network.

We performed a profile correlation analysis (Luo et al., 2008) for each group, and conducted t-tests to assess differences in personality similarity among the three groups. The profile correlation analysis involved transposing the personality items of each group, such that items are across the rows and participants are down the columns. Then, we computed Pearson correlation matrices and performed t-tests on the lower triangle of these matrices between groups. Conceptually, the percolation analysis captures how homogeneous the response patterns are across people in each group, which is similar to the profile correlation analysis. We would expect a stable personality structure to show larger correlations on average between people (i.e., more homogeneous response patterns) than one with unstable personality structure.

***Group difference statistical analysis*.** We tested for group differences in creative achievement scores in art and science, dimensions of personality, and network measures via a one-way analysis of variance (ANOVA) in JASP0.13. Post-hoc pairwise comparisons between any two groups were conducted if the main effect was statistically significant ($p < .05$).

Results

To form creative achievement groups for subsequent analyses, we first conducted the AP clustering approach on the CAQ data of Sample 1 (Fig. 1A). This analysis resulted in nine clusters, and each cluster had a representative exemplar determined by both artistic and scientific creative achievement scores. Then, four groups were identified by applying the cutoff line to separate the mean values of those clusters (Fig. 1B). In the following analysis, three expected groups were identified, consistent with our hypotheses: scientists (n = 264), artists (n = 463), and control group (n = 1441). The data-driven differences in creative achievement among three groups (Fig. 1C) were confirmed with a one-way ANOVA revealing a significant main effect of group in artistic, $F(2,2165) = 1657.95$, $p < .001$, $\eta^2 = .605$, and scientific creative achievement, $F(2,2165) = 1027.44$, $p < .001$, $\eta^2 = .487$. Post-hoc tests showed that the artist group indeed had the highest score in artistic creative achievement when compared to scientists, $t(725) = 38.02$, $p < .001$, Cohen's d = 1.922, and the control group, $t(1902) = 56.76$, $p < .001$, Cohen's d = 2.9, whereas there was no difference between scientists and control group on artistic creativity, $t(1703) = 1.49$, $p = .295$, Cohen's d = 0.175. Likewise, scientists had the highest score in scientific creative achievement compared to artists, $t(725) = 37.26$, $p < .001$, Cohen's d = 1.832, and the control group, $t(1703) = 44.88$, $p < .001$, Cohen's d = 2.771, and artists showed marginally higher score on scientific creativity than the control group, $t(1902) = 2.45$, $p = .05$, Cohen's d = 0.245.

The same approach was applied in Sample 2 (Fig. S1A&B) and three groups were identified: scientists (n = 161), artists (n = 202), and the control group (n = 784). A one-way

ANOVA revealed a significant main effect of group for both artistic, $F(2,1144) = 743.77$, $p < .001$, $\eta^2 = .565$, and scientific, $F(2,1144) = 1339.09$, $p < .001$, $\eta^2 = 0.701$, creative achievement. Post hoc tests (Fig. S1C) revealed that artists had the highest score in artistic creative achievement compared to scientists, $t(361) = 15.58$, $p < 0.001$, Cohen's d = 2.181, and the control group, $t(984) = 37.65$, $p < .001$, Cohen's d = 2.813, whereas no difference between scientists and control group were found, $t(943) = 1.20$, $p = .694$, Cohen's d = 0.146; likewise, scientists had the highest score in scientific creative achievement compared to artists, $t(361) = 41.58$, $p < .001$, Cohen's d = 2.472, and the control group $t(943) = 50.59$, $p < .001$, Cohen's d =4.002, whereas no difference between artists and the control group was found for, $t(984) = 0.09$, $p = .996$, Cohen's d = 0.082. These univariate results replicate the findings from Sample 1.

In Sample 3 (Big-C), participants were a priori classified into artists (N = 37), scientists (N = 42), and control group (N = 38; Fig. S2A). As expected, a significant main effect was found for both artistic, $F(2,144) = 6.59$, $p = .002$, $\eta^2 = .104$, and scientific, $F(2,114) = 3.83$, $p = .025$, $\eta^2 = .063$, creative achievement. Post hoc tests (Fig. S2B) revealed that artists (2031.16±4960.8) scored significantly higher in artistic creative achievement than scientists (6.75±8.97), $t(77) = 3.22$, $p < .01$, Cohen's d = 0.456, and the control group (32.4±27.31), $t(73) = 3.1$, $p < .01$, Cohen's d = 0.57; no difference between scientists and the control group was found for artistic achievement. Likewise, scientists (389.79±1076.49) scored significantly higher in scientific achievement than artists (4.81±8.51), $t(77) = 2.65$, $p < .05$, Cohen's d = 0.49, and the control group (4.66±7.59), $t(78) = 2.66$, $p < .05$, Cohen's d = 0.493; no difference between artists and the control group were found for scientific achievement. These univariate results replicate the findings from Sample 1 and Sample 2.

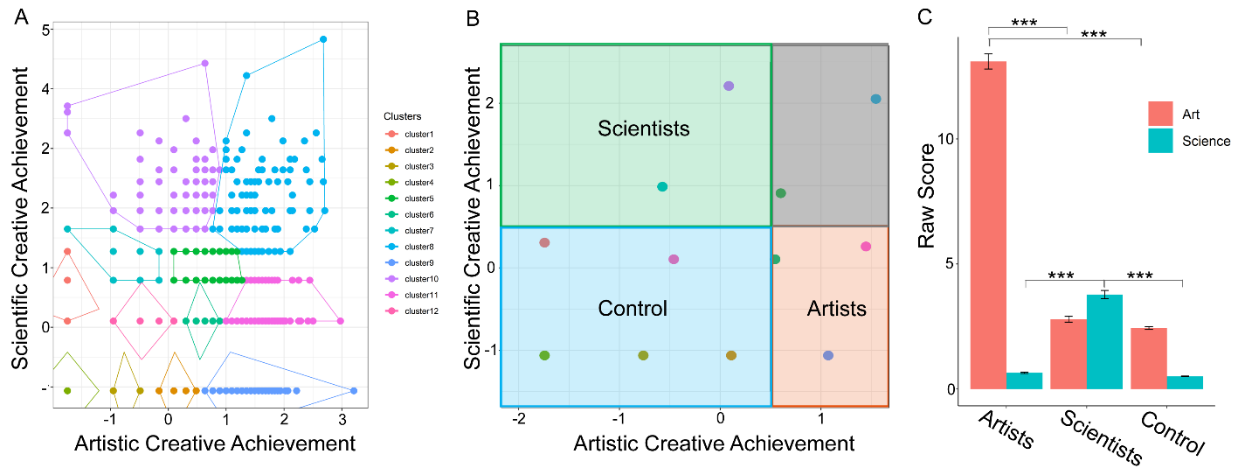

Fig. 1. Clustering analyses and univariate analyses in sample 1. (A) AP clustering analyses generates nine clusters. (B) Crosswire plot with 0.5 z-score cutoff results in four groups. (C) Group differences in artistic and scientific creative achievement among the three expected groups (i.e., artists, scientists, and control group). *** p < .001.

Next, we examined differences in the Big Five dimensions of personality among the three groups in Sample 1 (Fig. 2A & Table S2). Consistent with past work (Feist, 1998; Kaufman et al., 2016; Puryear et al., 2017; Silvia et al., 2009), we found a significant main effect of group for openness, F(2,2165) = 79.2, p < .001, η^2 = .068. Post-hoc t-test analyses revealed that openness in artists (3.49±0.30) was significantly higher than in scientists (3.36±0.30), t(725) = 5.33, p < .001, Cohen's d = 0.43, and the control group (3.28±0.32), t(1902) = 12.5, p < .001, Cohen's d = 0.664; and scientists showed significantly higher openness than the control group, t(1703) = 3.84, p < .001, Cohen's d = 0.254. Meanwhile, there was significant difference among the three groups for neuroticism, F(2,2165) = 6.94, p < .001, η^2 < .006; extraversion, F(2,2165) = 17.08, p < .001, η^2 = .016); agreeableness, F(2,2165) = 9.66, p < .001, η^2 = .009; and conscientiousness, F(2,962) = 4.19, p < .05,

η^2 = .009. More details and post-hoc *t*-test analyses show in Table S2.

In Sample 2 (Fig. 2B & Table S3), we found a significant main effect of group for openness, $F(2,1144) = 36.61$, $p < .001$, $\eta^2 = .06$, and extraversion, $F(2,1144) = 12.43$, $p < .001$, $\eta^2 = .021$. Post-hoc *t*-test analyses revealed that openness in artists (3.80±0.56) was significantly higher than in scientists (3.46 ± 0.48), $t(361) = 6.04$, $p < .001$, Cohen's d = 0.661, and the control group (3.44±0.55), $t(984) = 8.46$, $p < .001$, Cohen's d = 0.657; there was no significant difference between scientists and the control group in openness (p = 0.94). Extraversion was significantly higher for artists (3.44 ± 0.75) than scientists (3.20 ± 0.68), $t(361) = 2.95$, $p < .005$, Cohen's d = 0.323, and compared to the control group (3.14 ± 0.76), $t(984) = 4.99$, $p < .001$, Cohen's d = 0.388. There was no significant difference between scientists and the control group in extraversion ($p = 0.61$). We found no significant difference among the three groups for neuroticism, $F(2,1144) = 0.17$, $p = .844$, $\eta^2 < .001$, agreeableness, $F(2,1144) = 0.48$, $p = .621$, $\eta^2 < .001$, and conscientiousness, $F(2,1144) = 2.04$, $p = .13$, $\eta^2 = .004$), partially replicating findings from Sample 1.

In Sample 3 (Fig. 2C & Table S4), we found no significant difference among the three groups for neuroticism, $F(2,114) = 1.32$, $p = .27$, $\eta^2 = .023$, extraversion, $F(2,114) = 0.28$, $p = .76$, $\eta^2 = .005$, and agreeableness $F(2,114) = 0.47$, $p = .63$, $\eta^2 = .008$. There was a significant main effect of group for openness, $F(2,114) = 6.96$, $p = .001$, $\eta^2 = .109$, and for conscientiousness, $F(2,114) = 3.46$, $p = .035$, $\eta^2 = .057$. Post-hoc *t*-test analyses revealed that artists (4.19 ± 0.35) showed higher openness than scientists (3.91 ± 0.47), $t(77) = 2.68$, $p = .023$, Cohen's d = 0.649, and the control group (3.81 ± 0.51), $t(73) = 3.61$, $p = .001$, Cohen's d = 0.857, whereas there was no significant difference between scientists and the control group in openness (p = .56); scientists (4.09 ± 0.48) showed higher conscientiousness than the control group (3.80 ± 0.49), $t(78) = 2.57$, $p = .03$, Cohen's d = 0.60, whereas there was no significant difference between scientists and artists (p = .20). These results replicate past work (Feist, 1999) and partially replicate our findings in Sample 1 and Sample 2 with a sample of exceptionally creative individuals.

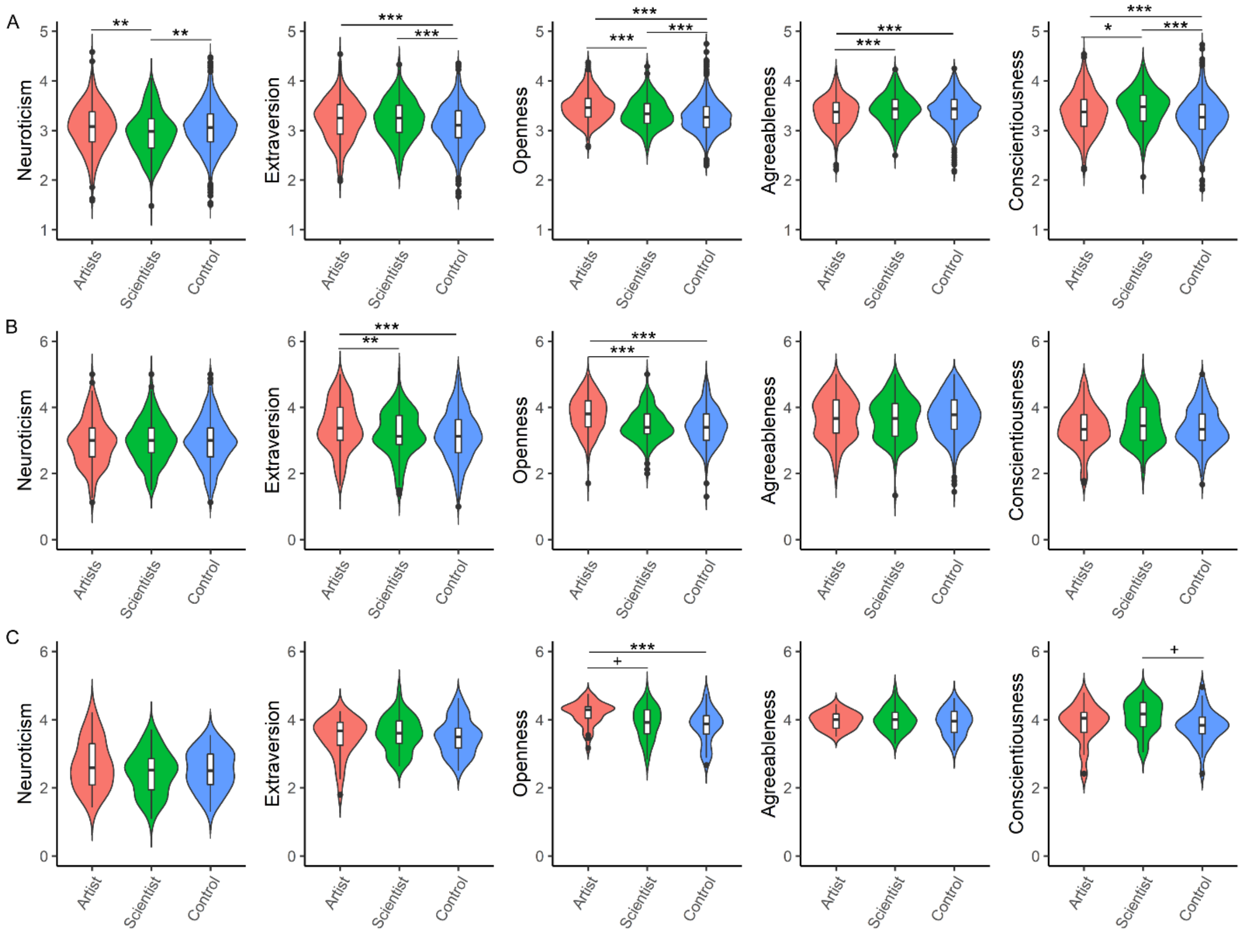

Fig. 2. Group differences in five dimensions of personality among the three groups. (A) Sample 1. (B) Sample 2. (C) Sample 3. $^{+}$ - p < 0.1, ** - p < .005, *** - p < .001.

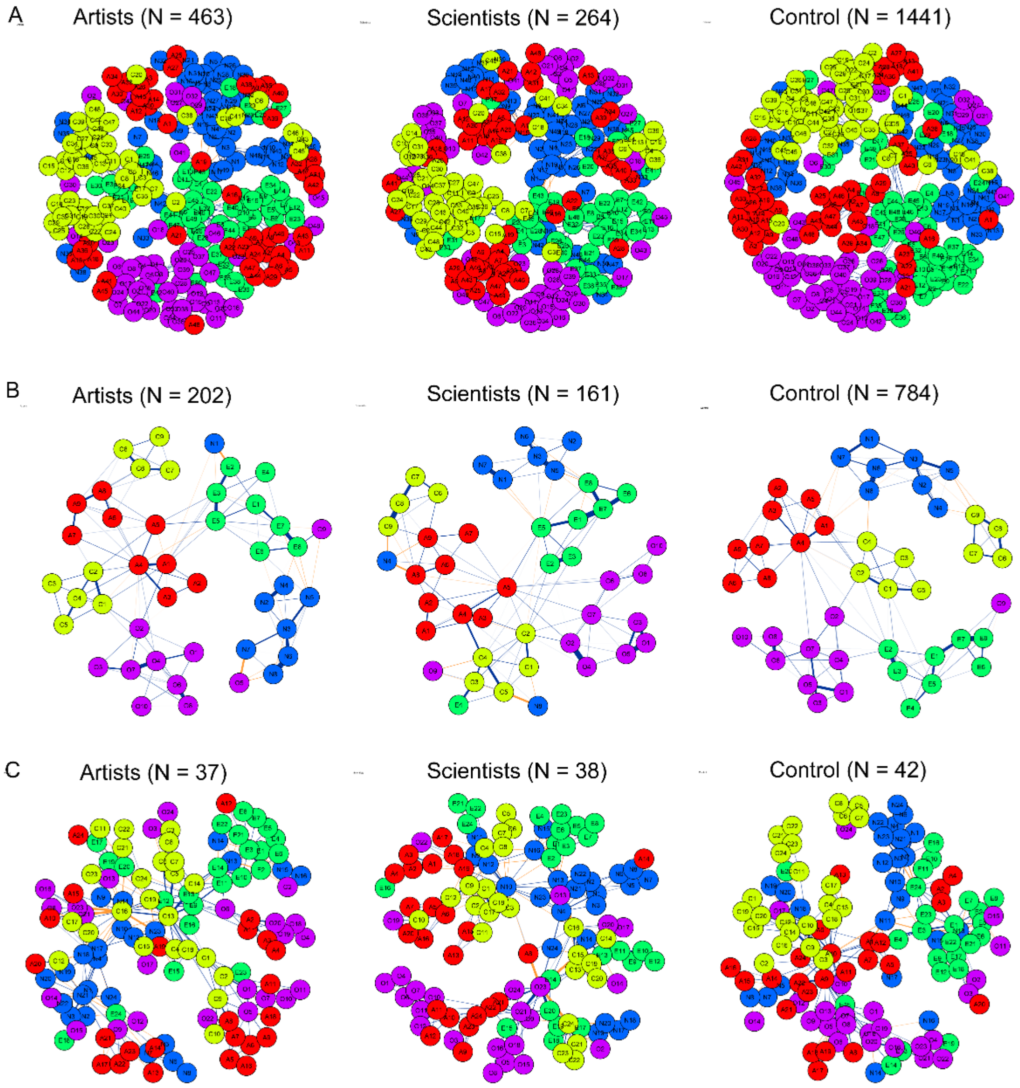

Fig.3. Psychometric network estimation among groups in three samples. Each node represents an item, each edge represents the polychoric correlations between two items, and the colors of the nodes correspond to detected dimensions in the personality network. Blue = Neuroticism; Green = Extraversion; Purple = Openness; Red = Agreeableness; Yellow = Conscientiousness. The Fruchterman-Reingold layout is used to display the results.

Next, we estimated and compared the personality networks of the different groups across the three samples. In Sample 1, the estimated networks contained 240 nodes and 714 edges (Fig. 3A). To assess the interactive characteristics between personality dimensions in the empirical networks, we calculated the out-module degree for each dimension. As shown in Table S8, artists (O = 1.58; p = .05) and scientists (O = 1.77; p = .03) show significantly high out-module degree than the control group (O = 1.1) for openness; and scientists (A = 2.44) show significantly higher out-module degree than the control group (A = 1.65) for agreeableness (p <*.005*). In sample 2, the personality networks of the three groups contained 44 nodes and 126 edges (Fig. 3B). Artists (1.75; p = .08) and scientists (2; p = .003) show relatively higher out-module degree than control group (1.5) in neuroticism (details show in Table S8). In addition, artists (1.2) have a higher out-module degree than control group (0.9) and scientists (1) in openness, albeit statistically insignificant. In sample 3, the personality networks of the three groups contained 120 nodes and 254 edges, and nine dimensions (Fig. 3C). Artists (3.25) show marginally higher out-module degree in openness than the control group (2.07, p < .001) but not scientists (3.04, p = .78); artists (3.79) and scientists (3.08) show significantly higher out-module degree in conscientiousness than the control group (2.04, p < .001); scientists show low out-module degree than artists in neuroticism (3.21, p = .007) and the control group in extraversion (3.5, p < .001). Notably, the control group (3.88) show higher out-module degree in agreeableness than artists (2.54, p < .001) and scientists (3.08, p < .001). Thus, across three samples with different personality scales, we found that artists show a relatively higher out-module degree than controls for openness, indicating that for highly creative artists, openness has a more dispersed connectivity in the personality network and more combinations of different traits within other dimensions.

Finally, to assess and compare the cohesiveness of the personality networks among the three groups, we applied the percolation analysis on the personality networks in all three samples. This was achieved by randomly removing edges between pairs of 10% of the nodes in the three networks (independently, iterated 500 times). In each iteration, we applied network percolation analysis by increasing edge thresholds from 0 to 1, with steps of .01 to calculate the percolation integral (i.e., AUC) for each network. In Sample 1, an independent samples *t*-test analysis found that the percolation integral in scientists (113 ± 1.34) was significantly higher than artists (112.43 ± 1.36), $t(998) = 6.62$, $p < .001$, and the control group (107.75 ± 1.24), $t(998) = 64.22$, $p < .001$. We also found that the percolation integral in the artists' network was significantly higher than the control group, $t(998) = 56.77$, $p < .001$ (see Fig. 4A).

The same analyses for Sample 2 (see Fig. 4B) revealed that the percolation integral in scientists (8.89 ± 0.37) was significantly higher than the percolation integral in the artists' network (8.48 ± 0.36), $t(998) = 17.30$, $p < .001$, and in the control group (8.64 ± 0.32), $t(998) = 11.15$, $p < .001$. In addition, the percolation integral in the control group was significantly higher than in the artists network, $t(998) = 7.19$, $p < .001$, partially replicating Sample 1 and indicating a more cohesive personality network in scientists. In Sample 3 (see Fig. 4C), the percolation integral of the scientists (72.00 ± 1.20) was marginally higher than that in the artists network (71.85 ± 1.31), $t(998) = 1.92$, $p = .055$; the percolation integral in the control group (69.12 ± 1.18) was significantly lower than in the artists network, $t(998) = 34.62$, $p < .001$ and the scientists network $t(998) = 38.24$, $p < .001$. These results replicate Samples 1 and 2 and suggest that the personality structure of scientists is more cohesive than artists and less creative people.

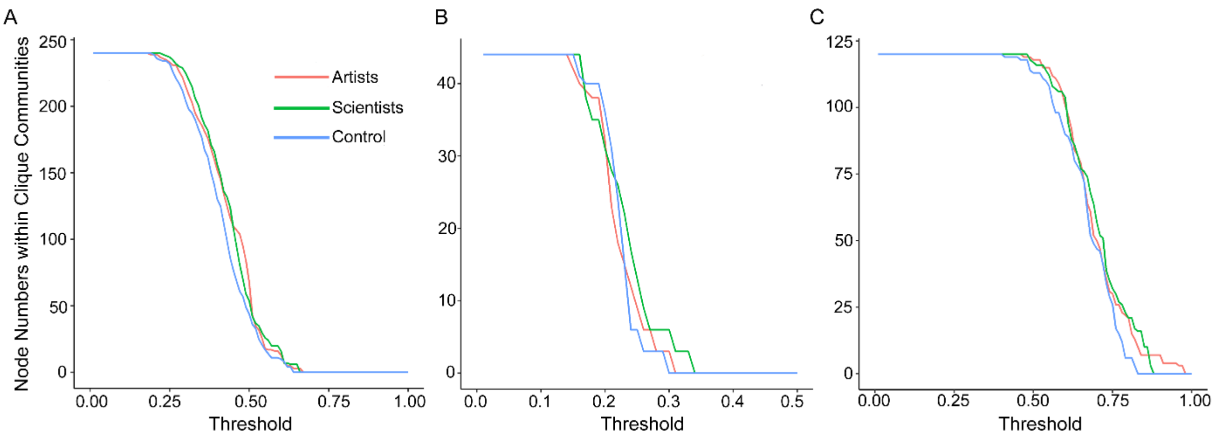

Fig.4. Percolation analysis of personality networks in artists (pink line), scientists (green line), and control group (blue line) among three samples.

The profile correlation analysis showed that scientists have more homogeneous response patterns in personality items than the control group across all three samples (see Table S6). Scientists also show more homogeneous response patterns in personality items than artists in Sample 2, $t(31669) = 2.265$, $p = .023$, and Sample 3, $t(1405) = 6.09$, $p < .001$; in Sample 1, artists have more homogeneous response patterns in personality items than scientists, $t(141667) = 2.82$, $p = .005$. In addition, there was no significant difference between artists and the control group in the homogeneous response patterns of personality items except for Sample 1, $t(1144471) = 44.44$, $p < .001$. These results generally point to a trend toward greater cohesion of personality structure in scientists.

Discussion

Across three samples, we provide the first network-based analysis of the relationship between personality and creativity. Psychometric network analysis was applied to identify and compare personality network characteristics among artists, scientists, and a (less creative) control group, classified by cluster analysis. As expected, a univariate analysis showed reliably higher levels of Openness to Experience in artists, compared to scientists and the control group, consistent with previous findings (Feist, 1998; Kaufman et al., 2016; Puryear et al., 2017; Silvia et al., 2009).

Critically, scientists were the most homogeneous in their personality characteristics than artists across three samples, exhibited by higher cohesiveness in the percolation analysis of their personality network. In addition, across all three samples, artists were characterized by a higher out-module degree in Openness, indicating higher connectivity (co-occurrence) of Openness with other personality traits. In conjunction with univariate analysis, this seems to suggest that Openness to Experience is a common trait across artists, such that other traits and characteristics tend to co-occur or extend from it. That is, Openness to Experience may operate as a "base" personality trait in artists. Taken together, highly creative individuals may be characterized by complex personality networks, with scientists showing a personality network that is significantly more homogeneous across people in the group compared to artists.

The complex relations between personality dimensions and creativity

To understand the complex relationship between personality dimensions and creativity, especially the interaction patterns of Openness, we further explored out-module degree of each personality dimension across the three samples. We found that artists are characterized by a higher out-module degree in openness. Using a theoretically sorting and meta-analytic approach, Connelly et al. (2014) identified 11 components related to openness to experience, including four core (aestheticism, openness to sensations, non-traditionalism, and introspection) and seven compound components (openness to emotions, innovation, variety-seeking, fantasy, tolerance, autonomy, and thrill-seeking). Similarly, Christensen et al. (2019) identified 10 components (aesthetic appreciation, diversity, fantasy, imaginative, intellectual curiosity, intellectual interests, non-traditionalism, openness to emotions, self-assessed intelligence, and variety-seeking) using a bottom-up network analytic approach, which is largely consistent with Connelly and colleagues' who used a top-down meta-analytic approach. These findings suggest that openness is a complex trait characterized by multiple components related to a broad range of human experience (Christensen, 2020), resulting in more possible interactions with other personality traits in a personality network—as was found for the out-module degree of openness in the present research. Our result is in line with another study on the four-factor model of openness and creative achievement, reporting that both affective engagement and aesthetic engagement were positively related to creative achievement in music, dance, theater, and film (Kaufman, 2013). Taken together, we posit that the personality network of artists is organized around openness to experience, whereby other traits "build on" it. Said differently, openness to experience is the foundation of the artistic personality and other personality characteristics extend from it.

Openness is also linked to neurocognitive characteristics that have been implicated in creative thinking. For example, neuroscience findings suggests that high openness is associated with more efficient functioning of the brain's default mode network, which supports mind-wandering, future thinking, and creative idea production and shows high connectivity with other cognitive brain networks, such as executive, salience, and dorsal attention networks in highly open people (Beaty et al., 2018; Beaty et al., 2016). In addition, highly open and creative individuals both tend to exhibit more interconnected semantic memory networks, which may allow them to flexibility connect concepts to come up with creative ideas (Christensen et al., 2018; Kenett et al., 2014; Kenett & Faust, 2019). Taken together, our findings indicate that the unified personality for artists is characterized by interactive patterns of multiple cognitive and affective traits, with openness as the core.

Percolation of personality networks

Interestingly, percolation analysis revealed that scientists have a more cohesive network structure across all three samples. Specifically, the cohesiveness of the scientists' networks was always higher than the artists' networks. From a network perspective, the percolation analysis quantifies the extent to which the network remains a cohesive system that derives from the strong inter-item correlation within and between personality dimensions, thereby resulting in a more stable personality structure. From a psychological perspective, this can be interpreted as the extent to which personality characteristics are homogeneous across the group. For example, the personality network of older adults exhibits increased number and magnitude of connections compared to younger adults, meaning that the personalities are less complex and emerged a more unified structure among older adults (Beck et al., 2022). Therefore, the faster the network "breaks" (via the simulation), the more heterogeneous personality-wise the people are in the group; the slower the network "breaks", the more homogeneous personality-wise the people are in the group. The rationale for this interpretation is driven by the fact that larger correlations between items reflect more similar response patterns between people.

To provide convergent validity for this interpretation of the percolation analysis, we performed a profile correlation analysis and found that scientists have more homogeneous response patterns in personality items than artists (except for Sample 1) and controls. The results are largely as expected, though we did not find more homogeneous response patterns in scientists than artists in Sample 1. One possible reason may be the difference in age distribution among the three samples, in which Sample 1 is almost entirely college students who have not had much time to obtain high levels of creative achievement in their young careers. In contrast, Sample 2 is more representative of the general population, with a wide age range (18-52 years), and Sample 3 is well-known creative professionals from the Big-C Project. Nonetheless, scientists show robustly higher homogeneous response patterns in personality items than controls, indicating that creative scientists have a more stable personality structure than the control group, in line with the percolation analysis.

To our knowledge, this is the first study to apply percolation analysis to examine personality networks. Given the lack of precedent, we advise caution in interpreting the results, but we offer a possible reason that scientists have more homogeneous response patterns in personality items than artists. Considering that fewer science domains are measured by the CAQ (e.g., science and engineering) compared to arts domains (e.g., dance, creative writing, visual arts, and music), there is a greater diversity of means by which artists can achieve success (i.e., higher CAQ scores). On the other hand, the cohesiveness of a personality network, to some extent, may also reflect the "stability" of personality, which is associated with psychological well-being (Anusic & Schimmack, 2016; Diener et al., 2009; Lucas & Diener, 2009). Empirical studies have also shown that scientists are less likely to suffer from mental illness compared with non-scientists (Ludwig, 1995; Rawlings & Locarnini, 2008). In contrast, artists (e.g., writers) have shown increased risk of schizophrenia, unipolar depression, anxiety disorders, bipolar disorder, substance abuse, and suicide (Kyaga et al., 2013). Kaufman found that reduced latent inhibition, which is highly associated with schizophrenia, was significantly correlated with creative achievement in the arts, but not the sciences (Kaufman, 2009). A recent polygenic risk study with a considerably larger sample suggested that artistic society membership (or creative professions) were associated with polygenic risk scores for schizophrenia and bipolar disorder (Power et al., 2015; but see Knudson, Bookheimer, & Bilder, 2019). It is possible (though speculative) that the stability of the scientists' network could reflect greater mental stability than artists. Further research is needed to better characterize the psychological significance of cohesiveness in personality networks, and how it varies across groups and individuals.

Limitations and Future Directions

Limitations of the current study should be taken into consideration. First, the "artists" and "scientists" in Samples 1 and 2 consisted of students and members of the general population who may not actually be working as creative professionals. Consistent with past work using the creative achievement questionnaire, the distribution of achievement scores was heavily skewed, with many zero values, meaning a few individuals attain higher levels of achievement, particularly in the "normal" populations of Samples 1 and 2. Although this limitation was partially addressed by Sample 3—who were internationally-recognized creative professionals—the number of participants in this sample was too few to reliably compare with Samples 1 and 2. Furthermore, supplementary analysis showed the level of creative achievement in the "smart control group" of Sample 3—who were selected to match the highly creative artists and scientists on intelligence and other factors—scored moderately (albeit not significantly) higher on artistic and scientific creative achievement than the artist and scientist groups in Samples 1 and 2. Nevertheless, the personality network findings were strikingly consistent across the three samples, pointing to the robustness of the results and suggesting that between-sample differences are relative. The stability of results across samples is particularly notable in light of the different personality scales in the three studies. At the same time, using different personality scales limited further qualitative comparisons across the samples.

Second, the personality networks derived in this work are based on cross-sectional/correlational data and therefore do not reflect causal relations. Longitudinal data over several years with repeated creative achievement and personality assessments would clarify causal relations among traits supporting creativity (Bringmann et al., 2013). Future research using longitudinal data can also examine test-retest reliability with respect to personality networks in a single sample. With respect to future directions, these findings point to the need for closer evaluations of the relationship between openness and creative achievement. Our network analyses found that increased interaction between openness and other traits may be considered a personality style linked to creativity. Future research should clarify the specific characteristics of the creative personality network with openness as the “core”. Additionally, future studies should attempt to replicate and characterize the cohesive structure of productive scientists, as well as clarify the psychological significance of this cohesive personality structure, such as whether having a more (or less) cohesive personality network relates to the stability of emotional or cognitive traits.

Conclusions

The present study is the first to investigate the multidimensional personality network structure of highly creative artists and scientists. A novel psychometric network analysis, combined with a multi-site and cross-cultural sampling approach, showed a consistent and reliable personality structure in different creative groups. We found that, compared to artists and less creative people, scientists showed greater cohesiveness in their personality networks, potentially reflecting a more homogeneous “archetype” of a personality structure that is relevant for high achievement in the sciences. We also found that artists are characterized by a higher out-module degree in openness, indicating higher co-occurrence of openness with other personality traits in highly creative artists. The results of this study have implications for understanding the creative personality, which is viewed as bridge between creative potential and creative achievement (Feist, 2010). Our study also offers a new approach to modeling personality using percolation analysis and provides insights into identifying underlying profiles in creative populations.

Data accessibility statement

Partial data and analysis scripts can be accessed at https://osf.io/sqgjp/?view_only=3004da48099d480a8872ee940ba6462d.

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