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Network Analysis:
A New Perspective on Personality Psychology

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To my father Danilo,

Because you are here, reading this page, today.

Abstract

A new conception of personality based on network analysis has been recently proposed to overcome some of the limitations of the latent-variable theory of personality. While the latent-variable theory assumes that the covariation among the thoughts, feelings, and behaviors characterizing a personality domain can be explained by the effect of an unobservable latent variable (e.g., extraversion), the network approach conceives personality as emerging from direct interactions among these thoughts, feelings and behaviors. The network perspective motivates new ways of analyzing personality data and it can be especially important for investigating the mechanisms underlying personality. In this work, we present the basic network concepts and discuss several alternative ways to define networks from the data that are typically collected in personality psychology. The most important network indices, such as indices of centrality and of clustering coefficient, are described.

We discuss why the distinction between positive and negative edges is important in the study of personality networks and propose three new indices of clustering coefficient that consider edge signs. The properties of the new indices are tested both on simulated networks and on networks based on actual personality psychology data.

We present two applications of network analysis. The first application considers a network of 24 personality facets: we show how these facets relate to each other, and discuss both the local and the global properties of the network. The second application focuses on the dimension conscientiousness: We show that while some mechanisms underlying conscientiousness are common to many facets, other mechanisms may specifically characterize some facets and not others. By means of network analysis, we draw a comprehensive maps of conscientiousness that can serve as a guidance for future studies.

The application of network analysis to the field of personality psychology is recent and its potentialities have not been fully explored yet: in the final part of this work, we discuss the limitations of our investigation and propose future developments of our research that can contribute to overcoming its limits.

Preface

A network is a simple and abstract representation of a group of entities and of their relationships as a set of nodes and a set of edges that connect the nodes. This kind of representation, as simple as it might seem, has important merits. Networks can be used to represent systems that would appear completely unrelated otherwise. A network is all of what is common among phenomena as different as scientists that collaborate (Newman, 2001), web pages that link to each other (Albert, Jeong, & Barabási, 1999), airports (Guimerà, Mossa, Turtschi, & Amaral, 2005), and the expression of genes (Zhang & Horvath, 2005), to name just a few examples. This is possible because networks allow to abstract from the properties that make these systems so different and to focus on what they have in common: elements (e.g., scientists, pages, airports, genes) with pairwise connections (papers, web links, flights, similarity of expression). As a consequence, networks allow to examine the properties that these systems have in common: without networks it would be difficult even to ask whether, for instance, the world wide web and metabolism react in a similar or in a different manner to targeted attacks and random failures (Albert, Jeong, & Barabási, 2000).

When a new system is represented as a network, one can investigate whether it enjoys relevant properties that have been discovered in other systems. For instance, recent findings showed that similar dynamics may affect systems as different as the climate, financial markets (Scheffer et al., 2012), and depression (van de Leemput et al., 2014). Recently, personality has been conceived of as emerging from a network of interacting thoughts, feelings and behaviors (Cramer et al., 2012a). The main aim of this dissertation is to further develop network analysis for personality research and to show how it can be applied to better understand personality mechanisms.

This thesis is divided into five chapters. In the first chapter, we introduce networks and show how they have been used in personality psychology and psychopathology so far. We discuss several methods to define a network from the data that are typically collected in personality psychology and present the strengths and limitations of each method. We also present the most important network indices, such as centrality and clustering coefficients. Parts of this chapter have been published in Costantini and Perugini (2012, 2014) and in Costantini et al. (2014). In the second chapter we introduce new indices of clustering coefficient that can be used on networks that have both positive and negative edges, such as those that are typically analyzed in personality psychology. We test the properties of the indices on simulated networks and on a network computed from personality data. This chapter has been published in Costantini & Perugini (2014). In the third chapter, we apply network analysis on a large dataset that includes six major personality dimensions and their facets. The study described in the third chapter has been published in Costantini et al. (2014). In the fourth chapter, we use network analysis to investigate the mechanisms underlying the dimension conscientiousness. This study is unpublished at this point in time although a manuscript will be submitted for publication soon. In the fifth and last chapter we discuss the main challenges for future research on networks in personality psychology and illustrate some lines of research that are now being developed and that we consider particularly promising.

The work presented in this dissertation would not have been possible without the help of many people. The studies presented here were performed in collaboration with Marco Perugini, Sacha Epskamp, Denny Borsboom, René Mõttus, Lourens Waldorp, and Anjélique Cramer. A particular thank goes to Renato Arco, for his help in collecting the data presented in Chapter 4.

I will be always grateful to Denny Borsboom for giving me the wonderful opportunity of staying at the Psychological Methods Department of Amsterdam for six months. His teachings, suggestions, and criticisms, together with those by Sacha Epskamp, Lourens Waldorp, Mijke

Rhemtulla, Anjelique Cramer, Claudia van Borkulo, and René Mõttus, that I could meet during the time that I spent there, made those six months the most valuable of my PhD.

I want to express my deepest gratitude to Marco Perugini, not only for having improved many parts of this dissertation with his corrections and suggestions, but for teaching me most of what I know and for constantly guiding, supporting, and encouraging me during these years.

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Chapter 1. Introduction to network analysis[1].

[1] Parts of this chapter have been published in Costantini & Perugini (2012, 2014) and in Costantini et al. (2014)

Highlights

- We introduce the general concept of a network.
- We compare the latent variable perspective and the network perspective in personality psychology.
- We present several kinds of networks and several strategies to define a network.
- We present important network indices, such as centrality, clustering coefficients and small-worldness.

Introduction to networks

A network is an abstract model composed of a set of nodes or vertices (*V*), a set of edges, links or ties (*E*) that connect the nodes, together with information concerning the nature of the nodes and edges (de Nooy, Mrvar, & Batagelj, 2011). Figure 1 reports the example of a simple network, with six nodes and seven edges. The nodes usually represent entities and the edges represent their relationships. The analysis of networks is essential in many fields of science and is at the basis of important insights that would not have been possible without it. The widespread adoption of network analysis has been allowed by the incredible flexibility of this technique: The kinds of entities that can be represented by nodes are potentially unlimited. For instance, nodes have been be used to represent web pages (Albert et al., 1999), genes (Zhang & Horvath, 2005), airports (Guimerà et al., 2005), proteins (Jeong, Mason, Barabási, & Oltvai, 2001), scientists (Newman, 2001), scientific journals (Garfield, 1972), psychopathological symptoms (Cramer, Waldorp, van der Maas, & Borsboom, 2010), and recently also personality items (Cramer et al., 2012a) and facets (Costantini et al., 2014). The scientific literature on networks is so vast and it embraces so many diverse branches of science that it would be impossible to provide a comprehensive presentation of it. In the following, we give a succinct overview of some key network concepts, accompanied by examples of networks from different fields of science. A more systematic presentation of these concepts is relegated to the next sections, when we will also discuss their relevance for personality psychology. For more exhaustive presentations of network analysis and its most important applications, see for instance de Nooy et al. (2011), Kolaczyk (2009), and Newman (2010).

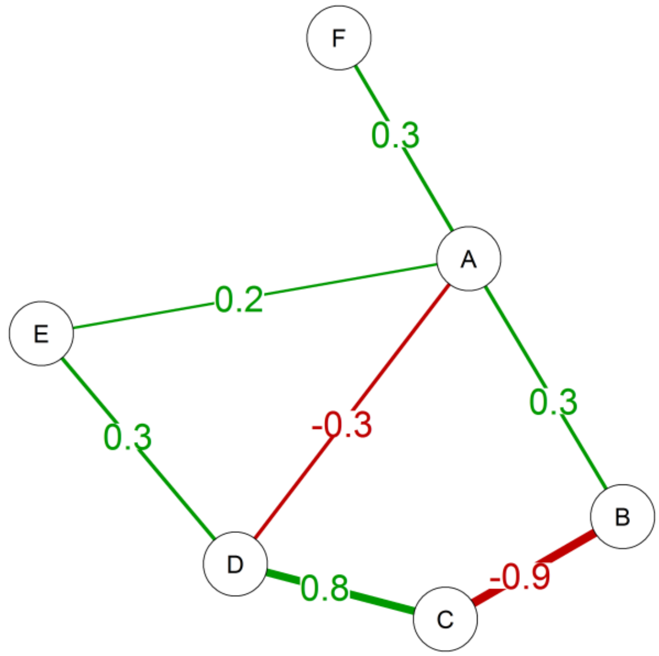

Figure 1. A network with six nodes and seven edges.
Positive edges are green and negative edges are red. The letters identify the nodes, the numbers represent weights associated to the edges. The figure was obtained with the R package *qgraph* (Epskamp et al., 2014; Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012; R Core Team, 2014).

The network in Figure 1 is characterized by the absence of arrowheads (that would have indicated a direction for the edges), by edges of different widths (edges with larger weights are wider), and by both green and red edges, that are associated to positive and negative signs respectively. Networks can be classified in broad categories according to the kind of relationships that are allowed among their nodes. A network is said to be *undirected* if the relationships among its nodes are symmetrical (e.g., "A and B are relatives"); conversely, if the represented relationships are not symmetrical (e.g., "A borrows school materials from B"), the network is said to be *directed*. For instance, in scientific collaboration networks nodes represent scientists that are connected to each other if they wrote a paper together (Batagelj & Mrvar, 2000; Newman, 2001), similarly in actor-collaboration networks actors are connected to each other if they took part to a movie together (Amaral, Scala, Barthélémy, & Stanley, 2000; Watts & Strogatz, 1998). This kind of relationship is symmetrical, if A is co-author of B then B is co-author of A, therefore collaboration networks are typically undirected. Figure 2A reports the example of a famous scientific collaboration network, the one centered on the mathematician Paul Erdős[2] (Batagelj & Mrvar, 2000; Grossman & Ion, 1995). Differently from collaboration networks, in citation networks, nodes can represent scientific journals (Garfield, 1972) or papers (Batagelj, 2003) and an arrow goes from node A to node B if A cited B[3]. Citations are not symmetrical, A can cite B without B citing A, hence citation networks are typically directed. Another example of a directed network is the World Wide Web (WWW), in which nodes represent web pages and an arrow goes from node A to node B if a webpage A includes an hyperlink to a webpage B (Albert et al., 1999): The WWW is represented in Figure 2B[4], the arrowheads indicate the direction of the hyperlinks.

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[2] During his life, Erdős published more than 1,400 papers in collaboration with hundreds of colleagues (Hoffman, 1998; Newman, 2001). He was very influential and among mathematicians is still common to express the proximity to him using the Erdős number, which takes value 0 for Erdős, value 1 for his co-authors, value 2 for the co-authors of his co-authors and so on (Grossman & Ion, 1995). In Figure 2A, each node represents a mathematician and the nodes are colored according to their Erdős numbers, number 0 (i.e., Erdős himself) being red, number 1 orange, and number 2 blue. The dataset was collected by Grossman (2014) and it was made publicly available in Pajek format (de Nooy et al., 2011) by Batagelj and Mrvar (Batagelj & Mrvar, 2006). This version of the network (last updated in 2002) includes authors with Erdős number up to 2; the connections among nodes with Erdős number 2 are not included in this version of the network (Batagelj & Mrvar, 2000).

[3] Such networks fundamental for computing indices such as the Impact Factor (Garfield, 2006).

[4] The plot was obtained using the dataset described by Albert and colleagues (Albert et al., 1999) and made publicly available in Pajek format by Batagelj and Mrvar (Batagelj & Mrvar, 2006). The original dataset included 325,729 nodes and 1,497,135 arrows and was too large to be represented graphically. We applied a clustering algorithm (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008;

A network is said to be *unweighted* if the edges can be either absent or present, but no information is coded about the intensity of the relationship; otherwise, if some kind of information about the intensity is coded (e.g., "how often A borrows school materials from B"), the network is said to be *weighted*. A straightforward way to obtain edge weights is to consider the frequency of an event. Figure 2C represents an online social network, the nodes are university students and the weights associated to the arrows (visualized as their color saturation) represent the number of messages exchanged between any two students[5]. Another way to define weights is to consider the association among nodes: in gene co-expression networks, nodes represent genes and edges represent the association of their expression patterns (Zhang & Horvath, 2005). Many network indices have been initially developed for unweighted networks and were extended only recently to the weighted case (e.g., Barrat, Barthélemy, Pastor-Satorras, & Vespignani, 2004; Opsahl, Agneessens, & Skvoretz, 2010; Saramäki, Kivelä, Onnela, Kaski, & Kertész, 2007).

A network is said to be *unsigned* if only positive relationships are allowed (e.g., "A likes B"). Some relationships however are naturally represented by the inclusion of both positive and negative edges (e.g., "A likes B, B dislikes C"). If both positive and negative edges are present, the network is said to be *signed*. For instance, some online websites allow to indicate whether a user likes/dislikes another user (Cartwright & Harary, 1956; B. Hu, Jiang, Ding, Xie, & Wang,

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Rotta & Noack, 2011), as implemented in Pajek (Batagelj & Mrvar, 1998; de Nooy et al., 2011), to partition the network into a small set of clusters. Each cluster was then represented as a single node. An arrow was drawn between two nodes A and B if at least one of the webpages of A sent an arrow to one of the webpages of B. The final shrunk network included 657 nodes and 2,554 arrows and it could be easily represented graphically.

[5] The network includes 1,899 students, among which 59,835 messages were exchanged. The dataset was described in Opsahl and Panzarasa (2009) and it was made publicly available by Opsahl (Opsahl, 2014).

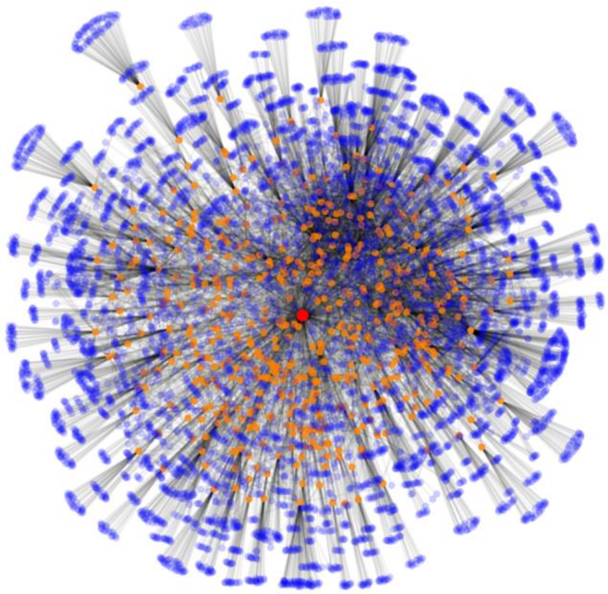
2005; Kunegis, Lommatzsch, & Bauckhage, 2009; Leskovec, Huttenlocher, & Kleinberg, 2010): in such networks, nodes represent users, connected by a positive edge if their relationship is positive and by a negative edge if their relationship is negative. Figure 2D represents part of the online social network Slashdot Zoo[6] (www.slashdot.org) in which the users are allowed to tag each other as friends or foes. Each node represents a user, a positive edge (green arrow) vs. a negative edge (red arrow) goes from node A to node B if A tagged B as a friend vs. foe. Later in this chapter, we will discuss how signed and weighted networks can be represented in matrix form and how they can be used to investigate the structure of personality psychology

The networks in Figure 2 were plotted using an energy-based algorithm, which considers the edges as if they represented forces in a two-dimensional space and attempts to minimize the total energy of the system by iteratively improving the position of the nodes (Fruchterman & Reingold, 1991). The simple visualization of such graphical representations can give important information. For instance, the role played by certain nodes is immediately apparent and one can see that some nodes occupy more important positions than others. In the Erdős collaboration plot (Figure 2A), Erdős himself is the most important node (this follows from the strategy used to build the network, see footnote 2). Erdős has the largest number of connections and if he was removed the network would break up into 16 separate components. A quick inspection the world-wide-web network (Figure 2B) reveals that also in this network some nodes are more important than others. For instance, in the left part of the plot one can see that a large group of nodes is connected to the rest of the network only by

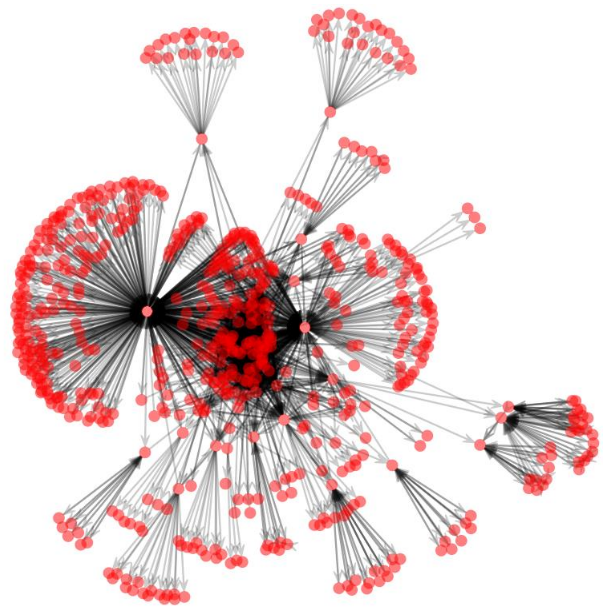
[6] The dataset was downloaded from the Stanford Large Network Dataset Collection (Leskovec & Krevl, 2014; Leskovec, Lang, Dasgupta, & Mahoney, 2009). The Slashdot Zoo network has been described by Leskovec and colleauges (2010) and by Kunegis and colleagues (2009). The original network included 77,360 nodes and 905,468 edges and was too large to be visualized entirely. We plotted only a subset including the first 2,000 nodes, which were connected by 20,292 edges.

means of a single node. Since in this network each node represents a cluster of web pages (see footnote 4), if that important cluster of pages was removed, the group of web pages on its left could not be reached anymore starting from the remaining pages; if however one of the nodes at the periphery of the network was removed, this would not have any substantial impact on the possibility for remaining webpages in the network to reach each other. The importance of a node is reflected by the most formal network concept of *centrality* (Freeman, 1978; Opsahl et al., 2010). There are several definitions of centrality, for instance a node can be central because it has a large number of connections (*degree centrality*), because it is possible to quickly reach all the other nodes from its position (*closeness centrality*), or because that node is fundamental for the other nodes to reach each other (*betweenness centrality*). We will present centrality in more detail later in this chapter, when we will discuss the most important network indices.

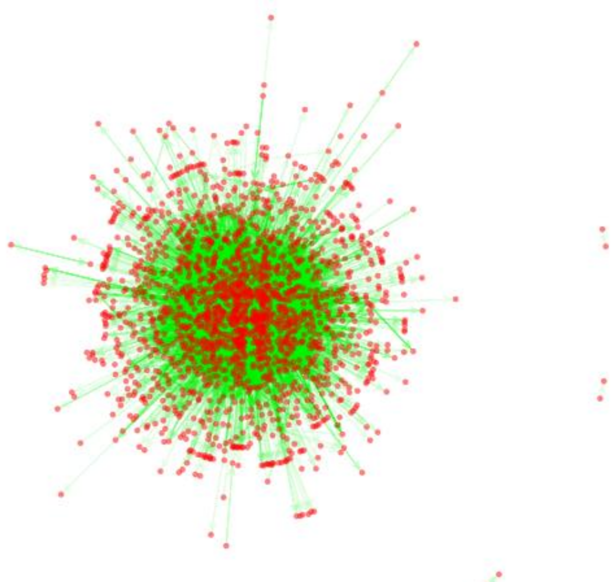
A. Erdős collaboration network.



B. The world-wide-web.



C. Online social network.



D. Slashdot Zoo network.

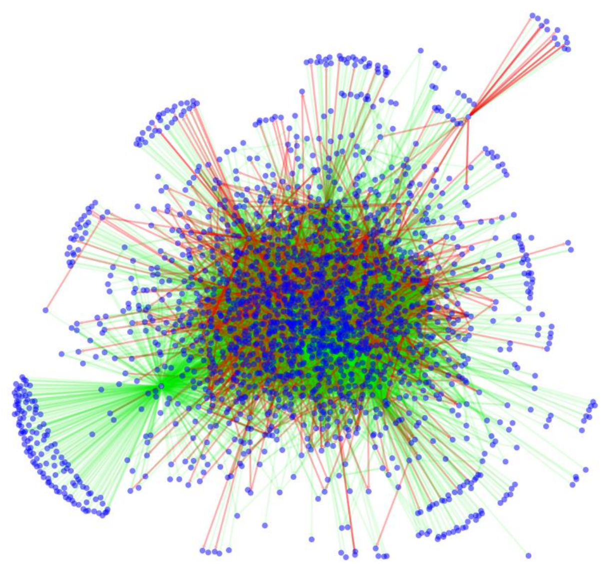


Figure 2. Examples of networks.

A. Colors represent the Erdős number (red = 0, yellow = 1, and blue = 2). **B**. Nodes represent clusters of webpages (see footnote 4). **C**. Arrow saturations represent edge weights. **D**. Green edges are positive and red edges are negative. The plots were obtained using the R package *networks* (Butts, Handcock, & Hunter, 2014; R Core Team, 2014). The datasets were made publicly available by Batagelj and Mrvar (2006), Opsahl (2014), Leskovec and Krevl (2014).

A visual inspections of the networks in Figure 2 reveals also that each network has a peculiar global appearance, reflecting a specific organization on the large scale. The large-scale organization of a network, namely its *topology*, gives rise to important properties and may provide interesting information about the processes that have generated a network. For instance, consider a hypothetical social network in which each individual has the same number of neighbors and all of these neighbors live close by. If the Earth was uniformly inhabited and if the possibilities for long travels and for distant communications were strongly limited, one's acquaintances would be restricted to one's adjacent nodes in this network. The structure of this social network would be similar to that in Figure 3A, a regular ring lattice (Watts & Strogatz, 1998). Even though this model has some departures from the real situation (some areas are much more densely inhabited than others, travels and communications are possible), one could wonder whether this model is nonetheless a reasonable approximation of the global social network: After all, most of a person's acquaintances usually live close by. However an important implication of the structure in Figure 3A is that, if an individual wanted to contact another randomly selected individual using a chain of mutual acquaintances, the required chain would be very long[7]. In a popular experiment by Milgram (1969), the participants were asked to send a letter to a target person by generating a similar chain of acquaintances. The surprising result is that on average it took only around six individuals to reach the target. This phenomenon, known as the *small-world* phenomenon (and popularized as the concept of "six degrees of separation"), was later investigated by Watts and Strogatz (1998). They showed that it is sufficient to randomly rewire a small proportion of the connections in a regular lattice for

[7] In the network in Figure 3A the average chain would require around 13 individuals, if the shortest possible path was always selected.

the emergence of the small-world phenomenon. The necessary proportion of connections to rewire is so small that the local structure of the network, as reflected in the *clustering coefficient*[8], is not substantially altered by this process. Figure 3B shows the same network in Figure 3A after rewiring only 14 out of 200 edges. This small portion of rewires was enough to reduce the average length of the chain from around 13 to around 5 individuals. For the real-world social networks this means that a few individuals that have a friend far away are sufficient to shorten the average distance between two individuals by a large amount, even assuming that most of one's acquaintances live close by. Watts and Strogatz (1998) showed that also non-social networks (e.g., neural networks, power-grid networks, collaboration networks) can have the small-world property. One of the implications of a small-world topology is that the length of the average shortest path that connects two random nodes increases slowly with the number of nodes (Watts & Strogatz, 1998). Albert and colleagues (Albert et al., 1999) showed the WWW network (Figure 2B) has the small-world property and estimated that, since the web was composed by around 800,000,000 pages at the time, each page was on average 19 clicks away from another randomly selected page. However they estimated that if the number of pages had become 10 times larger, this distance would have increased from 19 to only 21 clicks. The small-world property entails also that, even if a social network is very large, an infectious disease affecting a remote region of the network can spread very quickly to the rest of its nodes (Watts & Strogatz, 1998).

[8] The clustering coefficient of a node is the proportion of the connections among its neighbors over the maximum possible number of such connections (Watts & Strogatz, 1998). This index will be discussed later in this chapter, when we will describe the most important network indices. Furthermore, the entire Chapter 2 will be devoted to the clustering coefficient and to its alternative formulations.

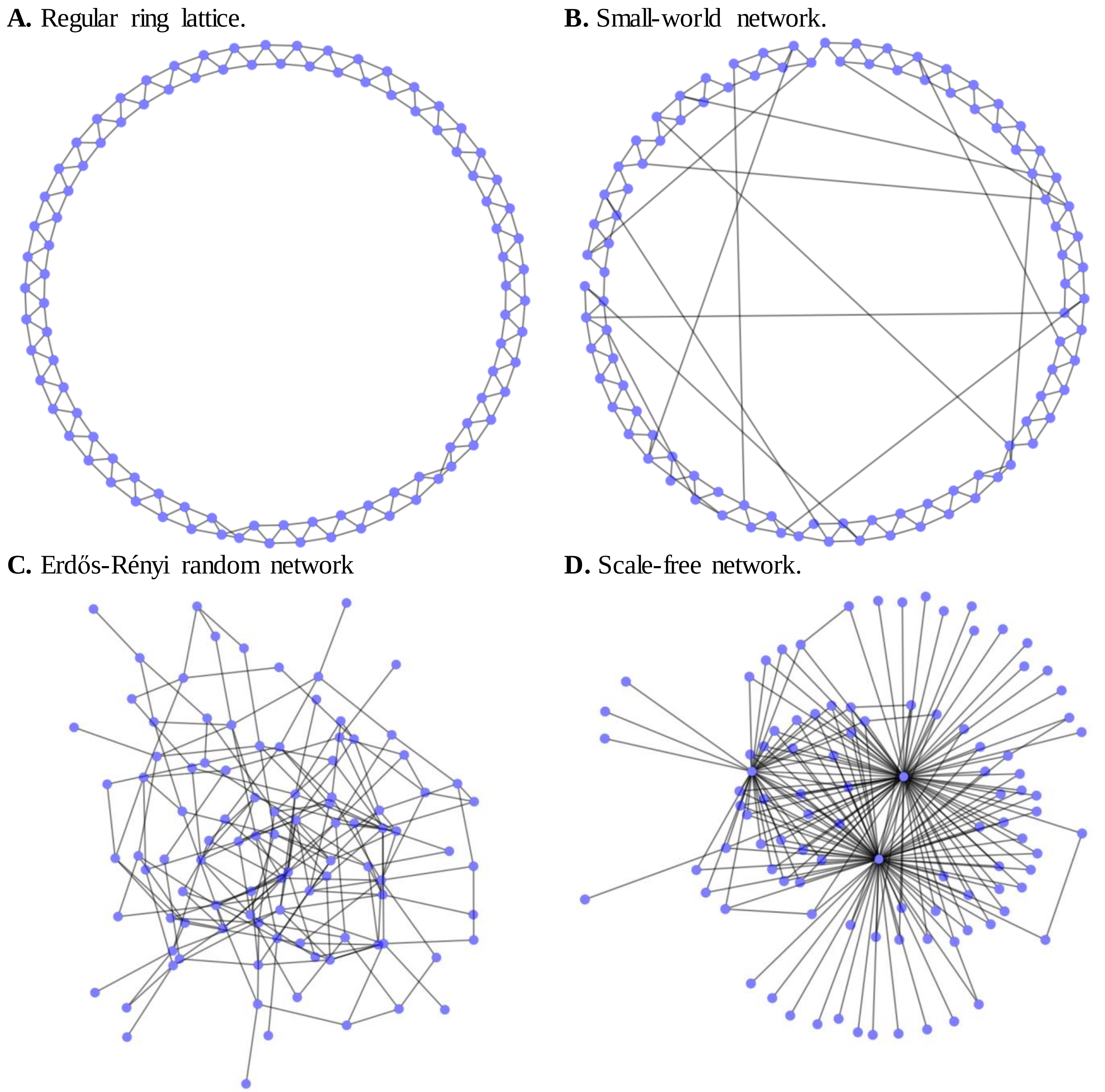


Figure 3. Four networks with 100 nodes and 200 edges.

A. A regular ring lattice, each node is connected with the four closest nodes. **B.** The same network in A, after rewiring 14 edges, shows the small-world property. **C.** Erdős-Rényi random network, the edges are placed randomly among nodes. **D.** A network simulated using the preferential attachment procedure (Barabási & Albert, 1999). The networks were simulated with the R package *igraph* (Csárdi & Nepusz, 2006) and the plots were obtained with package *network* (Butts et al., 2014).

In the network in Figure 2C, all the nodes are connected with each other, with the only exception of six nodes (the three pairs of nodes in the right part of the plot). One could wonder whether the fact that the most nodes are connected with each other is a characteristic of a particular network, or whether a group of connected nodes (a *component*) including a certain proportion of the nodes would arise even if the same amount of links had been placed randomly among the nodes. Erdős and Rényi (1959, 1960) examined the behavior of random graphs, defined only by a certain number of nodes and a certain probability that an edge between any two nodes is present, each edge being therefore equiprobable[9] (Figure 3C). They proved that the probability of a component that includes most nodes in a random network does not increase gradually with the number of edges, but it shows a *phase-transition*: When the number of edges is less than a certain threshold (half the number of the nodes), such component is almost certainly absent, but if the probability of an edge becomes higher than the threshold, the component is almost certainly present[10]. Similar phase transitions were proved to occur also for other properties of the network (Erdős & Rényi, 1960).

One may wonder whether some real-world networks could be approximated by an Erdős-Rényi random graph. Consider for instance the WWW, in which each website administrator does not have access to the global structure of the web, but decides from a local standpoint which hyperlinks to include in her page. One could hypothesize that the unsupervised behavior of many independent website administrators could give rise to a random structure. However, although a random process could in principle generate any possible structure, in random networks it is very unlikely to have nodes with many more connections than the rest of the nodes. Conversely in the WWW some webpages were

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[9] A random graph can be similarly defined by a randomly selected graph among all the possible ones that have a certain number of nodes and a certain number of edges.

[10] A similar component is characterized by the fact that its size grows proportionally with the number of nodes in the network and is called a *giant component* (Newman, 2010, p. 404)

shown to send or receive a number of links that is disproportionately larger than the number of links that involve the typical node (Albert et al., 1999). In the WWW network[11], 48.3% of the nodes has only one link (considering both incoming and outgoing connections), 93.0% has less than 20 links and 99.98% has less than 1000 links. However 0.02% of links with more than 1000 connections participate to 5% of the connections, the most connected node having more than 10000 links. Albert and colleagues (1999) showed that the probability of a node having a certain number of neighbors k in the WWW follows a power-law distribution ($\sim k^{-\gamma}$, where γ is a parameter that can be determined empirically for each network). This kind of topology has been found to characterize several real-world networks and has been called *scale-free topology* (Barabási & Albert, 1999; Barabási & Bonabeau, 2003). Scale-free networks are dominated by a few very central nodes, called *hubs* (Barabási & Bonabeau, 2003). Barabási and Albert (1999) identified the process of *preferential attachment* as the generating process of scale-free networks (Figure 3D): When a new node A enters the network (e.g., a new web-page is created), the probability that it will be connected to another existing node B (e.g., send a link to another web-page) depends on the number of connections of B: if B has many connections (e.g., B is a very important website) it is more likely that A will be connected to B than if B is peripheral. Besides the WWW, many other networks have been shown to be scale-free (Barabási & Bonabeau, 2003), among them also scientific collaboration networks (Newman, 2001) and metabolic networks (Jeong & Albert, 2000).

An important implication of scale-free networks is that if some nodes are randomly removed (e.g., some web-pages are randomly deleted) this will most likely have a minimal

[11] Figure 2B shows a plot of the main clusters of the WWW, the following data are referred to the original network with 325,729 nodes.

effect on the possibility for the remaining nodes to reach each other. A random deletion will be more likely to affect one of the many peripheral nodes than one of the very few hubs. On the other hand however, scale-free networks are very vulnerable to targeted attack: if one could remove even a small number of very central nodes (around the 7% for the world-wide-web, Albert et al., 2000), this would have a huge impact for the possibility of other nodes to communicate. This property does not hold only for the world-wide-web: for instance, Jeong and colleagues (2001) showed that also the network of interactions among the proteins in an organism has a scale-free topology: The removal of the most connected proteins is more likely to result in the death of the organism than the removal of peripheral proteins. Conversely, on random networks it does not make such an important difference if nodes are deleted randomly or if the most central nodes are selected for an attack. Henceforth, the topology of a network has important consequences for instance in the protection of important infrastructures from terrorist attacks (Latora & Marchiori, 2005), for the development of better drugs (Hopkins, 2008), and in general for network interventions (Valente, 2012).

In this section we presented some important network concepts, we emphasized the fact that different nodes can have a different role in a network and showed that networks can be characterized by a different topology. In the next sections we will discuss how personality can be conceived as a network and we will present in more detail the network concepts that will be used to analyze personality in this work.

Networks in personality psychology

A typical personality data set consists of cross-sectional measures of multiple subjects on a set of items designed to measure several facets of personality. In standard approaches in personality research, such data are used in factor analysis to search for an underlying set of latent variables that can explain the structural covariation in the data. In a causal interpretation of latent variables (Borsboom, Mellenbergh, & van Heerden, 2003), responses to items such as "I like to go to parties" and "I have many friends" are viewed as being causally dependent on a latent variable (e.g., extraversion). For example, McCrae and Costa's (2008) interpretation of the relation between extraversion and its indicators is explicitly causal: "extraversion causes party-going behavior in individuals" (McCrae & Costa, 2008, p. 288). This approach has culminated in currently influential models such as the Five Factor Model of personality (McCrae & Costa, 2008), in which five dominant latent variables are ultimately held responsible for most of the structural covariation between responses to personality items (additional latent factors such as facets may cause some of the covariation).

Recently, however, this perspective has been challenged in the literature (Cramer et al., 2012a). In particular, it has been put forward that the default reliance on latent variable models in personality may be inappropriate, because it may well be that the bulk of the structural covariation in personality scales results from direct interactions between the variables measured through personality items. For instance, one may suppose that people who like to go to parties gain more friends because they meet more people, and people who have more friends get invited to good parties more often. In this way, one can achieve an explanation of the relevant pattern of covariation without having to posit latent variables.

Thus, in this scheme of thinking, one may suppose that, instead of reflecting the pervasive influence of personality factors, the structural covariance in personality is actually due to local interactions between the variables measured. In this way of thinking, personality resembles an ecosystem in which some characteristics and behaviors stimulate each other, while others have inhibitory relations. Under this assumption, the proper way to analyze personality data is not through the a priori imposition of a latent variable structure, but through the construction of a network that represents the most important relations between variables; this way, one may get a hold of the structure of the ecosystem of personality. In this framework, traits have been conceived of as emerging phenomena that arise from networks of relations among thoughts, feelings and behaviors (Borsboom & Cramer, 2013; Cramer et al., 2012a; Schmittmann et al., 2013). An R package, *qgraph*, has been developed for the specific purpose of analyzing networks of personality and psychopathology data (Epskamp et al., 2014, 2012).

It is important to stress that not all personality scholars have embraced a causal view of latent factors. Some researchers for instance consider factors as the common elements shared by many observable variables and not as their causes (Ashton & Lee, 2005; Funder, 1991; J. J. Lee, 2012). Also from this different theoretical perspective, the heuristic value of network analysis remains important. Factor and network analysis differ, at the very least, in the fact that they direct the researcher's attention toward different aspects of personality. While factor analysis focuses almost exclusively on the elements shared among the indicators, whether or not interpreted causally, network analysis shifts the focus towards the direct relationships among the observable variables. We do not challenge the use of factor analysis as a statistical technique by itself: network analysis and factor analysis can in principle be combined (Cramer et al., 2012b; Steyer, 2012). However, a network perspective may foster important insights in the field that are unlikely to come by relying exclusively on a latent variable perspective.

In recent literature network analysis has been applied to grasp complex co-variation patterns in personality data that would be harder to notice otherwise in, say, factor loading matrices. Epskamp et al. (2012) showed how *qgraph* can be used to visualize the correlational structure of a 240 node dataset (Dolan, Oort, Stoel, & Wicherts, 2009) in which the NEO-PI-R (Costa & McCrae, 1992; Hoekstra, De Fruyt, & Ormel, 2003) was used to assess the five factor model for personality (McCrae & Costa, 2008). Cramer et al. (2012a) further analyzed this network and showed that it did not correspond to a correlation network that should arise had the data been generated by the five factor model for personality. Ziegler, Booth & Bensch (2013) constructed a correlation network on 113 personality facet scale scores from the NEO-PI-R, HEXACO, 6FPQ, 16PF, MPQ, and JPI and interpreted this network as a nomological network usable in scale development. Schlegel, Grandjean and Scherer (2013) investigated the overlap of social and emotional effectiveness constructs and found the correlation network to display four meaningful components. Franić, Borsboom, Dolan, and Boomsma (2013) used correlation networks to show the similarity between genetic and environmental covariation between items of the NEO-FFI.

A similar approach has been proposed in psychopathology, which shifted the focus from unobservable "latent" disorders, such as depression, to a network of interacting symptoms. According to the network model, disorders may arise from the direct causal connections among symptoms (Borsboom & Cramer, 2013; Schmittmann et al., 2013). Network models have been applied to investigate the dynamics underlying depression (Bringmann, Lemmens, Huibers, Borsboom, & Tuerlinckx, 2014; van de Leemput et al., 2014) and PTSD (McNally et al., 2014), and have been also advocated as an explanation of comorbidity (Borsboom, Cramer, Schmittmann, Epskamp, & Waldorp, 2011; Cramer et al., 2010).

In the following paragraphs, we give a more detailed presentation of different kinds of networks and illustrate several strategies to define personality networks.

Types of networks

Directed and undirected, weighted and unweighted networks

As we noted above, there are different types of networks, which yield different kinds of information and are useful in different situations. In a directed network, relationships between nodes are asymmetrical. Research on directed networks has seen extensive developments in recent years since the work of Pearl (2000) on causal systems. Methodology based on directed networks is most useful if one is willing to accept that the network under consideration is *acyclic*, which means that there are no feedback loops in the system (if A influences B, then B cannot influence A). A directed network without feedback loops is called a Directed Acyclic Graph (DAG). In contrast, in an *undirected* network, all relationships are symmetrical. These networks are most useful in situations where (a) one cannot make the strong assumption that the data generating model is a DAG, (b) one suspects that some of the relations between elements in the network are reciprocal, and (c) one's research is of an exploratory character and is mainly oriented to visualizing the salient relations between nodes. Since the latter situation appears more realistic for personality research, the current work focuses primarily on undirected networks.

Unweighted networks represent only the presence or absence of the edges, while weighted networks encode additional information about the magnitude of the connections. An unweighted network can be encoded in an *adjacency matrix* (A), a square matrix in which each row and column indicate a node in the network. The elements of the matrix, $a_{(i,j)} \in \{0,1\}$, convey information about the presence or the absence of an edge between any two nodes i and j. A weighted network can be encoded in a weights matrix (W). The elements of the matrix, $w_{(i,j)} \in [0,1]$, indicate the strength of connection between two nodes; a zero in row i and column j indicates that there is no edge between node i and node j. When it is important to distinguish large from small connections—such as in personality—weighted networks are preferred[12].

A signed network, which includes both positive and negative edges, can be represented by a signed adjacency matrix (A_s) whose elements $a_{s(i,j)} \in \{-1,0,1\}$ take value $a_{s(i,j)} = 1$ if i and j are connected by a positive edge, $a_{s(i,j)} = -1$ if i and j are connected by a negative edge, and $a_{s(i,j)} = 0$ if no edge connects the nodes. A signed weighted network can be represented by a signed weights matrix W_s that associates to each edge a weight $w_{s(i,j)} \in [-1,1]$ reflecting both the sign and the strength (i.e., absolute value) of the connection. For example, the network of Figure 1 can be represented with the following signed weights matrix:

	A	B	C	D	E	F
A	0	0.3	0	-0.3	0.2	0.3
B	0.3	0	-0.9	0	0	0
C	0	-0.9	0	0.8	0	0
D	-0.3	0	0.8	0	0.3	0
E	0.2	0	0	0.3	0	0
F	0.3	0	0	0	0	0

[12] For the sake of simplicity and without loss of generality, we consider $\max(w_{(i,j)}) = 1$. Since we deal only with undirected networks, we will always assume that the adjacency matrices and the weights matrices are symmetrical (e.g., we will use a_{ij} and a_{ji} interchangeably). All of the diagonal elements are assumed equal to zero.

In this network there are positive connections, for instance between nodes A and B, and negative connections, for instance between nodes A and D. The zeroes in the matrix indicate that there are absent connections in the network, such as between nodes A and C. Furthermore, we may note that the matrix is symmetric and that the diagonal values are not used in the network.

Correlation networks, partial correlation networks, adaptive lasso networks

Correlation networks. In personality networks, measured variables are represented as nodes and are connected by an edge if two variables interact with each other. A simple heuristic to build a personality network is to consider a node A connected to another node B if node A *is associated with* node B. A correlation matrix describes pairwise associations between personality items, facets or other constructs and therefore can be used for estimating such a network structure. A correlation matrix is symmetric and a value of zero indicates no connection. Thus, a correlation matrix, by default, has properties that allow it to be used as a weights matrix to encode an undirected network. Using this connection opens up the possibility to investigate correlation matrices visually as networks (e.g., Cramer et al., 2012; Ziegler, Booth, & Bensch, 2013). In the remainder, we will indicate this network as a *correlation network*.

Partial correlation networks. Correlation networks are highly useful to visualize interesting patterns in the data that might otherwise be very hard to spot. However, they are not necessarily optimal for the application of network analysis if the goal is to extract the structure of a data generating network. The reason is that correlations between nodes in the network may be spurious, rather than being due to a genuine interaction between two nodes. For instance, spurious correlations may arise as the consequence of shared connections with a third node. Often, therefore, a network is constructed using the partial correlation matrix, which gives the association that is left between any two variables after conditioning on all other variables (e.g., McNally et al., 2014). The partial correlation coefficients are directly related to the inverse of the correlation matrix, also called the precision matrix (Lauritzen, 1996; Pourahmadi, 2011). Networks constructed on this basis are called *partial correlation networks* or *concentration graphs* (Cox & Wermuth, 1993), and the statistical data generating structures that they encode are known as Markov random fields (Kindermann & Snell, 1980).

Adaptive LASSO networks. In weighted networks, two nodes are connected if and only if the strength of connection between them is nonzero; a value of zero in the weights matrix encodes no connection between two nodes. Both the correlation and the partial correlation networks are estimated based on an empirical sample and will therefore not result in exact zeroes. Thus, both networks will always be fully connected networks, possibly with arbitrarily small weights on many of the edges.

It has been argued that in social sciences everything is to some extent correlated with everything. This is akin to what Meehl and Lykken have called the *crud factor* or *ambient noise level* (Lykken, 1968, 1991; Meehl, 1990) and what may at least partly be responsible for the controversial general factor of personality (Musek, 2007). If a network model of pairwise interactions is assumed to underlie the data then all nodes that are indirectly connected will be correlated, mainly due to spurious connections. Therefore, even at the population level we can assume that most correlations in personality research will be nonzero, resulting in a fully connected correlation network.

While correlation networks of personality measures are likely to be fully connected in the population, partial correlation networks are not necessarily so. This is of specific interest since the absence of an edge in a partial correlation network entails that two nodes are conditionally independent given all other nodes in the network—they cannot directly interact. The model in which partial correlations are set to zero is called the Gaussian graphical model (GGM; Lauritzen, 1996) as it can be visualized as a network. An optimal GGM is both sparse (many absent edges) while maintaining a high likelihood. Finding such a model corresponds to checking which connections are absent in the population network. Default significance tests can be used for this purpose (Drton & Perlman, 2004).

However, significance tests require an arbitrary choice of significance level; different choices yield different results, with more stringent significance levels resulting in sparser networks. If one ignores this issue, one has a multiple testing problem, whereas if one deals with it in standard ways (e.g., through a Bonferroni correction), one faces a loss of power.

A practical way to deal with the issue of arbitrary choices is to construct networks based on different choices and to see how stable the main results are; however, a more principled alternative is to use a LASSO penalty (J. Friedman, Hastie, & Tibshirani, 2008) in estimating the partial correlation networks. This causes small connections to automatically shrink to be exactly zero and results in a parsimonious network. If the data indeed arose from a sparse network with pairwise interactions, such a procedure will in fact converge on the generating network (Foygel & Drton, 2011). This approach has been recently proposed for defining networks from binary data (van Borkulo et al., 2014).

The adaptive LASSO is a generalization of the LASSO that assigns different penalty weights for different coefficients (Zou, 2006) and outperforms the LASSO in the estimation of partial correlation networks, especially if the underlying network is sparse (Fan, Feng, & Wu, 2009; Krämer, Schäfer, & Boulesteix, 2009). The penalty weights can be chosen in a data-dependent manner, relying on the LASSO regression coefficients (Krämer et al., 2009). In simulation studies, the likelihood of false positives using this method resulted even smaller than that obtained with the LASSO penalization (Krämer et al., 2009), so if an edge is present in the adaptive LASSO network one can reasonably trust that there is a structural relation between the variables in question (of course, the network does not specify the exact nature of the relation, which may for instance be due to a direct causal effect, a logical relation pertaining to item content, a reciprocal effect, or the common effect of an unmodeled latent variable). The adaptive LASSO is also convenient practically, as it is implemented in the R-package *parcor* (Krämer et al., 2009). Since the adaptive LASSO, as implemented in package *parcor*, relies on k-fold cross validation, the R function `set.seed` can be used to ensure the exact replicability of the results, which might be slightly different otherwise. In Chapter 3 we will show a possible strategy to control for the uncertainty connected to the selection of a random seed when computing network indices.

Nodes in personality networks

We discussed several possible strategies for defining edges in personality networks, however what should correspond to a node in the personality network is not trivial. While in different applications of network analysis components may be readily defined as, for instance, individuals (Travers & Milgram, 1969), web pages (Albert et al., 1999), or proteins (Vazquez, Flammini, Maritan, & Vespignani, 2003), the definition of components within personality psychology is more complex. From a theoretical point of view, Cramer and colleagues (2012a) defined components as thoughts, feelings and acts that are associated with a unique causal system. From a measurement point of view, components have been equated to single questionnaire items, as opposed to latent variables (Cramer et al., 2012a; Schmittmann et al., 2013): Whereas latent variables are conceived as aggregations that emerge from the interconnections of different components, items are meant to reflect directly single basic units of cognitions, thoughts and acts. However one can argue that each single item already taps into an aggregation of thoughts, feelings and acts, by requiring to the respondent to make a generalization explicitly (e.g., with adverbs like “usually”, “typically” or “often”) or implicitly (e.g., by not specifying the temporal and the situational framework). For instance the HEXACO-PI item “People often joke with me about the messiness of my room or desk” (K. Lee & Ashton, 2004) is de facto aggregating both across time (i.e., often) and across situations (i.e., by referring at the same time to the messiness of the room and to the messiness of the desk). One could, for instance, have chosen to split this item into many, for a very specific investigation of trait orderliness.

One cannot not aggregate but, at best, can decide which level of aggregation is the most informative: Different units (components) may be useful for different purposes. Single items may be useful to provide a fine-grained understanding of the dynamic of a personality dimension, but they might also provide unreliable and unstable information. Aggregates of items (e.g. parcels, facets) may imply a loss in terms of definition but a gain in terms of reliability of the findings (e.g., Ziegler et al., 2013). Given the existence of different levels of aggregation of basic components, it becomes not obvious to what extent a network analysis can simply substitute a factor analysis or rather it represents a complementary but not alternative statistical tool. At some level, subcomponents (whatever they might be) will still need to be aggregated. In Chapter 2 we examine a network in which nodes represent personality items, in Chapter 3 we examine a network in which nodes represent personality facets, and in Chapter 4 we examine networks in which some of the nodes have been defined by means of factor analysis.

Network indices[13]

Once a network is estimated, several indices can be computed that convey information about network structure[14]. Two types of structure are important. First, one is typically interested in the *global* structure of the network: how large is it? Does it feature strong clusters? Does it reveal a specific type of structure, like a small-world (Watts & Strogatz, 1998)? Second, one may be interested in *local* patterns, i.e., one may want to know how nodes differ in various characteristics: which nodes are most central? Which nodes are specifically strongly connected? What is the shortest path from node A to node B? Here we discuss a limited selection of indices that we regard as relevant to personality research, focusing especially on centrality and clustering coefficients. We will devote the entire Chapter 2 to a deeper discussion of the clustering coefficients. More extensive reviews of network indices may be found in Boccaletti, Latora, Moreno, Chavez, and Hwang (2006); Butts, (2008a); de Nooy and colleagues (2011); Kolaczyk (2009); and Newman (2010).

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[13] The functions to implement the indices discussed here, such as centrality indices, clustering coefficients and small-worldness, have been included in the R package *qgraph* (Epskamp et al., 2014, 2012). Some of the functions rely on procedures originally implemented in packages *igraph* (Csárdi & Nepusz, 2006), *sna* (Butts, 2008), and *WGCNA* (Langfelder & Horvath, 2008, 2012). These packages are in our experience among the most useful for network analysis.

[14] The adaptive LASSO networks, the correlation and the partial correlation networks are characterized by the presence of both positive and negative edges. The importance of signed networks is apparent not only in the study of social phenomena, in which it is important to make a distinction between liking and disliking relationships (e.g., Leskovec et al., 2010), but also in the study of personality psychology (see Chapter 2; Costantini & Perugini, 2014). Some network indices have been generalized to the signed case (e.g., Costantini & Perugini, 2014; Kunegis et al., 2009), however most indices are designed to unsigned networks. For the computation of the latter kind of indices, we will consider the edge weights in absolute value.

Centrality

Not all nodes in a network are equally important in determining the network's structure and, if processes run on the network, in determining its dynamic characteristics (Kolaczyk, 2009).

Centrality indices can be conceived of as operationalizations of a node's importance, which are based on the pattern of the connections in which the node of interest plays a role. In network analysis, centrality indices are used to model or predict several network processes, such as the amount of flow that traverses a node or the tolerance of the network to the removal of selected nodes (Borgatti, 2005; Crucitti, Latora, Marchiori, & Rapisarda, 2004; Jeong et al., 2001) and can constitute a guide for network interventions (Valente, 2012). Several indices of centrality have been proposed, based on different models of the processes that characterize the network and on a different conception of what makes a node important (Borgatti & Everett, 2006; Borgatti, 2005). The following gives a succinct overview of the most often used centrality measures.

Degree and strength. First, degree centrality is arguably the most common centrality index and it is defined as the number of connections incident to the node of interest (Freeman, 1978). The degree centrality of node C in Figure 1 is 2 because it has two connections, with nodes B and D. Degree can be straightforwardly generalized to weighted networks by considering the sum of the weights of the connections (in absolute value), instead of their number. This generalization is called *strength* (Barrat et al., 2004; Newman, 2004). For instance, strength of node C in Figure 1 is 1.7, which is the highest in the network. Degree and strength focus only on the paths of unitary length (Borgatti, 2005). A strength-central personality characteristic (e.g., an item, a facet or a trait) is one that can influence many other personality characteristics (or be influenced by them) directly, without considering the mediating role of other nodes.

Closeness and betweenness. Several other measures exist that, differently from degree centrality and the related indices, consider edges beyond those incident to the focal node. An important class of these indices rely on the concepts of *distance* and of *geodesics* (Brandes, 2001; Dijkstra, 1959). The distance between two nodes is defined as the length of the shortest path between them. Since, in typical applications in personality psychology, weights represent the importance of an edge, weights are first converted to lengths, usually by taking the inverse of the absolute weight (Brandes, 2008; Opsahl et al., 2010). The *geodesics* between two nodes are the paths that connect them that have the shortest distance. Closeness centrality (Freeman, 1978; Sabidussi, 1966) is defined as the inverse of the sum of the distances of the focal node from all the other nodes in the network[15]. In terms of network flow, closeness can be interpreted as the expected speed of arrival of something flowing through the network (Borgatti, 2005). A closeness-central personality characteristic is one that is likely to be quickly affected by changes in another personality characteristic, directly or through the changes in other personality features. Its influence can reach other personality features more quickly than the influence of those that are peripheral according to closeness, because of the short paths that connect itself and the other traits. In the network in Figure 1, node D has the highest closeness. To compute the exact value of closeness, one should first compute the distances between D and all the other nodes: A (1/0.3), B (1/0.8+1/0.9), C(1/0.8), E (1/.3) and F (1/.3+1/.3). The sum of all the distances is 16.94 and the inverse, 0.59, is the closeness centrality of D.

Betweenness centrality is defined as the number of the geodesics between any two nodes that pass through the focal one. To account for the possibility of several geodesics between two nodes, if two geodesics exist, each one is counted as a half path and similarly for three or more (Brandes, 2001;

[15] The computation of closeness assumes that the network is connected (i.e., a path exists between any two nodes), otherwise, being the distance of disconnected nodes infinite, the index will result to zero for all the nodes. Variations of closeness centrality that address this issue have been proposed (e.g., Kolaczyk, 2009, p. 89; Opsahl et al., 2010, n. 1). Alternatively closeness can be computed only for the largest component of the network (Opsahl et al., 2010).

Freeman, 1978). Betweenness centrality assumes that shortest paths are particularly important (Borgatti, 2005): if a node high in betweenness centrality is removed, the distances among other nodes will generally increase. Both closeness and betweenness centrality can be applied to weighted and directed networks, as long as the weights and/or the directions of the edges are taken into account when computing the shortest paths (e.g., Opsahl et al., 2010).

The betweenness centrality of node A in Figure 1 is 4 and is the highest in the network. The four shortest paths that pass through A are those between F and the nodes B, C, D, and E. Betweenness centrality can also be extended to evaluate the centrality of edges instead of nodes, by considering the geodesics that pass through an edge: this generalization is called *edge betweenness centrality* (Brandes, 2008; Newman & Girvan, 2004; Newman, 2004). For instance, the edge-betweenness centrality of the edge (D,E) is 3 and the three shortest paths that pass through (D,E) are the one between D and E, the one between C and E (through D), and the between B and E (through C and D).

Betweenness-central personality characteristics and betweenness-central edges are particularly important for other personality characteristics to quickly influence each other. It is interesting to investigate the conditions in which some nodes become more or less central. For instance, a study that analyzed a network of moods showed that the mood "worrying" played a more central role for individuals high in neuroticism than for those with low neuroticism (Bringmann et al., 2013): the prominent role of worrying for neuroticism was recently confirmed by an experimental fMRI study (Servaas, Riese, Ormel, & Aleman, 2014).

Several other variants of the shortest-paths betweenness have been discussed by Brandes (2008), some of which are implemented in package *sna* (Butts, 2008). Generalizations of betweenness centrality that account for paths other than the shortest ones have been also proposed (Brandes & Fleischer, 2005; Freeman, Borgatti, & White, 1991; Newman, 2005). In addition, Opsahl and colleagues (2010) proposed generalizations of degree, closeness, and betweenness centralities by combining in the formula both the number and the weights of the edges. They introduced a tuning parameter that allows setting their relative importance: a higher value of the tuning parameter emphasizes the importance of the weights over the mere presence of the ties and vice versa. Another important family of centrality indices defines the centrality of a node as recursively dependent on the centralities of their neighbors. Among the most prominent of those indices are *eigenvector centrality* (Bonacich, 1972, 2007), *Bonacich power* (Bonacich, 1987) and *alpha centrality* (Bonacich & Lloyd, 2001).

Clustering coefficients[16]

Besides centrality, other network properties have been investigated that are relevant also for personality networks. The local clustering coefficient is a node property defined as the number of connections among the neighbors of a focal node over the maximum possible number of such connections (Watts & Strogatz, 1998). If we define a triangle as a triple of nodes all connected to each other, the clustering coefficient can be equally defined as the number of triangles to which the focal node belongs, normalized by the maximum possible number of such triangles. The clustering coefficient is high for a node *i* if most of *i*'s neighbors are also connected to each other and it is important to assess the small-world property (Humphries & Gurney, 2008; Watts & Strogatz, 1998), as we detail below. Consider for instance the node D in Figure 1, which has three neighbors, A C, and E. Of the three possible connections among its neighbors, only one is present (the one between A and E), therefore its clustering coefficient is 1/3.

The clustering coefficient can be also interpreted as a measure of how much a node is redundant (Latora, Nicosia, & Panzarasa, 2013; Newman, 2010): if most of a node's neighbors are also connected

[16] Some of the concepts presented in this paragraph will be discussed in more detail in Chapter 2, when we will present three new indices of clustering coefficient for signed networks.

with each other, removing that node will not make it harder for its neighbors to reach or influence each other. A personality characteristic that has a high clustering coefficient is mainly connected to other personality features which are directly related to each other. In personality questionnaires the strongest connections are usually among nodes of the same subscale: in these cases, having a high clustering coefficient may coincide with having most connections with other nodes belonging to the same subscale, while having no large connection with nodes of other scales.

While in its original formulation the clustering coefficient can be applied only to unweighted networks (or to weighted networks, disregarding the information about weights), it has been recently generalized to consider positive edge weights (Saramäki et al., 2007). The first of such generalizations was proposed by Barrat and colleagues (2004) and has been already discussed in the context of personality psychology and psychopathology (Borsboom & Cramer, 2013). Onnela and colleagues (Onnela, Saramäki, Kertész, & Kaski, 2005) proposed a generalization that is based on the geometric averages of edge weights of each triangle centered on the focal node. A different generalization has been proposed in the context of gene co-expression network analysis by Zhang and Horvath, which is particularly suited for networks based on correlations (Kalna & Higham, 2007; Zhang & Horvath, 2005). All of these generalizations coincide with the unweighted clustering coefficient when edge weights become binary (Saramäki et al., 2007). Recently three formulations of clustering, the unweighted clustering coefficient (Watts & Strogatz, 1998), the index proposed by Onnela (2005) and the one proposed by Zhang and Horvath (2005) have been generalized to signed networks and the properties of such indices have been discussed in the context of personality networks (Costantini & Perugini, 2014). We will present these generalizations in Chapter 2.

Transitivity (or global clustering coefficient) is a concept closely connected to clustering coefficient that considers the tendency for two nodes that share a neighbor to be connected themselves for the entire network, instead than for the neighborhood of each node separately. It is defined as three times the number of triangles, over the number of connected triples in the network, where a connected triple is a node with two edges that connect it to an unordered pair of other nodes (Newman, 2003). Differently from the local clustering coefficient, transitivity is a property of the network and not of the single nodes. For instance, the network in Figure 1 has one triangle (A, D, E) and 12 connected triples, therefore its transitivity is (3*1)/12 = 1/4. Transitivity has been extended by Opsahl and Panzarasa (2009) to take into account edge weights and directions, and by Kunegis and collaborators to signed networks (Kunegis et al., 2009).

Topology

The transitivity and clustering coefficient can be used to assess the network *small-world property*. The small-world property was initially observed in social networks as the tendency for any two people to be connected by a very short chain of acquaintances (Milgram, 1967). The small-world property is formally defined as the tendency of a network to have both a high clustering coefficient and a short average path length (Watts & Strogatz, 1998). Small-world networks are therefore characterized by both the presence of dense local connections among the nodes and of links that connect portions of the network otherwise far away from each other. An index of *small-worldness* for unweighted and undirected networks has been proposed as the ratio of transitivity to the average distance between two nodes. Both transitivity and path length are standardized before the computation of small-worldness, by comparing them to the corresponding values obtained in equivalent random networks (with the same N and the same degree distribution). Alternatively, the index can be computed using the average of local clustering coefficients instead of transitivity. A network with a small-worldness value higher than three can be considered as having the small-world property, while a small-worldness between one and three is considered a borderline value (Humphries & Gurney, 2008). Because the assessment of small-worldness relies on shortest paths between all the pairs of nodes, it can be computed only for a connected network or the giant component of a disconnected network.

Scale-free networks are characterized by a few very influential nodes (hubs) having a disproportionately large number of connections and by a majority of the nodes having only a few neighbors (Albert et al., 1999). The assessment of the *scale-free property* of a network requires to inspect whether the distribution of the degree centralities of its nodes can be fitted by a power-law (Albert et al., 1999; Barabási & Albert, 1999). Since personality networks are ultimately based on correlations, they are typically dense; furthermore, they are relatively small in size, including from a few nodes to a couple of hundreds of nodes (e.g., Cramer et al., 2012a). Conversely, scale-free networks must be sparse (Del Genio, Gross, & Bassler, 2011) and large, otherwise the power-law distribution cannot be observed. Therefore, when we will examine real personality networks in Chapters 3 and 4, we will perform formal test of their small-worldness, but not of their scale-free property.

Chapter 2. Clustering coefficients[17]

[17] The studies described in this chapter have been published in Costantini and Perugini (2014)

Highlights

- The concept of clustering coefficient and the existing indices are presented in detail.
- The clustering coefficient is generalized to signed networks: three new indices are introduced that take edge signs into account.
- The performances of the new indices are illustrated and compared with the performances of the unsigned indices, both on a signed simulated network and on a signed network based on actual personality psychology data.
- The results show that the new indices are more resistant to sample variations in correlation networks and therefore have higher convergence compared with the unsigned indices both in simulated networks and with real data.

Introduction

For some applications of network analysis, edge signs are typically neglected: the clustering coefficient (Saramäki et al., 2007; Watts & Strogatz, 1998) represents a primary example of such a strategy (Borsboom & Cramer, 2013; Goekoop, Goekoop, & Scholte, 2012; Zhang & Horvath, 2005). The clustering coefficient assesses the connectivity in a node's neighborhood: a node has a high clustering coefficient if its neighbors tend to be directly connected with each other. This coefficient is fundamental to assessing the small-world property (Humphries & Gurney, 2008), and it can be interpreted as an index of the redundancy of a node (Borgatti, 1997; Burt, 1992; Latora et al., 2013; Newman, 2010). This last property is particularly important in personality and psychopathology networks, in which the identification of the most redundant nodes in a network could help in identifying items that do not add unique information to the network.

In this chapter we generalize clustering coefficients to signed correlation networks. The remainder of this chapter is organized as follows. First, we formally present the clustering coefficient for both unweighted and positively weighted networks. Second, we discuss why a generalization to the signed case is needed. Third, we propose modifications of the indices to extend their use to signed correlation networks. Finally, we show the performance of the new indices using both simulated networks and networks based on real data.

Definition of the clustering coefficient for unweighted and weighted networks

A triangle is a subgraph of three nodes all connected to each other. It can be conceived of as a direct connection of a node j with a node q, given by (j, q), plus an indirect connection that travels through another node, i, given by (j, i, q). If the direct edge (j, q) is null, the indirect path that travels through i is especially important because it conveys unique information about the relationship between j and q. In this case, the missing direct edge between j and q is said to constitute a structural hole (Burt, 1992). Conversely, if the direct edge *(j, q)* is present, the importance of the indirect path is reduced and *i* can be considered redundant in establishing a connection between *j* and *q*. This idea can be applied to the whole neighborhood of a node *i*; the local clustering coefficient was initially defined by Watts and Strogatz (Watts & Strogatz, 1998) for unweighted networks as the number of connections among the neighbors of a focal node over the maximum possible number of such connections,

$$C_{i,W} = \frac{\sum_{j,q} (a_{(j,i)} a_{(i,q)} a_{(j,q)})}{k_i \left(k_i - 1\right)} \text{, (1)}$$

where k_i is the degree of node *i* (Freeman, 1978), and $a_{(i,j)} \in \{0,1\}$ represents the element at the *i*-th row and *j*-th column of the $n \times n$ adjacency matrix (A). The clustering coefficient can be equivalently conceived of as the number of triangles in the neighborhood of a focal node (t_i), normalized by the maximum possible number of such triangles,

$$C_{i,W} = \frac{2t_i}{k_i \left(k_i - 1\right)} \quad (2)$$

and it can be interpreted as a measure of how much a focal node *i* is redundant in establishing connections in its neighborhood (Latora et al., 2013; Newman, 2010).

Several generalizations of the clustering coefficient have been proposed for positively weighted networks (Saramäki et al., 2007). We consider here two generalizations that are well-known, proposed by Onnela and colleagues (Onnela et al., 2005) and by Zhang and Horvath (Kalna & Higham, 2007; Zhang & Horvath, 2005). Onnela and colleagues defined the intensity of a subgraph in a network as the geometric average of its edge weights and proposed a weighted version of the clustering coefficient by substituting the number of triangles in the numerator of (1) with the sum of triangle intensities

$$C_{i,O} = \frac{\sum_{j,q} \left(w_{(j,i)} w_{(i,q)} w_{(j,q)} \right)^{\frac{1}{3}}}{k_i \left(k_i - 1 \right)} \quad . \quad (3)$$

Where $w_{(i,j)} \in [0,1]$ is the element at the i-th row and j-th column of the weights matrix (W). This index requires an underlying binary network for computing the unweighted degree in the denominator (Kalna & Higham, 2007) and takes into account the weights of all edges in the triangles (Saramäki et al., 2007).

Zhang and Horvath (2005) generalized the clustering coefficient to networks with positive weights,

$$C_{i,Z} = \frac{\sum_{j,q} \left(w_{(j,i)} w_{(i,q)} w_{(j,q)} \right)}{\left(\sum_q w_{(i,q)} \right)^2 - \sum_q w_{(i,q)}^2} \quad . \quad (4)$$

The numerator of (4) is a generalization of Watts and Strogatz's (1998) clustering coefficient to a matrix of weights instead of to the adjacency matrix, whereas the denominator represents the maximum possible value that can be obtained by the numerator, such that $C_{i,Z} \in [0,1]$. It can be equivalently expressed with the formula

$$C_{i,Z} = \frac{\sum_{j,q}(w_{(j,i)} w_{(i,q)} w_{(j,q)})}{\sum_{j \neq q} w_{(j,i)} w_{(i,q)}} \quad . (5)$$

Both $C_{i,Z}$ and $C_{i,O}$ coincide with $C_{i,W}$ if binary edge weights {0, 1} are considered (Kalna & Higham, 2007; Saramäki et al., 2007). In contrast to Onnela's formulation, $C_{i,Z}$ is not influenced by the weights of all the edges, being insensitive to the weights of the edges incident to *i* (Saramäki et al., 2007).

Why is a generalization of clustering coefficient to signed networks needed?

In the framework of balance theory, the sign of a cycle is the product of the signs of its lines, and the degree of balance of the network has been defined as the proportion of positive cycles (Cartwright & Harary, 1956). Starting from this framework, Kunegis and colleagues operationalized the concept of multiplicative transitivity for signed networks as the tendency for any two incident edges "to be completed by a third edge having as a weight the product of the two edges' weights" (Kunegis et al., 2009). Relying on the concept of multiplicative transitivity, they also showed that it is possible to predict the edge signs in a social network by using the signs in the square adjacency matrix, in which each entry is the sum of the signs of the length-2 paths between any pair of nodes i and j. If there are more positive than negative paths joining two nodes, then the predicted direct path between them is positive. Otherwise, the predicted direct path is negative. Consider the task of guessing whether two individuals, John and Paul, are friends or enemies by knowing their relations with other people. If they have many friends and/or many enemies in common, it is also likely that they are friends themselves, while if the friends of Paul are in general the enemies of John and vice versa, John and Paul are more likely to be foes. Similarly, the evolution of a social connection between two individuals can be modeled as a function of the product of the signed links among the two focal individuals and their common neighbors (B. Hu et al., 2005). If Mary and Anne have many friends and/or enemies in common, it is likely that they will become friends themselves, while if the enemies of Mary are the friends of Anne and vice versa, it is likely that they will become foes.

The distinction between positive and negative triangles is relevant not only in social networks but also in correlation networks, especially for assessing the redundancy of a node. $C_{i,W}$, $C_{i,O}$ and $C_{i,Z}$ can all be interpreted as measures of redundancy (Latora et al., 2013; Newman, 2010), but this interpretation is only meaningful as long as the presence of a direct path (j, q) makes the indirect path (j, i, q) less important or less informative. Conversely, when the sign of the direct path is different from the sign of the indirect path (computed as the product of the edge signs), if one attempted to predict the sign of the direct edge using just the indirect path (Kunegis et al., 2009), one would hypothesize a relationship of exactly the opposite sign between j and q relative to the one expressed by the direct edge. In this case, the information conveyed by the indirect path cannot be considered redundant with regard to that of the direct path. In the case of correlation networks, in which nodes represent variables and edge weights their connections, note that simply reversing one or more variables (e.g., recoding a variable from “extraversion” to “introversion”) cannot convert a negative triangle into a positive one. Reversing a variable changes the signs of two of the connections of the triangle, but being the sign of a triangle defined by the product of the signs of its edges, this modification leaves the sign of the triangle unchanged. Reversing a variable can change the sign of the direct edge and of the indirect path together, but not the sign of one of the two independently of the other.

When $C_{i,W}$, $C_{i,O}$ and $C_{i,Z}$ are applied to a signed network considering the absolute values of weights, they do not distinguish negative from positive triangles and cannot be interpreted as indices of redundancy for those nodes that are involved in negative triangles. Therefore, in this work, we propose adaptations of $C_{i,W}$, $C_{i,O}$ and $C_{i,Z}$ such that positive triangles are considered positively and negative triangles are considered negatively in the summation. The signed clustering coefficient of a node i is high (low) if the pairs of nodes that have a connection of the same sign to i are also connected by a positive (negative) edge and if the pairs of nodes that have a connections of opposite signs with i are more likely to be connected by a negative (positive) edge. The signed clustering coefficient is high if the node i is generally involved in triangles with 0 or 2 negative edges and is low if i is generally involved in triangles with 1 or 3 negative edges.

An important reason to consider signed versions of $C_{i,W}$, $C_{i,O}$ and $C_{i,Z}$ is that the signed indices are expected to be more resistant than the corresponding unsigned indices to the presence of noise. Correlation networks are typically based on sample estimation: especially when the sample size is not large, many small correlations might still be unstable estimates of the population values (Schönbrodt & Perugini, 2013). These small correlations tend to form a large number of very small triangles that are expected to be equally distributed among positive and negative: although in the computation of the unsigned indices they can have a large influence, their effect should cancel out when computing the signed indices given that the negative triangles are subtracted and the positive triangles are added in the computation of the indices.

The new signed indices of the clustering coefficient

The unweighted clustering coefficient can be generalized to signed networks by simply replacing the unsigned adjacency values with the signed values in the formula

$$\hat{C}_{i,W} = \frac{\sum_{j,q}(a_{s(j,i)}a_{s(i,q)}a_{s(j,q)})}{k_i\left(k_i - 1\right)} \text{ , (6)}$$

Where $a_{s(i,j)} \in \{-1,1\}$ represents the element at the i-th row and j-th column of the signed adjacency matrix (A_s) and the degree (k_i) in the denominator is computed considering the unsigned values. The index $\hat{C}_{i,W}$ varies in [-1,1] and assumes the values 1 and -1 when all of the i's neighbors are directly connected in pairs and these pairs form only, respectively, positive and negative triangles with i. The value zero indicates that i participates in positive and negative triangles in equal number or that no edge connects i's neighbors to each other.

Additionally, $C_{i,O}$ can be similarly generalized to signed networks by replacing the unsigned weights with the signed ones in Formula (3): in Formula (7), when the sign of a triangle is negative, the intensity of that triangle is subtracted in the sum

$$\hat{C}_{i,O} = \frac{\sum_{j,q}\left(w_{s(j,i)}w_{s(i,q)}w_{s(j,q)}\right)^{1/3}}{k_i\left(k_i - 1\right)} \text{ , (7)}$$

Where $w_{s(i,j)} \in [-1,1]$ represents the element at the i-th row and j-th column of the signed weight matrix (W_s). $\hat{C}_{i,O}$ varies in [-1,1] and takes value 1 if all of i's pairs of neighbors form only positive triangles with *i* and the weights of all such connections are equal to one in absolute value; it takes value -1 if all of *i*'s pairs of neighbors form only negative triangles with *i* and the weights of all such connections are equal to one in absolute value, and it takes value 0 if the positive and negative triangles in which *i* participates are balanced or if the neighbors of *i* are all disconnected from each other. In correlation networks, exactly null correlations are unlikely: if one considers all the non-null correlations in the computation of the degree in (3) and (7), the denominator becomes a constant that is dependent solely on the size of the network. The alternative possibility would be to set the correlations that are below a threshold to zero; however, this procedure has important theoretical disadvantages (Zhang & Horvath, 2005). Moreover, although small correlations can be individually unreliable estimates of the population values, they can convey reliable information when they are considered together (e.g., Sherman & Funder, 2009), and their exclusion from the computation would ultimately result in loss of information. Therefore, we suggest considering all of the edges in the computation of both the numerator and the denominator.

The generalization of $C_{i,Z}$ is slightly less straightforward. In its original formulation, $C_{i,Z}$ includes the weights of the indirect paths both in the numerator and in the denominator, making the index particularly sensitive to the direct paths *(j, q)* of the triangles, which is included in the numerator but not in the denominator (cf. Formula 5). If the unsigned weights were replaced with the signed weights both in the numerator and in the denominator, the index would be dependent especially on the sign of the direct paths in the neighborhood of *i*. Making the index sensitive to the sign of the direct path would be particularly problematic in correlation networks, in which nodes represent variables and reversing a variable can arbitrarily change the signs of the direct path and of the indirect path, even if it cannot change the sign of the triangle. This would make the sign of the clustering coefficient dependent on the variable orientation. For instance, recoding a variable from "extraversion" to "introversion" and changing the signs of the correlations consequently would change the clustering coefficients. Therefore, we propose a generalization in which the numerator considers the signed weights and the denominator considers the weights in absolute value:

$$\hat{C}_{i,Z} = \frac{\sum_{j,q}(w_{s(j,i)} w_{s(i,q)} w_{s(j,q)})}{\sum_{j \neq q} | w_{s(j,i)} w_{s(i,q)} |} \text{ . (8)}$$

$\hat{C}_{i,Z}$ varies in [-1,1] and takes value 1 if all of *i*'s pairs of neighbors form only positive triangles with *i* and the absolute weights of the edges between the neighbors are equal to 1 (irrespective of the absolute weights of the indirect paths); it takes value -1 if all of *i*'s neighbors form only negative triangles with *i* and all of the absolute weights of the direct edges between *i*'s neighbors are equal to 1, and it takes value 0 if the positive and negative triangles in which *i* participates are balanced or if *i*'s neighbors are disconnected from each other.

Kunegis and colleagues (Kunegis et al., 2009) introduced a measure of global clustering coefficient for signed networks, $C_S(G)$. $C_S(G)$ and $\hat{C}_{i,Z}$ differ in the fact that whereas the first is a property of the network (global clustering coefficient, e.g., Opsahl & Panzarasa, 2009), the second is a property of each node in the network (local clustering coefficient). Some similarities between $\hat{C}_{i,Z}$ and $C_S(G)$ become apparent if we express $C_S(G)$ as

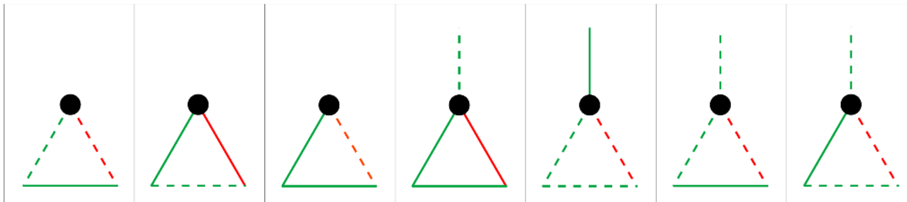
$$C_S(\mathrm{G}) = \frac{\sum_{i}\sum_{j,q}(w_{s(j,i)} w_{s(i,q)} w_{s(j,q)})}{\sum_{i}\sum_{j \neq q} | w_{s(j,i)} w_{s(i,q)} | + \sum_{i}\sum_{j} | w_{s(i,j)} w_{s(j,i)} |} \quad (9)$$

and compare it with Formula (8). The numerator of $C_S(G)$ is equal to the sum of the numerators of $\hat{C}_{i,Z}$ for all of the nodes, whereas the denominator of $C_S(G)$ is equal to the sum of the denominators of $\hat{C}_{i,Z}$ of all of the nodes plus the term $\sum_i \sum_j | w_{s(i,j)} w_{s(j,i)} |$. In undirected networks, in which $w_{s(i,j)} = w_{s(j,i)}$, this last term is equal to the sum of all of the squared elements of the weight matrix.

Figure 4 shows the values of the unsigned and the signed indices for the case in which the focal node participates in a single negative triangle. The examples are those shown in Saramäki et al. (2007, fig. 1), with the main difference that one edge in each triangle is negative. To illustrate the properties of the proposed indices of the clustering coefficient, we tested them on simulated networks and on networks based on real data. Based on the definitional features of these indices, we hypothesize that:

1. The signed and the unsigned indices of the clustering coefficient should have an increasingly strong correlation as a function of the presence of positive triangles in the network, and they should diverge as a function of the presence of negative triangles.
2. The signed indices of the clustering coefficient should be consistently more resistant to the presence of noise in correlation networks, compared with the unsigned indices, and should therefore show higher agreement.

The analyses were performed with R using packages *qgraph* (Epskamp et al., 2012), *WGCNA* (Langfelder & Horvath, 2008, 2012), *Matrix* (Bates & Maechler, 2013) and *psych* (Revelle, 2014). Functions for computing the new indices of clustering coefficient have been included in package *qgraph*.



$C_{i,W}$	1	1	1	1/3	1/3	1/3	1/3
$C_{i,O}$	~0	~0	~0	1/3	~0	~0	~0
$C_{i,Z}$	1	~0	1	~1	~0	1/3	~0
$\hat{C}_{i,W}$	-1	-1	-1	-1/3	-1/3	-1/3	-1/3
$\hat{C}_{i,O}$	~0	~0	~0	-1/3	~0	~0	~0
$\hat{C}_{i,Z}$	-1	~0	-1	~-1	~0	-1/3	~0

Figure 4. Examples of clustering coefficients for different sign and weight configurations.

$C_{i,W}$, $C_{i,O}$ and $C_{i,Z}$ are the clustering coefficient indices proposed by Watts and Strogatz (1998), Onnela and colleagues (Onnela et al., 2005) and Zhang and Horvath (2005), respectively. $\hat{C}_{i,W}$, $\hat{C}_{i,O}$ and $\hat{C}_{i,Z}$ are the corresponding indices generalized to the signed case. Solid lines (—) represent edges of weight equal to 1 in absolute value, and dashed lines (---) represent edges of weight close to 0. Green lines are positive and red lines are negative. Edge weights are ignored in the computation of the unweighted clustering coefficients $C_{i,W}$ and $\hat{C}_{i,W}$. In each triangle one edge is negative. Note however that it is irrelevant for the value of the signed clustering coefficients which of the three edges is the negative one. We considered the case of a negative triangle with one negative edge, but we could have equally considered the case of a negative triangle with three negative edges without affecting the results.

Study 1: simulated networks

The aim of this simulation was to inspect how the unsigned and signed formulations of the clustering coefficient converge in correlation networks as a function of the proportion of negative triangles in the network. Furthermore, we manipulated the presence of noise in the network to test how the indices were affected by the presence of completely random correlations.

Method

We generated a simple correlation network in which we regulated the proportion of negative triangles. To create the network, we first generated a matrix of $N = 100$ random variables (1000 observations) from a standard normal distribution. For each variable *i*, we imposed a positive correlation with variable $i+1$, the Nth variable being correlated to the first variable (correlations were imposed by multiplying a pair of variables by a random variable from a standard normal distribution). We additionally imposed a positive correlation between each variable *i* and the variable $i+2$, the variable $N-1$ being correlated with the first one and variable N being correlated with the second one. The matrix W_s was defined as the correlation matrix, with the diagonal elements set to zero, the nodes therefore represented the variables and the edge weights represented their correlations. This network could be straightforwardly represented using a circular layout (Figure 5A), in which each node *i* was connected to nodes in positions $i-2$, $i-1$, $i+1$ and $i+2$. In this initial network, each node *i* participated in three triangles whose edges were intentionally controlled (we call them *main triangles*) and that had all positive signs. For each node *i*, the three main triangles had vertices i-2, i-1, i; i-1, i, i+1; and i, i+1, i+2. We considered any node *i* as the reference point of the main triangle of vertices $i-1$, i and *i*+1 and used node *i* to define univocally one indirect path (*i*-1, *i*, *i*+1) and one direct edge (*i*-1, *i*+1) for the triangle. We stress that, because of the particular structure of the network, each direct edge corresponded to one and only one main triangle and vice versa, therefore the modification of the direct edge of a main triangle affected only that specific main triangle. We progressively modified the signs of the main triangles, one at a time in random order, by reversing the signs of only the direct edges of the triangles. The proportion of negative triangles was varied until all the main triangles had negative signs. The output of the simulation included 101 networks in which the proportion of negative main triangles ranged from 0% to 100% (Figure 5A).

On average, the absolute weight of the manipulated links was .20 (SD = .03). The networks, however, included noise because of correlations that were not intentionally controlled, which had an average weight of .03 (SD=.02) in absolute value and which were equally distributed among positive and negative edges. Therefore, each node participated additionally in $\binom{99}{2}-3=4848$ triangles whose signs were not manipulated but whose weights were small (we call them *random triangles*). In the *noise-present* condition, we computed all of the statistics without removing the random triangles from the network, whereas in the *noise-absent* condition, all edges lower than .1 were set to zero before computing all of the indices of the clustering coefficient, therefore removing most random triangles[18]. The simulation was repeated 1000 times.

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[18] The threshold of .1 seems a reasonable choice in the light of the weights distribution. However, we are aware that any fixed threshold has a degree of subjectivity and that other choices could be valid as well. Therefore, we repeated the analyses using a less subjective method by fixing to zero all edges that were not intentionally controlled irrespective of their weight. The pattern of results was substantially similar.

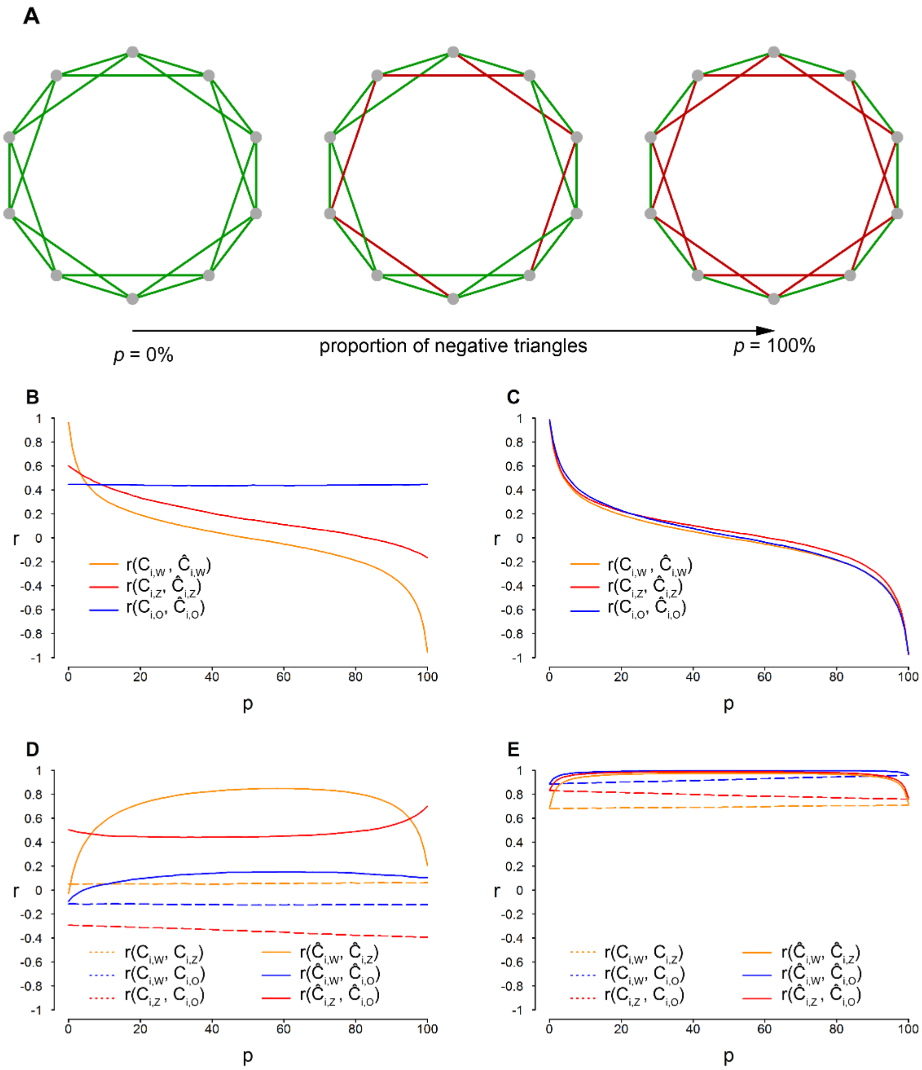

Figure 5. Correlation (r) between clustering indices as a function of the proportion of negative triangles (p).

$C_{i,W}$, $C_{i,O}$ and $C_{i,Z}$ are the clustering coefficient indices proposed by Watts and Strogatz (1998), Onnela and colleagues (Onnela et al., 2005), and Zhang and Horvath (2005) respectively. $\hat{C}_{i,W}$, $\hat{C}_{i,O}$ and $\hat{C}_{i,Z}$ are the corresponding indices generalized to the signed case. **A** Scaled model of the simulated networks. Green lines represent positive edges and red lines represent negative edges. The network in figure includes only 10 nodes, but in the actual simulation we considered larger networks (100 nodes). Moreover, only the edges that were intentionally manipulated are represented. **B** Correlations between the corresponding signed and unsigned indices of the clustering coefficient in the noise-present condition. **C** Correlations between the corresponding signed and unsigned indices of the clustering coefficient in the noise-absent condition. **D** Correlations between different clustering coefficient indices, both signed and unsigned, in the noise-present condition. **E** Correlations between different clustering coefficient indices, both signed and unsigned, in the noise-absent condition.

Results

We computed $C_{i,W}$, $C_{i,O}$ and $C_{i,Z}$, as well as the corresponding signed indices, $\hat{C}_{i,W}$, $\hat{C}_{i,O}$ and $\hat{C}_{i,Z}$, respectively, for each node in each network. In the *noise-present* condition, for the computation of $C_{i,W}$ and $\hat{C}_{i,W}$, an edge was considered present if its weight was higher than .1 in absolute value, absent otherwise. For the computation of the denominator of $C_{i,O}$ and $\hat{C}_{i,O}$, we considered all of the nonzero edges as present in the adjacency matrix. Figure 2B and Figure 2C report the correlation between the corresponding signed and unsigned indices of the clustering coefficient in the noise-present and noise-absent conditions, respectively, as a function of the proportion of negative main triangles induced in the networks. Because the same threshold of .1 was used to manipulate the presence of noise and to compute the unweighted indices of the clustering coefficient, the correlations between $C_{i,W}$ and $\hat{C}_{i,W}$ were identical in the noise-present and the noise-absent conditions, being close to r = 1 when only positive main triangles were present, null when both positive and negative main triangles were present in equal proportion, and close to r = -1 when only negative main triangles were induced. In the noise-present condition, this pattern was similar, albeit less accentuated for $C_{i,Z}$ and $\hat{C}_{i,Z}$. No systematic variation in correlations was present for $C_{i,O}$ and $\hat{C}_{i,O}$ as a function of the proportion of negative main triangles because of the exponents in the numerators of Formulas (3) and (7), which make $C_{i,O}$ and $\hat{C}_{i,O}$ relatively more sensitive than $C_{i,Z}$ and $\hat{C}_{i,Z}$ to triangles that are small in absolute weight. Conversely, in the noise-absent condition (Figure 2B), the pattern of correlations was substantially identical for the three indices.

Figure 5D reports the correlation among the different indices in the noise-present condition. The correlation between the unsigned indices was close to zero or negative. In particular, the correlation between $C_{i,Z}$ and $C_{i,O}$ was negative and ranged between r=-.40 and r=-.29. A negative correlation may appear surprising between indices that are meant to assess a similar property, but it can be explained by the different effect that many random triangles have on the two indices, despite their small weight. A positive variation in the absolute weight of the random triangles incident to a node *i* appreciably increases $C_{i,O}$ because of the exponent in the numerator of (3) that magnifies the small triangles, but it decreases $C_{i,Z}$ because its effect is stronger in increasing the denominator of (4) than the numerator. Conversely, the correlations between the two signed measures $\hat{C}_{i,Z}$ and $\hat{C}_{i,O}$ were all positive and ranged between r = .44 and r = .70. The correlation between the signed indices was high and positive, with the exception of the correlation between $\hat{C}_{i,O}$ and $\hat{C}_{i,W}$, which was close to zero. This is because whereas $\hat{C}_{i,W}$ was computed only considering triangles with weights higher than .1, $\hat{C}_{i,O}$ was also affected by triangles with smaller weights.

Figure 5E reports the correlation among the different indices in the noise-absent condition. Removing the noise from the network increased the correlations both between the signed and between the unsigned indices of the clustering coefficient. The correlation between the signed indices was always higher than or equal to the correlation between the corresponding unsigned indices. The reversed “U” shape of the pattern of correlations between the signed indices was attributable to the restriction of range when almost only positive or almost only negative main triangles were present.

Discussion

To test Hypothesis 1, we inspected the correlations between the corresponding signed and unsigned indices of the clustering coefficient. As expected, the correlations between the clustering coefficient indices varied according to the proportion of negative main triangles. Even a small proportion of negative triangles in a network can make a substantial difference between the indices of a clustering coefficient computed considering or disregarding the edge signs. Consider, for instance, that when the proportion of negative main triangles increased from 0% to 25%, the correlation between the corresponding signed and unsigned indices decreased from $r \sim 1$ to $r < .25$ for all of the indices. This trend, however, was apparent for $\hat{C}_{i,O}$ and was more accentuated for $\hat{C}_{i,Z}$ only when the noise was removed from the network because of the influence of many small random triangles on the unsigned weighted indices $C_{i,Z}$ and $C_{i,O}$.

To better understand the influence of small random triangles on the weighted indices, we inspected the correlation between the weighted indices that considered or disregarded the signs in the noise-present condition (Figure 2D). Whereas the signed indices $\hat{C}_{i,Z}$ and $\hat{C}_{i,O}$ clearly converged, the unsigned indices $C_{i,Z}$ and $C_{i,O}$ showed a marked divergence. In the computation of the signed indices, positive and negative random triangles tend to cancel each other; conversely, they have an additive effect on the unsigned indices that can obscure the effect of systematic variation. In the noise absent condition, after removing the random triangles, all the indices showed a much stronger convergence (Figure 2E). In conclusion, Hypothesis 2 was also confirmed: the signed indices of the clustering coefficient were more resistant than were the unsigned indices to the presence of random edges.

Study 2: Clustering coefficient on personality psychology data

The simulation showed the behavior of the unsigned and the signed indices in a simplified and idealized condition. We tested the behavior of the indices on a real dataset of personality data in which the correlation coefficients could not be divided *a priori* into random and systematic edges.

Method

There-hundred-fifty-five participants (275 female and 76 male, M age = 23.4, SD = 6.4, plus four participants who did not indicate gender and age) were administered the HEXACO-60 (Ashton & Lee, 2009), a short 60-item inventory that assesses six major dimensions of personality: honesty-humility, emotionality, extraversion, agreeableness vs. anger, conscientiousness and openness to experience (Ashton & Lee, 2007). Moreover, for each dimension there are four facet scores, lower-order traits that are subsumed by the major dimensions: facet scores can be computed as the average of two or three items, depending on the facet (Ashton & Lee, 2009).

For the item labeling, we followed this convention both in the text and in the figures. We used a letter to indicate the personality dimension that the item measures: H indicates honesty-humility, E indicates emotionality, X indicates extraversion, A indicates agreeableness vs. anger, C indicates conscientiousness and O indicates openness to experience. The items are then numbered in order of administration, the same as was reported by Ashton and Lee (Ashton & Lee, 2009), in which the complete item content is available. Twenty-nine items of the HEXACO-60 assessed the negative poles of the traits and were therefore reverse-scored.

Results

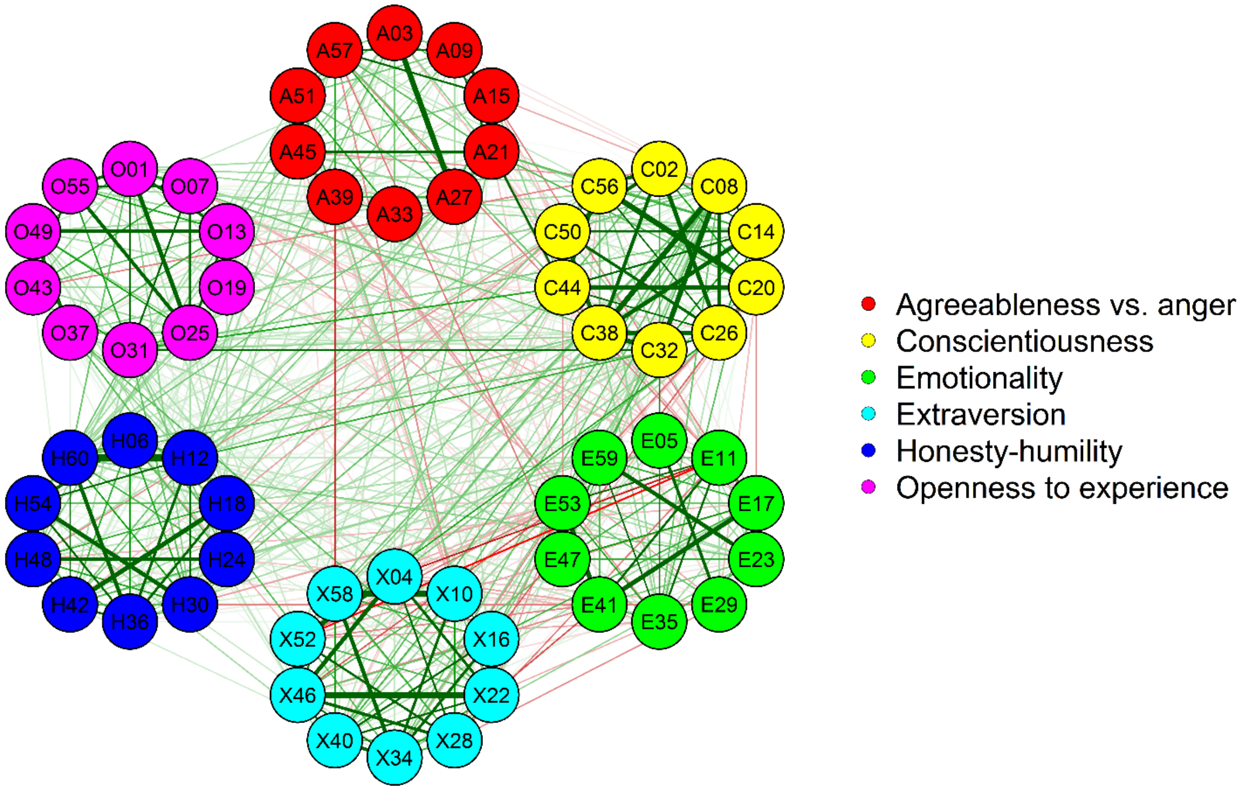

Figure 6. Graphical representation of the network of the HEXACO-60.

Items are grouped by the personality factor that they assess. Green lines represent positive correlations, and red lines represent negative correlations, the thicker the line, the stronger the correlation. The figure was obtained with the R package *qgraph* (Epskamp et al., 2014, 2012).

The W_s matrix was defined as the correlation matrix between the HEXACO-60 items, and the diagonal elements were set to zero. The resulting network is represented in Figure 6. The number of positive edges was 1206, and the number of negative edges was 564. The number of positive triangles was 20600, and the number of negative triangles was 13620. These numbers show that negative triangles are substantially present in empirical data that can be considered typical in personality psychology. However, positive triangles were on average higher in weight than were negative triangles. We defined the weight of a triangle as the product of its edge weights, in absolute value. The average weight of a positive triangle was higher (M = .0018, SD = .0047) than was the average weight of negative triangles (M = .0005, SD = .0007), and this difference was largely significant, as emerged from an independent samples t-test, t(34218) = 32.97, $p < 10^{-15}$.

Table 1. Correlations between the clustering coefficient indices computed on the HEXACO-60.

	$C_{i,O}$	$C_{i,Z}$	$\hat{C}_{i,O}$	$\hat{C}_{i,Z}$
$C_{i,O}$	1	.10	.79**	.31*
$C_{i,Z}$	.07	1	.19	.82**
$\hat{C}_{i,O}$	.84**	.08	1	.58**
$\hat{C}_{i,Z}$	.38**	.80**	.58**	1

*p<.05, **p<.01. N = 60. Spearman-rank correlations are reported above the diagonal; Pearson's correlations are reported below the diagonal. $C_{i,O}$ and $C_{i,Z}$ are the clustering coefficient indices proposed in (Onnela et al., 2005) and (Zhang & Horvath, 2005), respectively. $\hat{C}_{i,O}$ and $\hat{C}_{i,Z}$ are the corresponding indices generalized to the signed case.

The indices of the weighted clustering coefficient $C_{i,O}$ and $C_{i,Z}$, $\hat{C}_{i,O}$ and $\hat{C}_{i,Z}$ were computed for each node. We inspected the correlation among all the unsigned and signed measures of the clustering coefficient (Table 1). The correlations among the corresponding signed and unsigned indices were substantial both between $C_{i,Z}$ and ,$\hat{C}_{i,Z}$ and between $C_{i,O}$ and $\hat{C}_{i,O}$. As expected, the signed indices $\hat{C}_{i,O}$ and $\hat{C}_{i,Z}$ showed a much stronger agreement than the unsigned indices $C_{i,O}$ and $C_{i,Z}$, for which the correlation did not reach statistical significance.

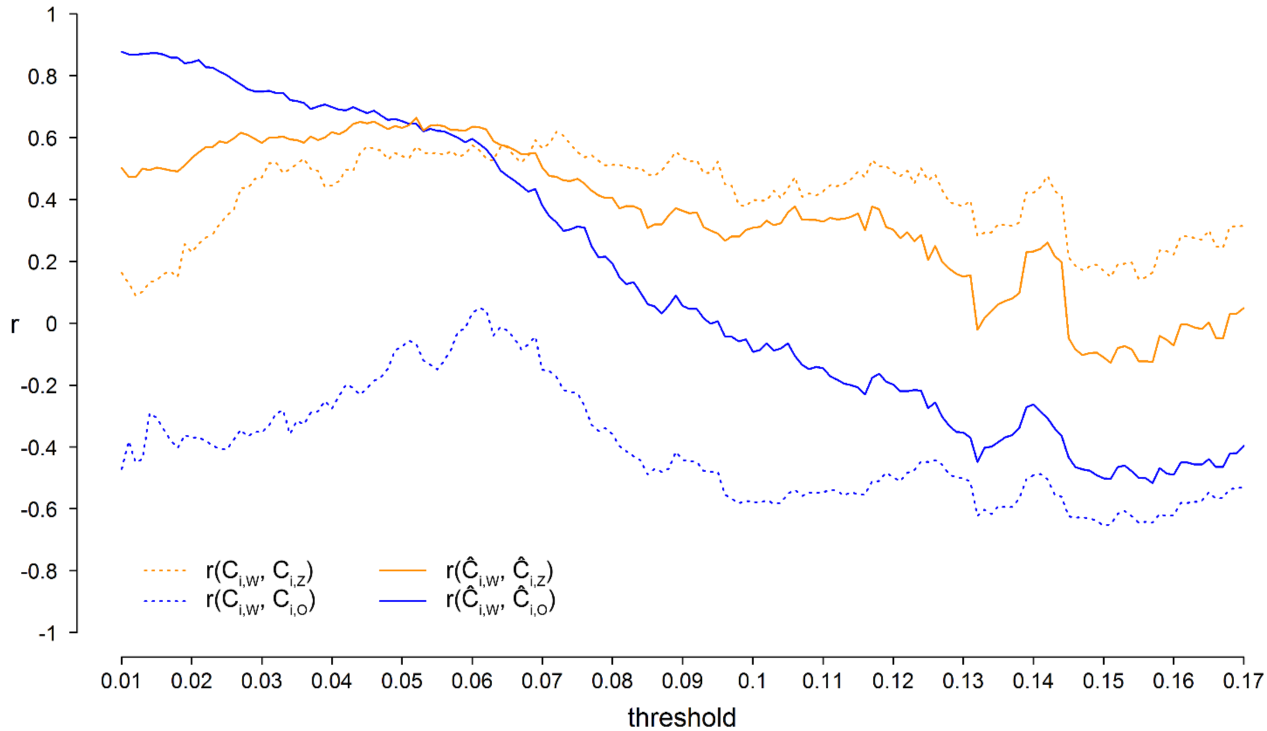

Figure 7. Correlation (r) between the unweighted and the weighted indices of clustering coefficient. $C_{i,W}$, $C_{i,\mathrm{O}}$ and $C_{i,\mathrm{Z}}$ are the clustering coefficient indices proposed by Watts & Strogatz (1998), Onnela and colleagues (2005), and (2005), respectively. $\hat{C}_{i,W}$, $\hat{C}_{i,\mathrm{O}}$ and $\hat{C}_{i,\mathrm{Z}}$ are the corresponding signed indices. $C_{i,W}$ and $\hat{C}_{i,W}$ are unweighted because they do not depend on edge weights and require a binary network, whereas $C_{i,\mathrm{O}}$, $\hat{C}_{i,\mathrm{O}}$, $C_{i,\mathrm{Z}}$ and $\hat{C}_{i,\mathrm{Z}}$ consider edge weights. The correlations are shown as a function of the threshold used for the dichotomization of the network to compute $C_{i,W}$ and $\hat{C}_{i,W}$.

For the computation of $C_{i,W}$ and $\hat{C}_{i,W}$, a dichotomization was necessary; however, in contrast with the simulation study, it was not possible to select a value that would easily divide the edges into random and systematic. Therefore, we chose to examine the results as a function of different thresholds. Figure 4 shows the correlations between the unweighted indices $C_{i,W}$ and $\hat{C}_{i,W}$ and the weighted indices $C_{i,Z}$, $\hat{C}_{i,Z}$, $C_{i,O}$ and $\hat{C}_{i,O}$ when the threshold varied between a minimum value of .01 and a maximum of .17. Using higher thresholds would not have guaranteed the presence of two neighbors for each node, which is essential to computing the clustering coefficient for every node. Figure 5 shows that the most substantial correlations between the signed indices were reached for low thresholds, but important variations in the agreement of both signed and unsigned indices arose as a function of the threshold.

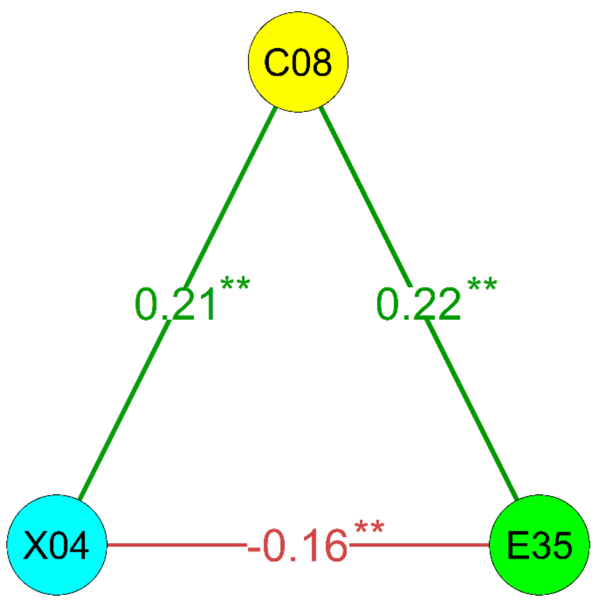

Figure 8. An example of a triangle that emerged from real data.

**p<.01. Edge weights are defined as the Pearson's correlation coefficients among the three items. The letters indicate the personality dimension assessed by the item, C = conscientiousness, E = emotionality and X = extraversion, and the numbers indicate their order of administration on the questionnaire (see Ashton & Lee, 2009).

One reason it is important to consider signed indices is in their potential implications in terms of understanding and interpreting network relations. To provide a psychologically meaningful example, we present a triangle that emerged from the data that can provide some insight on possible interpretative differences between considering and disregarding triangle signs. The triangle (Figure 8) contains nodes C08 ("I often push myself very hard when trying to achieve a goal"), E35 ("I worry a lot less than most people do"; this item is reverse-scored, indicating greater worries) and X04 ("I feel reasonably satisfied with myself overall"). The triangle is discussed from the perspective of node C08 as the focal node (one could equally interpret the direct and the indirect paths using another node as the focal one). The indirect path (E35, C08, X04) suggests that anxiety (E35) is positively related to diligence (C08), which in turn is positively related to social self-esteem (X04). Therefore, if one attempted to predict the direct path (X04, E35) with no knowledge other than the indirect path, one would hypothesize a positive relationship between social self-esteem and anxiety. However, social self-esteem (X04) and anxiety (E35) are negatively correlated: the direct path and the indirect path are not redundant. If one considers the edge signs, one may hypothesize that nodes E35 and X04 are negatively connected *despite* the effect of diligence (C08) but not that they are connected because of it. The same pattern is also present at the level of facets (for facets in the HEXACO, see Ashton & Lee, 2007, 2009), with anxiety being positively related to diligence ($r = .26$, $p < .01$), diligence positively related to social self-esteem ($r = .18$, $p < .01$) and social self-esteem negatively related to anxiety, $r = -.34$ ($p < .01$). One could speculate that this triangle reflects a negative feedback loop, as described by Cramer and colleagues (2012a). A reasonable level of anxiety can help in focusing one's goals (e.g., Keeley, Zayac, & Correia, 2008), and pursuing goals may lead to higher self-esteem (e.g., Erol & Orth, 2011; Orth, Trzesniewski, & Robins, 2010), which in turn reduces anxiety and reinstates the equilibrium. Negative feedback loops are essential in maintaining homeostasis, yet this relationship pattern would have been lost or misinterpreted by disregarding the edge signs when computing the clustering coefficient in correlation networks. In short, disregarding signs can entail the loss or misinterpretation of important information.

Discussion

This analysis showed how the indices of the clustering coefficient performed when applied to real data from a personality network. Among the weighted indices, the signed indices $\hat{C}_{i,Z}$ and $\hat{C}_{i,O}$ converged with each other whereas the unsigned indices $C_{i,O}$ and $C_{i,Z}$ did not show a significant convergence. Hypothesis 2 therefore was also confirmed with real data: a higher convergence was reached when negative triangles were considered with negative signs.

With the real data, it was not possible to find a convincing binary division between systematic and random edges. For the computation of the unweighted indices $C_{i,W}$ and $\hat{C}_{i,W}$, we examined different possible thresholds: the indices, and therefore their convergence with the other clustering indices, were noticeably dependent on the selection of the threshold parameter.

Conclusions

We presented three modified indices of clustering coefficient especially conceived for correlation networks, that account for negative interactions. The new measures have both theoretical and practical advantages: they distinguish positive from negative triangles, which have a different meaning in correlation networks and in psychological data in particular. Moreover, they are more resistant than are the unsigned measures to random sample variation in correlation matrices. The first measure that we introduced, $\hat{C}_{i,W}$, does not take weights into account and is particularly indicated in the analysis of signed unweighted networks or for those situations in which it is sensible to divide the edges of a weighted network into systematic and random to obtain a binary network. The other two measures, $\hat{C}_{i,O}$ and $\hat{C}_{i,Z}$, take both weights and signs into account and are particularly useful for the analysis of correlation networks based on real data, in which a clear division between systematic and random edges cannot be performed without substantially affecting the results.

In the psychological data that we considered, positive triangles showed on average higher weights than did negative triangles, causing higher correlations between the signed and the unsigned measures of the clustering coefficient. Personality questionnaires are typically assembled relying on techniques based on the concept of simple factor structure (e.g., Kaiser, 1958; Thurstone, 1947): a factor analysis or a principal component analysis is performed, the initial factorial structure is rotated to achieve the simplest possible factor structure given the data, and those items are finally selected that show high primary loadings and low secondary loadings (i.e., the highest item-factor correlation should be much stronger than the second highest, Ashton & Lee, 2009; Fabrigar, Wegener, MacCallum, & Strahan, 1999). The strongest correlations in the matrix are therefore among items belonging to the same factor, which form only positive triangles with each other: this is likely to determine the much stronger weight of positive triangles in these networks. Personality questionnaires that have been assembled using different criteria (e.g., Block, 2010; Funder, Furr, & Colvin, 2000; Hofstee, De Raad, & Goldberg, 1992; Sherman, Nave, & Funder, 2010) are expected to produce stronger negative triangles and should be targeted by future research.

The aim of the research presented in this chapter was to tailor a number of tools by bearing in mind the specific issues and data that are typical of research in personality psychology. Although the signed generalizations of the clustering coefficient have originated from this perspective, their potential usefulness and applicability go beyond the realm of personality. In brief, whenever negative triangles can be expected to be present in a network, such as in social networks (Kunegis et al., 2009) or biological networks (Kalna & Higham, 2007), using indices based on signed correlation networks can be quite valuable. They can be particularly useful when there is some level of random noise in the correlation matrix because we have shown that they are much more resistant to such noise than are equivalent unsigned indices. We suspect that these conditions can be present in several other network analysis application contexts and therefore that these proposed indices can have a wide range of applicability for other domains and topics.

Chapter 3. The HEXACO-60 network[19]

[19] The study described in this chapter has been published in Costantini et al. (2014). An introductory part has been included to improve the readability of the chapter.

In Chapter 2 we considered the HEXACO-60 (Ashton & Lee, 2009) as an example of application for the clustering coefficients. In Chapter 3 we deepen the structure of the HEXACO-60 network, using a larger sample[20] and focusing on facets instead of items to achieve more stable and interpretable results (see Chapter 1).

The HEXACO structure has been developed to reflect the consistent emergence of six major personality factors in several languages (Ashton et al., 2004, 2006; K. Lee & Ashton, 2008; Saucier, 2009). Three of these factors, extraversion, conscientiousness, and openness to experience, are largely similar to those recovered in the Big Five structure (e.g., Boele de Raad, 2000; Goldberg, 1990; Saucier & Goldberg, 1996) and in the Five Factor Model (Costa & McCrae, 1992; McCrae & Costa, 1987, 2008). Factor emotionality in the HEXACO is similar to the Big Five factor neuroticism, but without the anger-related aspects, and includes sentimentality aspects that were part of the agreeableness factor in the Big Five model. Factor agreeableness vs. anger in the HEXACO is similar to the Big Five agreeableness, but without sentimentality, and includes in its low pole the anger aspects that were part of the Big Five factor neuroticism (Ashton, Lee, & de Vries, 2014; Ashton & Lee, 2007). However the characteristic that most clearly distinguishes the HEXACO model from the Big Five model is the addition of a sixth factor, honesty-humility, that subsumes aspects such as "honesty, fairness, sincerity, modesty, and lack of greed" (K. Lee & Ashton, 2004, p. 332). The introduction of honesty-humility allowed to include variance that was not present in the Big Five model and especially a portion of variance that had been associated to machiavellianism, narcissism and psychopathy, the traits that of the dark triad of personality (Paulhus & Williams,

[20] Additional participants were included in the HEXACO-60 dataset after the publication of Chapter 2 (Costantini & Perugini, 2014). The larger sample presented here (N = 964) includes also the 355 participants presented in Chapter 2.

2002). For instance, the addition of honesty-humility allowed to explain differences in the adoption of cooperative vs. exploitative interpersonal strategies and to improve the predictions of important outcome variables, such as those connected to sex, money and power, that had been previously associated to the dark triad (e.g., Ashton et al., 2014; K. Lee & Ashton, 2014; K. Lee et al., 2013).

The HEXACO model has been operationalized in the HEXACO personality inventory (K. Lee & Ashton, 2004), of which the HEXACO-60 is the short form (Ashton & Lee, 2009). Several studies considered networks defined starting from the FFM framework (Cramer et al., 2012a; Epskamp et al., 2012; Franić et al., 2013). In this chapter we analyze a network obtained from the HEXACO model using the HEXACO-60 questionnaire. For the definition of the network and for its analysis we employ some of the analytic tools that we presented in Chapters 1 and 2. Some of them, such as the adaptive LASSO penalty and the signed clustering coefficients, have been adopted here for the first time in a personality psychology network analysis.

Method

Participants and procedure

The dataset that we analyze here includes nine-hundred-sixty-four participants (704 female and 256 male, M age = 21.1, SD = 4.9, plus four participants who did not indicate gender and age) who completed the HEXACO-60 in the context of a number of different studies performed over the last few years.

Materials

The HEXACO-60 (Ashton & Lee, 2009) is a short 60-items inventory that assesses six major dimensions of personality: honesty-humility, emotionality, extraversion, agreeableness vs. anger, conscientiousness and openness to experience. Each of the major dimensions subsumes four facets

(Ashton & Lee, 2007). Participants indicated their agreement with each statement on a scale from 1 (*strongly disagree*) to 5 (*strongly agree*). An example of an item (of trait emotionality) is "When I suffer from a painful experience, I need someone to make me feel comfortable".

Results

Structure of the dataset

To provide a general idea of the structure of the dataset, we performed exploratory factor analysis using the R package *psych* (Revelle, 2014). Both the scree-test and parallel analysis indicated that six factors adequately described the data. The first seven eigenvalues were 3.52, 2.71, 2.27, 1.92, 1.73, 1.33, 0.86, while the first seven eigenvalues extracted from random data were 1.29, 1.25, 1.22, 1.19, 1.16, 1.13, 1.11. Six factors explained 42% of the total variance. We extracted six orthogonal factors, factor loadings are reported in Table 2 and reproduce the expected structure (Ashton & Lee, 2009). For each facet Table 2 reports also the squared multiple correlation with all the other facets and the Hofmann's row-complexity index, which represents the number of latent variables needed to account for each manifest variable (Hofmann, 1978; Pettersson & Turkheimer, 2010).

Table 2. Factor loadings of the HEXACO-60. Factors are labeled according to their highest loadings.

	E	C	O	X	H	A	Uniq.	Compl.	Smc
Hsi	-.05	.11	.11	.05	**.60**	-.05	.61	1.17	.26
Hfa	.14	.22	.15	-.04	**.63**	.19	.48	1.69	.39
Hga	.11	-.01	.24	.03	**.54**	.14	.62	1.65	.29
Hmo	.04	-.01	.05	-.05	**.44**	.07	.79	1.12	.16
Efe	**.48**	.03	-.16	-.22	-.07	-.04	.69	1.72	.27
Ean	**.55**	.17	.08	-.12	.11	-.11	.63	1.54	.30
Ede	**.66**	-.01	-.11	-.08	-.01	-.03	.55	1.10	.34
Ese	**.68**	.07	.02	.10	.13	.08	.50	1.18	.36
Xss	-.36	.18	.06	**.53**	-.08	.00	.54	2.14	.38
Xsb	-.05	.08	.07	**.63**	-.02	-.25	.52	1.40	.36
Xso	.17	-.02	.03	**.65**	.06	.01	.55	1.17	.33
Xli	-.11	.06	.02	**.67**	.00	.12	.52	1.13	.37
Afo	.09	-.09	.04	.13	.16	**.43**	.75	1.68	.20
Age	.09	-.06	-.02	.04	.13	**.54**	.68	1.21	.23
Afl	-.06	-.02	-.01	-.10	.06	**.67**	.53	1.08	.29
Apa	-.11	.10	.14	-.01	.09	**.49**	.71	1.45	.22
Cor	.01	**.73**	-.07	.06	.01	.00	.46	1.03	.37
Cdi	.19	**.58**	.19	.21	.18	-.03	.51	1.99	.41
Cpe	.08	**.70**	.18	.05	.06	-.08	.46	1.22	.41
Cpr	-.21	**.52**	.12	-.12	.15	.12	.62	1.87	.32
Oaa	-.04	.17	**.71**	-.04	.15	.04	.44	1.23	.42
Oin	-.25	.09	**.59**	.04	.15	-.01	.56	1.55	.35
Ocr	.15	.01	**.62**	.14	.01	.08	.56	1.26	.32
Oun	-.07	.01	**.57**	.10	.11	-.08	.65	1.22	.29

Note. E = loading on emotionality, C = loading on conscientiousness, O = loading on openness to experience, X = loading on extraversion, H = loading on honesty-humility, A = loading on agreeableness versus anger. Smc = squared multiple correlation of each facet with all the others. Uniq. = uniqueness. Compl. = Hofmann's row-complexity index (1978).

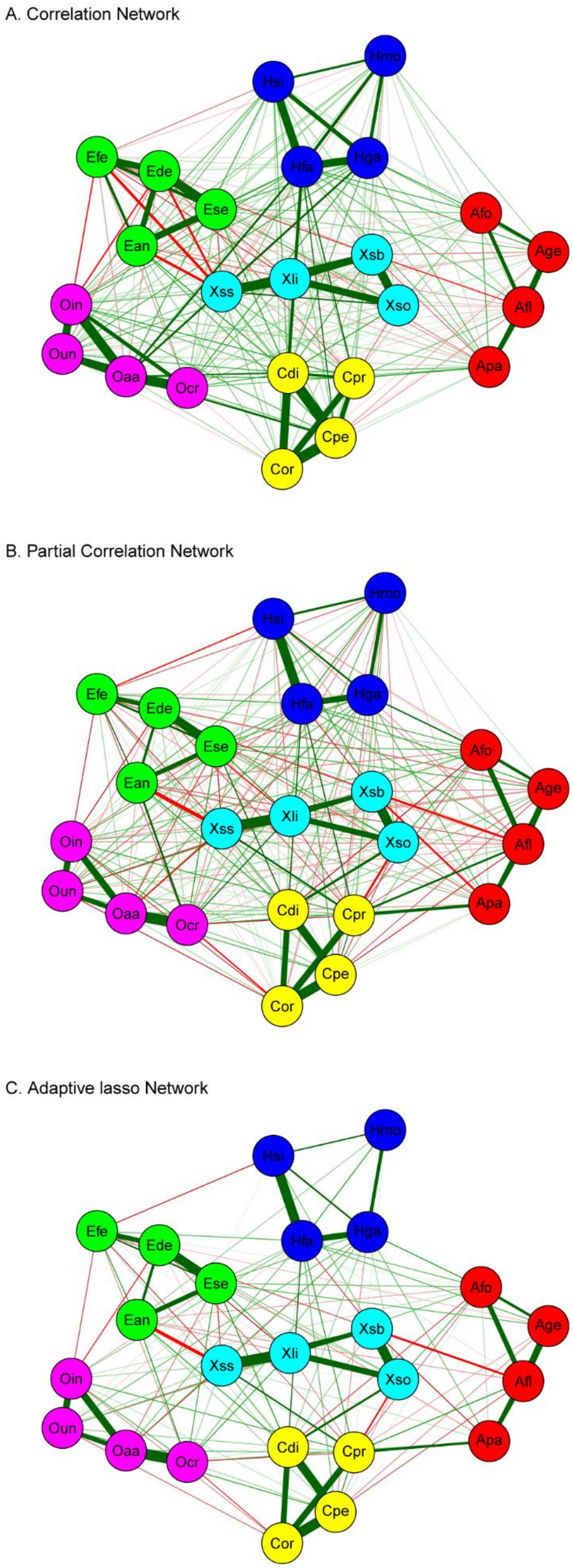

Figure 9. Networks of the HEXACO-60. Nodes represent personality facets (a description of each facet is provided in Table 3), green lines represent positive connections and red lines represent negative connections. Thicker lines represent stronger connections and thinner lines represent weaker connections. The node placement of all graphs is based on the adaptive LASSO network to facilitate comparison. The width and color are scaled to the strongest edge and are not comparable between graphs; edge strengths in the correlation network are generally stronger than edge strengths in the partial correlation network.

Table 3. Centrality Indices for the HEXACO-60 network.

Node	Dimension	Facet	Betweenness	Closeness	Strength
Hsi	Honesty-Humility	Sincerity	5	2.66	0.73
Hfa	Honesty-Humility	Fairness	**31**	3.03	**1.46**
Hga	Honesty-Humility	Greed-avoidance	14	2.83	1.13
Hmo	Honesty-Humility	Modesty	0	2.14	0.45
Efe	Emotionality	Fearfulness	6	2.70	1.03
Ean	Emotionality	Anxiety	2	3.04	1.10
Ede	Emotionality	Dependence	3	3.02	1.05
Ese	Emotionality	Sentimentality	17	3.17	**1.40**
Xss	Extraversion	Social self-esteem	11	3.11	**1.35**
Xsb	Extraversion	Social boldness	**23**	**3.33**	1.21
Xso	Extraversion	Sociability	7	**3.19**	1.07
Xli	Extraversion	Liveliness	12	3.12	1.29
Afo	Agreeableness vs. anger	Forgiveness	5	2.70	1.00
Age	Agreeableness vs. anger	Gentleness	5	2.66	0.80
Afl	Agreeableness vs. anger	Flexibility	14	2.90	1.02
Apa	Agreeableness vs. anger	Patience	5	2.85	0.85
Cor	Conscientiousness	Organization	7	3.09	0.99
Cdi	Conscientiousness	Diligence	**26**	**3.34**	1.30
Cpe	Conscientiousness	Perfectionism	5	3.13	1.26
Cpr	Conscientiousness	Prudence	**19**	**3.52**	**1.45**
Oaa	Openness to experience	Aesthetic appreciation	14	2.95	1.24
Oin	Openness to experience	Inquisitiveness	5	2.71	1.08
Ocr	Openness to experience	Creativity	10	3.00	1.26
Oun	Openness to experience	Unconventionality	3	2.63	0.98

Note. The four most central nodes according to each index are reported in **bold**.

Definition of the networks

Three networks were computed from the dataset, in each network nodes represent personality facets. Figure 9A represents the correlation network (see Chapter 1). Green lines represent positive correlations, while red lines represent negative correlations. The wider and more saturated an edge is drawn, the stronger the correlation. As the reader may expect, the figure shows that the correlations of facets within traits are generally higher than the correlations of facets between traits, which is likely to reflect the fact that in psychometric practice items are typically grouped and selected on the basis of convergent and discriminant validity (Campbell & Fiske, 1959). The partial correlation network is shown in Figure 9B. We can see that nodes still cluster together; the partial correlations within traits are generally stronger than the partial correlations between traits. Comparing Figure 9A and 7B we can see structure emerging in for example the Openess (purple) cluster: the creativity node (Ocr) is no longer directly connected to the inquisitiveness (Oin) and unconventionality (Oun) nodes but now indirectly via the aesthetic appreciation (Oaa) node. Furthermore, we can see that the conscientiousness node prudence (Cpr) now has a more central role in the network and obtained relatively stronger connections with nodes of different traits: flexibility (Afl) and patience (Apa) of the agreeableness vs. anger trait and sociability (Xso) and social self-esteem (Xss) of the extraversion trait. The adaptive LASSO network (Krämer et al., 2009) is shown in Figure 9C. One can see that, compared to the partial correlation network, the adaptive LASSO yields a more parsimonious graph (fewer connections) that encodes only the most important relations in the data. In this network 134 (48.6%) of the edges are identified as zero.

Analyzing the structure of the HEXACO-60 network

In the following, we focus on the adaptive LASSO network (Figure 9C) and we analyze it according to the indices presented in Chapters 1 and 2. The network is undirected, therefore the corresponding weights matrix is symmetric and each edge weight is represented twice, above and below the main diagonal. The network has 142 unique edges, of which 100 are positive and 42 are negative. In this network, positive edges are generally associated to larger weights (M = .11, SD = .09) than the negative edges (M = .06, SD = .04), and the t-test indicates that this difference is significant, $t(140) = 3.13$, $p = .0022$.

Centrality analyses

We implemented the function `centrality_auto` in the package *qgraph* (Epskamp et al., 2014, 2012), which allows to quickly compute several centrality indices. It requires the weights matrix as input: The function automatically detects the type of network and can handle both unweighted and weighted networks, and both directed and undirected networks. For a weighted and undirected network, the function gives as output the node strength, the weighted betweenness and the weighted closeness centralities. The edge betweenness centrality is also computed. The values of centrality for each node are reported in Table 3. The function `centralityPlot` can be used to plot the centrality indices in a convenient way that allows to quickly compare them.

Table 4. Correlation of node centralities, row-complexity and squared multiple correlation (SMC)

	1	2	3	4	5
1. Betweenness	1	.61**	.72***	.32	.54**
2. Closeness	.61**	1	.75***	.15	.69***
3. Strength	.70***	.82***	1	.47*	.75***
4. Complexity	.41*	.28	.43*	1	.11
5. SMC	.56**	.73***	.79***	.12	1

Note. *p<.05, **p<.01, ***p<.001. Pearson correlations are reported below the diagonal, Spearman correlations are reported above the diagonal. Complexity = Hofmann's row-complexity index. SMC = squared multiple correlation.

Table 4 reports the correlations among the three indices of node centrality together with Hofmann's (1978) row-complexity and the squared multiple correlation of each facet with all the others. All indices of centrality have positive significant correlations with each other. Strength centrality and, to a lower extent, betweenness centrality, seem to be favored by row-complexity: sharing variance with more than one factor allows a facet to play a more central role. This results suggest that, in this network, facets tend to be central to the whole network and not only to their purported parent traits. All centrality indices, especially strength and closeness, correlate with the squared multiple correlations: The more variance a facet shares with other facets, the stronger are its connections and the more central results the corresponding node[21].

The three indices of centrality converge in indicating that node Cpr (prudence) is among the four most central nodes in this network. Cpr is also the more closeness central node and owes its high centrality to the very short paths that connect it to other traits. For instance, facets Apa (patience), Xso (sociability), and Xss (social self-esteem) are even closer to Cpr than other conscientiousness facets

[21] Despite being substantial, the correlations of centrality indices with row-complexity and squared multiple correlations do not suggest that the indices fully overlap. Moreover, the relations can vary substantially and it is possible to imagine situations in which the relations are absent or even in the opposite direction.

are[22]. This suggests that in the personality network it is very easy that a change in some portion of the network will eventually make a person either more reckless or more prudent. On the other hand, if a person becomes more reckless or more prudent, we can expect important changes in the overall network. This result, although it should be considered as preliminary, is in line with studies that investigated the evolution of conscientiousness. Impulse-control, a facet of conscientiousness that is very similar to prudence (Cpr), shows the most marked variation through the individual development compared to other conscientiousness facets (Jackson et al., 2009). It is possible that this is the case also because changes in other personality traits are expected to affect prudence more quickly than other facets, as revealed by its high closeness.

Hfa (fairness) is the most betweenness-central and strength-central node, but it is not particularly closeness-central (it is ranked 10th in closeness centrality). Figure 10 highlights the edges lying on the shortest paths that travel through node Hfa, in a convenient layout. The high betweenness centrality of Hfa is due the role that Hfa plays in transmitting the influence of other honesty-humility facets to

[22] As an anonymous reviewer pointed out, one could wonder how can the length of the path between Cpr and other conscientiousness facets be longer than the path between Cpr and other nodes, given that Cpr's strongest correlations are those with the other conscientiousness facets. This happens because we did not consider the network defined by the zero-order correlations, but the adaptive LASSO penalized network of partial correlations (Krämer et al., 2009). As an example, consider the shortest path between Cpr and Cdi (diligence), which is slightly longer (8.80) than the shortest path between Cpr and Apa (patience; 6.82). Although the correlation among Cpr and Cdi is stronger (r = .26) than the correlation between Cpr and Apa (r = .22), in the adaptive LASSO network, the direct connection between Cpr and Cdi is smaller (pr = .04) than the one with Apa (pr = .15). While the shortest path between Cpr and Apa travels through their direct connection, the shortest path between Cpr and Cdi travels through node Cor (organization): prudence seems to influence (or to be influenced by) diligence especially through changes in orderliness, but this path of influence is longer than the direct path between Cpr and Apa.

different traits, and vice versa. The edge between nodes Hsi (sincerity) and Hfa is also the most betweenness-central in the whole network: most of the shortest paths between Hsi and other personality traits travel through this edge and therefore through Hfa. These results suggest that, if it was possible to reduce the possibility for fairness (Hfa) to vary, the influence of the other honesty-humility facets would propagate less easily to the rest of personality facets and vice versa. Such hypotheses could be tested for instance by comparing the personality networks of individuals that typically face situations in which their fairness is allowed to become active to the networks of individuals that usually face situations in which their fairness cannot be activated (Tett & Guterman, 2000). The characteristics of situations for instance could be assessed by using valid instruments such as the Riverside Situational Q-sort (Sherman et al., 2010), which includes items such as “It is possible for P to deceive someone”, or “Situation raises moral or ethical issues” that would be relevant for this case.

Clustering Coefficients

Many indices of clustering coefficient can be easily computed using function `clustcoef_auto` that we implemented in package *qgraph* (Epskamp et al., 2014, 2012). The function requires the same input as `centrality_auto` and is similarly programmed to recognize the kind of data given as input and to choose an appropriate network representation for the data. The function `clusteringPlot` can be used to plot the clustering coefficients in a convenient layout. Table 5 reports the correlation among several clustering coefficients. The unsigned indices are computed using the absolute values of the weights. In the following analyses we will use the signed version of the Zhang’s clustering coefficient (see Chapter 2; Costantini & Perugini, 2014; Zhang & Horvath, 2005), which resulted more resistant to random variations in the network (see below, the section stability of the results).

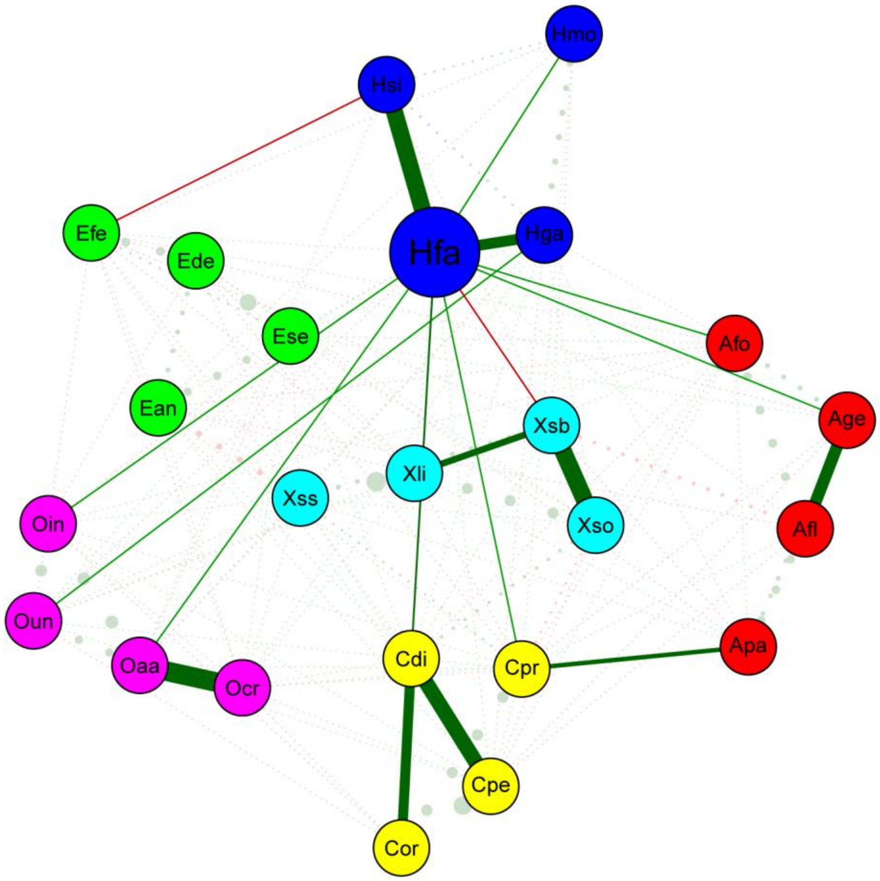

Figure 10. Shortest paths that pass through node Hfa (fairness)

The edges belonging to the shortest-paths are full, while the other edges are dashed.

Table 5. Correlation among indices of local clustering coefficient.

	1	2	3	4	5	6	7
1. $C_{i,W}$, Watts and Strogatz (1998)	1	.25	.65***	.51*	.90***	.57**	.94***
2. $\hat{C}_{i,W}$, Watts and Strogatz, signed (Costantini & Perugini, 2014)	.26	1	.28	.45*	.29	.76***	.25
3. $C_{i,Z}$, Zhang and Horvath (2005)	.49*	.30	1	.89***	.50*	.59**	.71***
4. $\hat{C}_{i,Z}$, Zhang and Horvath, signed (Costantini & Perugini, 2014)	.34	.33	.94***	1	.37	.79***	.53**
5. $C_{i,O}$, Onnela et al. (2005)	.89***	.25	.37	.24	1	.55**	.84***
6. $\hat{C}_{i,O}$, Onnela et al., signed (Costantini & Perugini, 2014)	.61**	.76**	.59**	.64**	.66***	1	.53**

Note. *p<.05, **p<.01, ***p<.001. Pearson correlations are reported below the diagonal, Spearman correlations are reported above the diagonal.

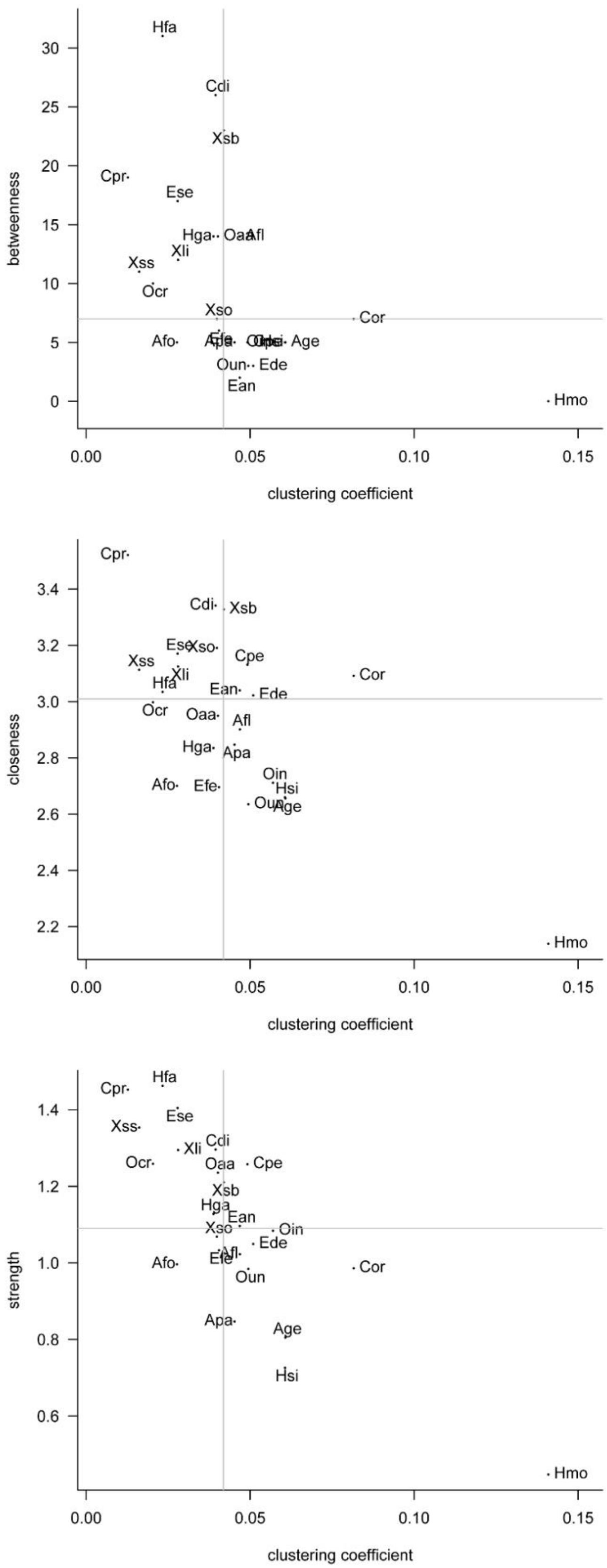

Figure 11. Centrality and clustering coefficient. The horizontal and the vertical lines represent the median values of centrality and clustering coefficient respectively. The closeness values are multiplied by 1000.

The signed clustering coefficient can be interpreted as an index of a node's redundancy in a node's neighborhood (Chapter 2; Costantini & Perugini, 2014): the importance of the unique causal role of highly clustered nodes is strongly reduced by the presence of strong connections among their neighbors. In general, it is interesting to inspect whether there is a relation between centrality indices and clustering coefficients: in our experience, we found that the centrality indices were often inflated by the high clustering in correlation networks. However this might be not true for networks defined with adaptive LASSO, which promotes sparsity (Krämer et al., 2009).

Figure 11 shows a plot of the Zhang's signed clustering coefficient and of the centrality indices. It is apparent that the most central nodes do not have a particularly high clustering coefficient in this case and this is especially true for nodes Hfa and Cpr, which are among the most central in this network. The clustering coefficient correlates negatively with closeness centrality ($r = -.67, p < .001$), with strength ($r = -.82, p < .001$), and with betweenness centrality ($r = -.50, p = .013$).

One node, Hmo (modesty), emerges as both particularly high in clustering coefficient and low in all the centrality measures. Modesty correlates almost exclusively with other honesty-humility facets and has the lowest multiple correlation with all the other variables in our dataset and this is likely to have determined its peripherality. A closer exam of its connections reveals that Hmo has seven neighbors, the three other facets of honesty-humility (His, Hfa, and Hga), facets anxiety and fearfulness of emotionality (Ean), facet social boldness of extraversion (Xsb) and facet prudence of conscientiousness (Cpr), the connections with fearfulness, social boldness and prudence having very small weights. Moreover many of its neighbors are connected with each other. Even if the edges incident in node Hmo were blocked, its neighbors would be nonetheless connected to each other directly or by a short path. Modesty therefore does not seem to play a very important unique role in the overall personality network.

Transitivity and small-world-ness.

The function `smallworldness` that we implemented in package *qgraph* (Epskamp et al., 2014, 2012) computes the small-worldness index (Humphries & Gurney, 2008). First the function converts the network to an unweighted one, which considers only the presence or the absence of an edge. Then the average path length and the global transitivity of the network are computed and the same indices are calculated on B = 1000 random networks, with the same degree distribution of the focal network. The resulting values are entered in the computation of the small-worldness index. The output includes the small-worldness index, the transitivity of the network, and its average path length. It also returns summaries of the same indices computed on the random networks: the mean value and the .005 and .995 quantiles of the distribution. The small-worldness value for our network is 1.01. An inspection of the values of transitivity and of average path length shows that they are not significantly different from those emerged from similar random networks. Therefore we may conclude that this personality network does not show a clear small-world topology.

Emerging insights.

In this Chapter, we showed how it is possible to perform a network analysis on a real personality dataset. We identified the most central nodes and edges, discussed centrality in the light of clustering coefficient and investigated some basic topological properties of the network, such as the small-world property. Two nodes resulted particularly central in the network and were the facet prudence of conscientiousness (Cpr) and the facet fairness of honesty-humility (Hfa).

Our network did not show the small-world property. The absence of a strong transitivity means that the connection of two nodes with a common neighbor does not increase the probability of a connection between themselves. The absence of a particularly short path length implies that it is not generally possible for any node to influence any other node using a short path. This result is not in line with the small-worldness property that emerged in the DSM-IV network reported by Borsboom and colleagues (2011). It has been hypothesized that the small-world property might be at the basis of phenomena connected to the comorbidity that arise in psychopathology (Cramer et al., 2010); this also may simply not be a property of normal personality. This difference could reflect the fact that different personality characteristics represent distinct systems, while psychopathology systems seem to be more integrated. This result may be also attributable to the strategies that were used for defining this network and the DSM-IV network and may have been influenced by the particular personality scales under study. Future research may be directed towards the question of what network structure characterizes normal versus abnormal personality.

We do stress that many of our results are preliminary in nature. The primary reason for this is that current personality questionnaires are built according to psychometric methodology that is tightly coupled to factor analysis and classical test theory (Borsboom, 2005). This makes their behavior predictable from pure design specifications, which in turn limits their evidential value. That is, if one makes the a priori decision to have, say, 10 items per subscale, and selects items on the basis of their conformity to such a structure, many of the correlations found in subsequent research are simply built into the questionnaire. Therefore, it is hardly possible to tell to what extent results reflect a genuine structure, or are an artifact of the way personality tests are constructed. Trait perspectives are not immune to this problem, as in some cases the factors of personality may simply appear from questionnaire data because they have been carefully placed there. Future research should investigate potential solutions to this issue, for instance by considering variable sets consisting of ratings on the familiar personality-descriptive adjectives of a language, as in lexical studies (Ashton & Lee, 2005; de Raad et al., 2014; Goldberg, 1990; Saucier et al., 2014), and by comparing the characteristics of such networks to networks that emerge from questionnaire data.

Stability of results

The adaptive LASSO chooses the LASSO penalty parameter based on k-fold crossvalidation, subdividing the dataset in k (10 by default) random samples. Because of this, under different random seeds slightly different network structures will be obtained. To investigate the stability of the results discussed in this section, we repeated the network estimation procedure 900 times under different random seeds and recomputed the strength, closeness and betweenness centrality measures and the signed versions of the clustering coefficients proposed by Zhang and by Onnela.

Visually the resulting graphs looked remarkably similar and only differed in the weakest edges in the graph. Figure 10 shows a histogram of the amount of nonzero connections present in each of the replications; the median amount of estimated edges was 138. Figure 11 shows the estimated centrality and clustering coefficients for both the graph used in the analyses (colored line) and the 900 replications (vague gray lines). It can be seen that overall the measures are stable across different replications. Among the three centrality measures, more stable results were obtained for closeness and strength than for betweenness. Between the clustering coefficients we can see that Zhang's clustering coefficient is much more stable than Onnela's; in Onnela's clustering coefficient especially the Hmo node shows divergent behavior. This behavior is due to the number small of connections of Hmo obtained in each replication, ranging from 3 to 11 (M = 3.96, SD = 0.64). Onnela's clustering coefficient is scaled to the number of connections regardless of weight. Therefore the relatively small difference in connections can have a large impact on this clustering coefficient.

From these results, we advise that Zhang's clustering coefficient should be preferred over Onnela's clustering coefficient in adaptive LASSO networks. Furthermore, we advise the reader to replicate these measures under different random seeds and to check for the stability of the results before substantively interpreting them.

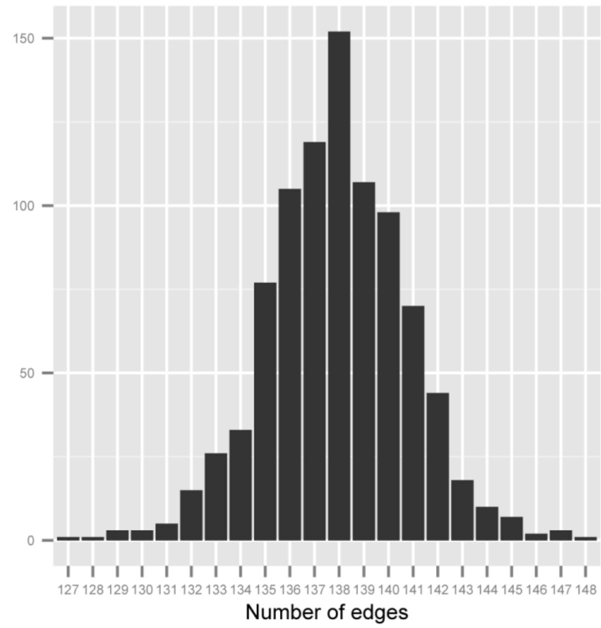

Figure 12. Histogram of the number of edges estimated in 900 replications of the adaptive LASSO.

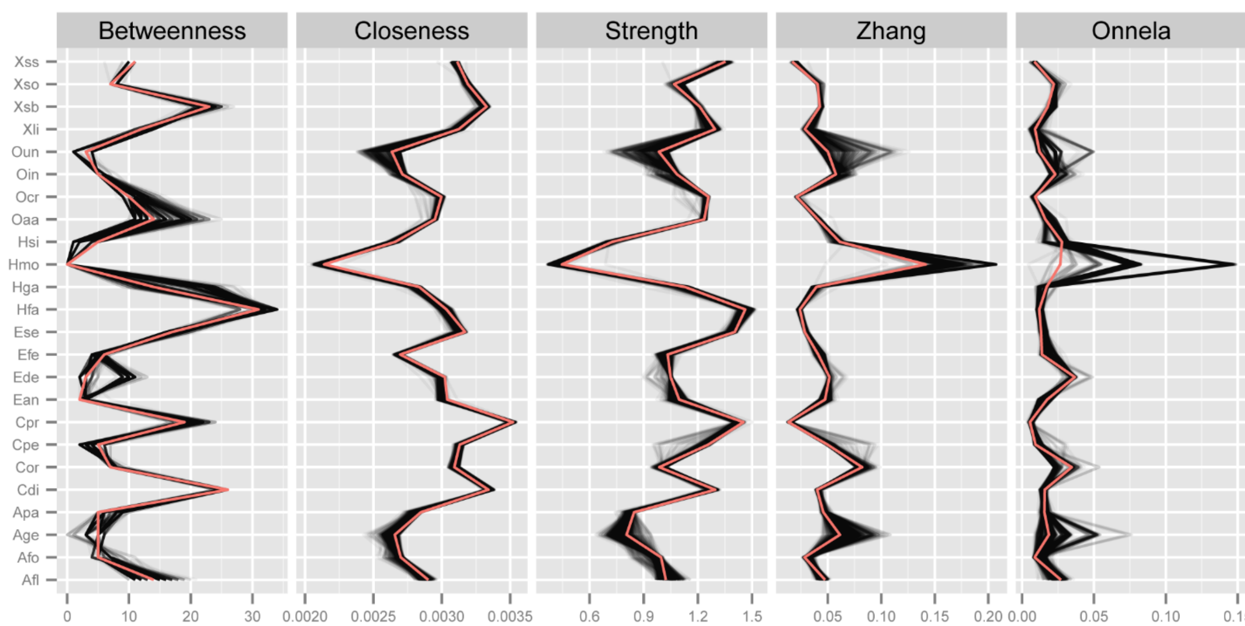

Figure 13. Estimated centrality and clustering coefficients under 900 replications of the adaptive LASSO.

The colored line represents the results discussed in the paper.

Chapter 4. The network of conscientiousness

Highlights

- We investigated the mechanisms that are shared by all facets of conscientiousness and the nonshared mechanisms that distinguish the facets from each other.
- We administered questionnaires to two samples (N = 210 and N = 230) and analyzed them by means of network analysis and multiple regressions.
- Self-control and orientation toward the future emerged as the mechanisms that are shared by all facets of conscientiousness.
- Consistently with previous studies, a proactive pole and an inhibitive pole emerged, which were characterized by unique mechanisms.
- A third facet, orderliness, seems to share characteristics of both poles, but is also characterized by unique features, such as the need for closure.

Introduction

In Chapter 3, we used network analysis to inspect the global structure of a personality inventory that included six major dimensions and their facets. In this chapter, we focused on a single personality dimension and used network analysis to investigate its potential mechanisms.

Personality dimensions are aggregations of lower order traits that encompass a considerable portion of variability in personality. Each personality dimension subsumes lower level traits or "facets" that, although being correlated with each other, are distinguishable from a psychometric point of view (Costa & McCrae, 1995; Perugini & Gallucci, 1997). Within hierarchical models of personality, facets are conceived as subordinate traits underlying a single broader dimension (e.g., Costa & McCrae, 1995), while circumplex models include in the definition of facets also blends of different personality dimensions (Hofstee et al., 1992). Within a personality domain, a considerable portion of the facets' variance is shared and this suggests that different facets of the same major personality dimension may be characterized by a few broad mechanisms. However several studies showed that facets improve the prediction of specific criteria (MacCann, Duckworth, & Roberts, 2009; O'Connor & Paunonen, 2007; Paunonen & Ashton, 2001, 2013) and change differently in the course of life (Jackson et al., 2009; Soto & John, 2012). These findings suggest that each facet might be also characterized by narrower mechanisms that are not shared with other facets (Costantini & Perugini, 2012; Eisenberg, Duckworth, Spinrad, & Valiente, 2014; Perugini, Costantini, Hughes, & De Houwer, 2014). Identifying mechanisms underlying these personality traits is important: From a psychometric point of view, because it provides the theoretical ground for the identification of facets that are meaningful beyond a merely descriptive approach; from a theoretical point of view, because it allows to understand how personality is linked to its antecedents and to its outcomes (e.g., Baumert, Gollwitzer, Staubach, & Schmitt, 2011; Hampson, 2012); from an applied point of view, because understanding the mechanisms of personality is a necessary condition to conceive meaningful manipulations of personality itself (McNally et al., 2014; van de Leemput et al., 2014).

In this chapter, we focused on the dimension of conscientiousness, with the goal of investigating both the broader mechanisms that are responsible for the facets of conscientiousness to clump into a single trait, and the narrower mechanisms that are responsible for these facets to be distinguishable from each other. By means of network analysis, we drew a series of maps of conscientiousness that can serve as a guidance for more targeted studies.

Conscientiousness and its facets

Conscientiousness is defined as the "socially prescribed impulse control that facilitates task- and goal-directed behavior, such as thinking before acting, delaying gratification, following norms and rules, and planning, organizing and prioritizing tasks" (John & Srivastava, 1999, p. 121). Conscientious individuals, compared to the unconscientious ones, tend to live longer (Kern & Friedman, 2008) and healthier lives (Bogg & Roberts, 2004; H. S. Friedman & Kern, 2014; Roberts, Walton, & Bogg, 2005), to perform better in academia (Poropat, 2009), to succeed at work (Barrick & Mount, 1991), and in general to face more positive outcomes in their lives (Ozer & Benet-Martínez, 2006).

Conscientiousness is conceptualized "as having both proactive and inhibitive aspects: The proactive side of Conscientiousness is seen most clearly in the need for achievement and commitment to work; the inhibitive side is seen in moral scrupulousness and cautiousness" (Costa, Mccrae, & Dye, 1991). These two sides of the traits emerged also from analyses of behaviors (Jackson et al., 2010) and of questionnaire items (Roberts, Chernyshenko, Stark, & Goldberg, 2005). Several taxonomies have been proposed for the lower-order structure of conscientiousness. Peabody and De Raad (2002) examined the content of personality descriptors in six languages and identified four facets: work, impulse-control, orderliness, and responsibleness. Roberts and associates identified eight facets from the analysis of lexical markers (Roberts, Bogg, Walton, Chernyshenko, & Stark, 2004), six facets from the analysis of questionnaire items (Roberts, Chernyshenko, et al., 2005), and eleven facets of behaviors related to conscientiousness (Jackson et al., 2010). Four facets were very similar across these studies and, although with slightly different labels, closely resembled those identified by Peabody and De Raad. These facets were industriousness/laziness, self-control/impulse-control, order/orderliness, and reliability/responsibility. In a more recent investigation on questionnaire items seven facets emerged[23] (MacCann et al., 2009): industriousness, control and cautiousness (two different aspects of impulse-control), task planning and tidiness (two different aspects of orderliness), procrastination refrainment, and perfectionism. Perugini and Gallucci (1997) analyzed the Italian lexicon and recovered five facets: superficiality (close to industriousness, but reverse-coded), recklessness (close to impulse-control, but reverse-coded), meticulousness (close to orderliness), reliability, and inaccuracy. Several personality questionnaires include scales for assessing conscientiousness. The NEO-PI-R (Costa & McCrae, 1992) and the corresponding IPIP scales (Goldberg et al., 2006) include six facets. According to Roberts and colleagues, in the NEO-PI-R three facets tap into industriousness and are achievement striving, competence/self-efficacy, and self-discipline, while the remaining three facets are similar to those emerged in other studies, and are dutifulness (similar to reliability), deliberation/cautiousness (similar to impulse-control), and order/orderliness (Roberts, Chernyshenko, et al., 2005). The HEXACO-PI (Ashton & Lee, 2009; K. Lee & Ashton, 2004) includes four facets: diligence (similar to

[23] An eighth facet, perseverance, was found to be interstitial between conscientiousness and neuroticism.

industriousness), prudence (similar to impulse-control), organization, and perfectionism. In the circumplex model AB5C (Hofstee et al., 1992) seven facets have been identified: organized-disorganized, cautious-reckless, ambitious-unambitious, reliable-unreliable, consistent-inconsistent, perfectionistic-haphazard, and conventional-unconventional, each one is characterized by a secondary loading on another major personality factor, with the exception of orderliness which loads solely on conscientiousness.

Although complete consensus on the lower-level structure of conscientiousness does not seem to have been achieved, some important regularities emerge. All taxonomies have identified facets that broadly refer to exerting a control over one's impulses (labeled for instance deliberation, impulse-control, prudence), and facets that broadly refer to being industrious and striving for achievement and persisting in the face of challenges (e.g., achievement striving, industriousness, ambitiousness). We refer to these facets as *impulse-control* and *industriousness* respectively. Impulse-control clearly taps into the inhibitive pole of conscientiousness, while industriousness taps into the proactive pole of the trait (Jackson et al., 2010; Roberts, Chernyshenko, et al., 2005). All taxonomies also identified one or more facets of *orderliness* (e.g., order, organization, tidiness, task planning), which has been considered part of the proactive pole of conscientiousness (Jackson et al., 2010; Roberts, Chernyshenko, et al., 2005) and taps into the core of conscientiousness (Hofstee et al., 1992). Most studies also identified a facet *responsibility* (labeled for instance reliability, responsibility, or dutifulness), that refers to following rules and keeping one's commitments to others and is closer to the inhibitive pole (Jackson et al., 2010; Roberts, Chernyshenko, et al., 2005). However responsibility has been also considered as a blend of conscientiousness and agreeableness (Roberts et al., 2004; Roberts, Lejuez, Krueger, Richards, & Hill, 2012). Of these four facets, order and industriousness have been also identified as conscientiousness's aspects, constructs that have a level of abstraction in between the major personality dimensions and their facets (DeYoung, Quilty, & Peterson, 2007).

An additional facet, perfectionism, requires a specific discussion. Perfectionism has been considered a facet of conscientiousness (K. Lee & Ashton, 2004; MacCann et al., 2009) and conscientiousness has been considered part of perfectionism (Cruce, Pashak, Handal, Munz, & Gfeller, 2012). Perfectionism however is also a multidimensional construct that has complex connections with other personality factors. Previous studies distinguished two main dimensions of perfectionism (Dunkley, 2012), which entail similar behaviors, but differ in the its attribution (Hewitt & Flett, 1991). The self-oriented perfectionism is enacted to meet one's personal standards, while the socially prescribed perfectionism is enacted to meet other people's standards (Dunkley, 2012; Hewitt & Flett, 1991). The self-oriented perfectionism has been shown to be connected with conscientiousness (Dunkley & Kyparissis, 2008; Dunkley, 2012; Stoeber, Otto, & Dalbert, 2009), while the socially prescribed perfectionism has stronger connections with neuroticism (Dunkley & Kyparissis, 2008; Dunkley, 2012; but see Stoeber et al., 2009) and depression (Sherry et al., 2013). Additionally, perfectionism has been considered as a maladaptive form of conscientiousness itself (Flett & Hewitt, 2007). In our study, we investigated the role of perfectionism by including both its dimensions in the conscientiousness network.

Candidate mechanisms of conscientiousness

Conscientiousness and its facets are likely to subsume a large system of mechanisms that involve many aspects of the individual. Developmental studies converged in identifying self-regulatory abilities such as effortful control as the core underlying conscientiousness (Eisenberg et al., 2014;

Roberts et al., 2012), while in adults one of the core aspects of conscientiousness is constituted by self-control (de Vries & van Gelder, 2013; Roberts et al., 2012; Tangney, Baumeister, & Boone, 2004). De Boer and colleagues distinguished two facets of self-control: start-control is the proactive component of self-control, connected to initiating desirable behavior, while stop-control is the inhibitory side of self-control, connected to inhibiting undesirable behavior (De Boer, Van Hooft, & Bakker, 2011). Start control might be especially important for facets such as industriousness, which require to initiate and persevere in desirable behaviors, while stop control might be especially important for impulse-control, which is connected to inhibiting or avoiding undesirable behaviors (e.g., see Jackson et al., 2010).

The control over oneself is often exercised in the pursuit of a goal. The motivation towards achieving goals is considered a central component of conscientiousness (Denissen & Penke, 2008; John & Srivastava, 1999) and a recent study showed that the genetic variance in the failure to activate and maintain goals is largely overlapped with the genetic variance shared by impulsivity (close to the negative pole of impulse-control) and procrastination (close to the negative pole of industriousness; Gustavson, Miyake, Hewitt, & Friedman, 2014). In the framework of the regulatory focus theory (Higgins, 1997, 1998), two motivational tendencies both central for goal-pursuit have been distinguished. On the one hand, promotion focused individuals aim at reducing the discrepancy with their ideal self-guide (representing their hopes and aspirations), are especially sensitive the presence or absence of positive outcomes and, in pursuing their goals, tend to persist in goal-directed behaviors; on the other hand, prevention focused individuals aim at reducing the discrepancy with their ought self-guide (their beliefs about their duties and obligations), are concerned with the presence or absence of negative outcomes, and when pursuing goals, are focused on abstaining from behaviors that could impair the goal-attainment (Higgins et al., 2001). In meta-analytic investigations, conscientiousness was found to correlate with both promotion and prevention focus (Gorman et al., 2012; Lanaj, Chang, & Johnson, 2012), therefore promotion and prevention focus might be both part of the network of the mechanisms of conscientiousness. Industriousness however is associated to behaviors, such as hard-working, that in general entail the pursuit of positive outcomes, while impulse control is typically associated to (refraining from) behaviors that would have negative outcomes, such as buying things that one cannot afford (Jackson et al., 2010). Therefore, we hypothesize that promotion focus could play a stronger role for industriousness than for impulse control, while an opposite pattern is expected for prevention focus.

The reinforcement sensitivity theory (Corr, 2004) postulates two systems that have overlapping features with the promotion and prevention focus (e.g., Summerville & Roese, 2008), but that are also dissociable from regulatory focus (Cunningham, Raye, & Johnson, 2005; Eddington, Dolcos, Cabeza, Krishnan, & Strauman, 2007). The behavioral inhibition system (BIS) is responsible for stopping behavior that may lead to punishment and nonrewards, while the behavioral activation system (BAS) is responsible for activating behaviors that can lead to rewards or lack of punishment. In the framework of the cybernetic model of personality, conscientiousness has been conceived as the disposition to select the best system according to the situational requirements (Van Egeren, 2009). Previous studies found a negative correlation between conscientiousness and the fun-seeking subscale of BAS and positive correlations with the other BAS scales (L. Leone, Pierro, & Mannetti, 2002; Smits & Boeck, 2006). In a more recent study that considered the NEO-PI-R facet scales, BIS was positively associated to deliberation and order and negatively associated with competence and self-discipline, while BAS correlated positively with competence and achievement striving and negatively with deliberation (Keiser & Ross, 2011). In our study we aim at further clarifying also the role of these subsystems in the mechanics of conscientiousness.

Pursuing positive outcomes and preventing negative outcomes often requires postponing one's immediate enjoyment. Both conscientiousness and self-control are strongly connected to delay of gratification (Duckworth, Tsukayama, & Kirby, 2013; Mahalingam, Stillwell, Kosinski, Rust, & Kogan, 2013; Roberts et al., 2012), the tendency to prefer a delayed (but more consistent) gratification over an immediate (but scarcer) one. From a functional perspective, the sensitivity to delayed reinforcements has been conceived as a function of both the delay and of stable personality characteristics, and especially conscientiousness, that moderate the relationship by influencing the amount of delay discounting (Perugini et al., 2014). The delay of gratification can be successfully assessed in children using the "marshmallow task" (Duckworth et al., 2013; Mischel, Schold, & Rodriguez, 1989), but measuring it in adults with equally meaningful behavioral tasks is more difficult (Roberts et al., 2012): For adults, the delay of gratification is encompassed in broader constructs, such as the consideration of future consequences, the extent to which individuals consider the distant outcomes of their behavior, which correlates with conscientiousness (Strathman, Gleicher, Boninger, & Edwards, 1994), and the orientation towards the future (Zimbardo & Boyd, 1999). The ability of anticipating the future consequences of a behavior is a prerequisite of delaying gratification and could be a common feature of both the proactive and the inhibitive poles of conscientiousness. Industrious individuals could be more willing to pay an immediate cost (e.g., working hard) to achieve a positive outcome in the future (e.g., success), while self-controlled individuals could be more willing to sacrifice their immediate enjoyment (e.g., refrain from buying something on a whim) to limit the negative outcomes that they might experience in the future (e.g., being out of money).

While regulatory focus and delay of gratification might be especially important for industriousness and impulse-control, they might not play a similarly important role for facet orderliness. Behaviors that are typical of ordered individuals, such as organizing the objects in their environment, making lists and scheduling their routines (Jackson et al., 2010), might reflect a different class of motivational tendencies with a more complex relation to goal-attainment: the need to structure one's environment to ultimately reduce the amount of information that needs to be processed (Neuberg & Newsom, 1993). Experimental studies on creativity tasks showed that if individuals higher in need for structure are given the choice, they prefer organized tasks and if structured tasks are given to them, they improve their performance (Rietzschel, Slijkhuis, & van Yperen, 2014). The need for structure has been encompassed in the broader construct of need for closure (Kruglanski & Webster, 1996; C. Leone, Wallace, & Modglin, 1999), a general discomfort with ambiguity that leads to prefer order, predictability, decisiveness and to be closed-minded (Roets & Van Hiel, 2007). Need for closure is inversely related to openness to experience, but it also showed a positive correlation with conscientiousness (Roets & Van Hiel, 2011). We hypothesize that facet orderliness might be especially responsible for the relationship between the need for closure and conscientiousness.

Besides motivation, also emotions play an important role in shaping both goal-pursuit and success (Bagozzi & Pieters, 1998; Lyubomirsky, King, & Diener, 2005) as well as personality (Fayard, Roberts, Robins, & Watson, 2012; Revelle & Scherer, 2009; Van Egeren, 2009). Since goal-pursuit is central for many aspects of conscientiousness, the emotions that are most relevant for goal-pursuit might also be important in the dynamics of conscientiousness. Positive and negative emotions have been found to influence goal-directed behavior (Bagozzi & Pieters, 1998) and although they have been especially associated to extraversion and neuroticism respectively (Revelle & Scherer, 2009), they are also relevant for conscientiousness. Conscientiousness is negatively related to negative affect and positively related to positive affect, as well as to trait-like dispositions connected to the chronic experience of positive-affectivity, such as happiness and life-satisfaction (DeNeve & Cooper, 1998; Heller, Watson, & Ilies, 2004). Furthermore daily variations in conscientiousness were found to predict variations in positive affect and in life-satisfaction (Smith, Ryan, & Röcke, 2013). Also positive orientation, a high-order latent dimension that is defined by the variance shared by self-esteem, life-satisfaction, and optimism (Alessandri, Caprara, & Tisak, 2012), showed a positive correlation with conscientiousness (Caprara et al., 2012; Grassi et al., 2014). Several hypotheses have been advanced on the mechanisms through which conscientiousness contributes to increased positivity, well-being, and to the experience of positive affectivity more than negative affectivity. Self-esteem was found to mediate the effects of conscientiousness on life-satisfaction (Benet-Martínez & Karakitapoglu-Aygun, 2003) and recent results showed that conscientious individuals might be able in quickly down-regulating negative emotions (Javaras et al., 2012), although this second hypothesis is not in line with research on job loss (Boyce, Wood, & Brown, 2010). Self-conscious emotions might also play an important role. A recent meta-analysis found that guilt mediates the effect of conscientiousness on negative affect (Fayard et al., 2012): Conscientious individuals seem to be more prone to experience guilt, but since they seldom violate their internal standards, they tend to experience less guilt, and therefore less negative affect. Also the positive self-conscious emotion of pride is connected to goal-attainment. Tracy and Robins (2007) distinguished two facets of pride, authentic pride results from the attribution of success to internal, unstable, and controllable causes, while hubristic pride results from the attribution of success to internal, stable and uncontrollable causes. These two facets of pride have opposite relationships with conscientiousness, with authentic pride being positively correlated with conscientiousness and hubristic pride being negatively correlated with conscientiousness (Tracy & Robins, 2007). Fayard and colleagues (2012) also identified a negative relationship between conscientiousness and the emotion of surprise, although small in size. This correlation might seem of difficult interpretation, but if orderliness is connected to need for closure (Kruglanski & Webster, 1996) as we argued, one could expect also a connection with surprise: structuring one's environments and tasks might have the effect of preventing the unexpected events which are responsible for the experience of surprise.

Emotions relevant to goal-attainment have been investigated also in the framework of regulatory focus theory (Higgins, Shah, & Friedman, 1997; Shah & Higgins, 2001): promotion focused individuals are quicker in appraising objects in terms of cheerfulness (vs. dejection) and tend to experience these emotions as a consequence of successes (failures) in reducing the discrepancies with their ideal selves; prevention focused individuals are quicker in appraising objects in terms of quiescence (vs. agitation) and tend to experience these emotions as a consequence of successes (failures) in reducing the discrepancies with their ought selves. Regulatory focus was also found to moderate the effect of anticipated emotions on the attitudes towards goal-directed actions (L. Leone, Perugini, & Bagozzi, 2005). If conscientiousness facets are differentially connected to promotion and prevention focus, one might expect that they share also similar emotional correlates. In our studies, we investigated the role of the emotions that could be relevant to conscientiousness and to goal-attainment.

Overview of the study

Several studies have identified many correlates and potential mechanisms of conscientiousness, however many of these mechanisms have been identified in separate studies, which in some cases focused on conscientiousness as a major personality dimension, disregarding the facets structure. We argue that by investigating conscientiousness at the level of its facets is possible to make finer grained distinctions among those mechanisms that shape all the aspects of conscientiousness and those that underlie some facets and not others or that characterize different facets in different ways.

We administered three batteries of questionnaires to two different samples of participants, the first sample took two batteries of questionnaires while the second sample took one. The first battery investigated especially the mechanisms that may underlie the proactive and the inhibitive poles of conscientiousness: self-control, regulatory focus, BIS/BAS, and positive orientation. The second battery focused especially on the affective correlates of conscientiousness[24]. The second sample took only one battery, which was meant to investigate the role of time perspective and the mechanisms that we hypothesized that could characterize facet order, such as need for closure and surprise. Additionally, this battery was meant to deepen the role of perfectionism. We also considered three criterion measures: the grade-point average (GPA) was obtained for all participants and, for the second sample only, we also assessed the use of alcohol and tobacco, which are known important mediators of the effects of conscientiousness on longevity (Bogg & Roberts, 2004; H. S. Friedman & Kern, 2014).

Sample size determination analysis

Personality networks are ultimately based on correlation coefficients, therefore it is very important to have reasonably precise estimates of the correlations among the measures. Our sample size analysis

[24] For exploratory purposes, we included in the second battery of questionnaires a short questionnaire that was aimed at assessing regulatory emotional self-efficacy for emotions connected to promotion and prevention focus (the measure was inspired by Caprara et al., 2008). Since this measure had been never administered before and it needs further psychometric refinement, we decided not to discuss it.

was not based only on the null-hypothesis testing (i.e., showing that a value is significantly different from zero), but on the necessity of having sufficiently small confidence intervals around the correlation estimates. Figure 14 shows the width of the 95% confidence intervals around each absolute value of the product-moment correlation (r), for five possible sample sizes: for $N < 200$ the confidence intervals increases quickly as the sample gets smaller, while for $N > 300$ important increases in the sample size produce small improvements in the confidence intervals. We thus planned to collect samples of at least 200 participants. For a population correlation coefficient of $|r| = .40$, relatively common in personality psychology, this sample size guarantees a 95% confidence interval between .28 and .51. Consider also that the focus of this study is on the structure and correlates of a single factor, Conscientiousness. Under these conditions is therefore reasonable to assume a majority of relatively sizeable correlations. A sample size of $N = 200$ allows to detect a correlation as small as $|r| = .2$ with a power of $\beta = .81$ ($\alpha = .05$).

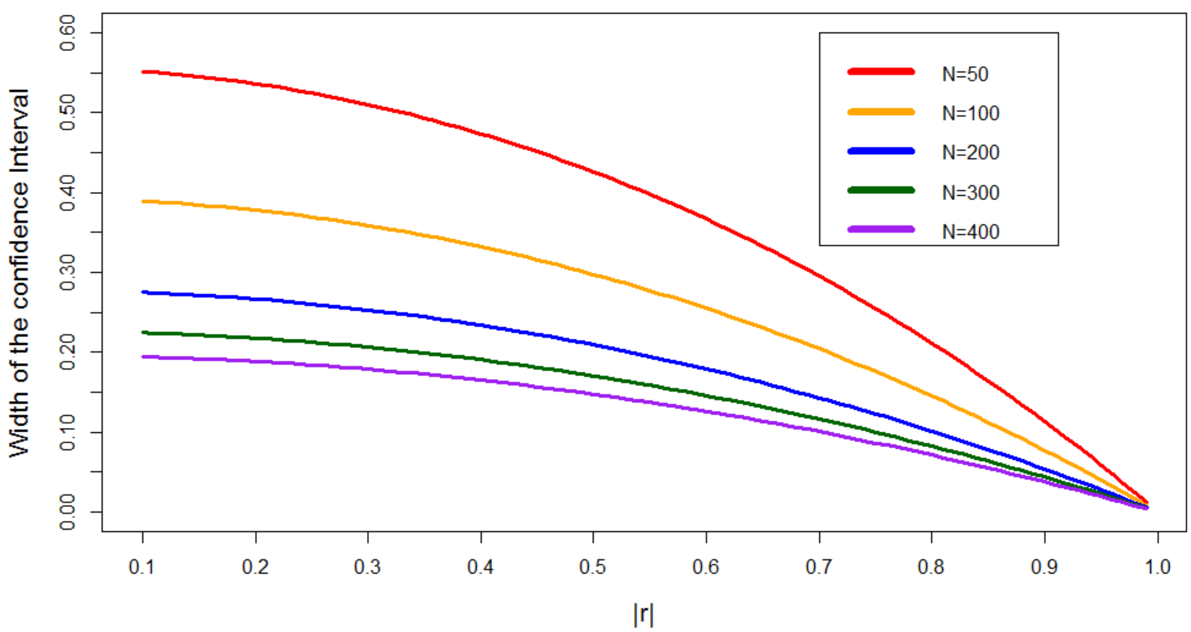

Figure 14. Confidence interval width from |r| = .1 to |r| = .99, for five different sample sizes.

Materials and Methods

Participants

Sample 1. Two-hundred-thirty-seven high-school students took part to the study. Of these, 27 were removed: 18 because they completed only the first questionnaire, 9 because completed only the second questionnaire. The analyses were therefore performed on 210 participants (174 females, mean age = 18.51, SD = 1.29).

Sample 2. Two-hundred-thirty-nine high-school students took part to the study. Nine participants were excluded from the analyses for having too many missing values (from 12 to 76, mostly because of skipping entire pages or not finishing the questionnaire). The final sample therefore included 230 participants (161 females, mean age = 18.85, SD = .84).

Materials

HEXACO-PI (Ashton & Lee, 2009; K. Lee & Ashton, 2004). The short version of the HEXACO-PI, the HEXACO-60 (Ashton & Lee, 2009) was administered to assess five major personality factors, with 10 items each: honesty-humility (H, $\alpha_{sample1} = .67$ and $\alpha_{sample2} = .77$), emotionality (E, $\alpha_{sample1} = .70$ and $\alpha_{sample2} = .76$), extraversion (X, $\alpha_{sample1} = .78$ and $\alpha_{sample2} = .78$), agreeableness (A, $\alpha_{sample1} = .56$ and $\alpha_{sample2} = .68$), and openness to experience (O, $\alpha_{sample1} = .75$ and $\alpha_{sample2} = .73$). Conscientiousness (C-hexaco, $\alpha_{sample1} = .89$ and $\alpha_{sample2} = .85$) was assessed more in depth using the 32 conscientiousness items of the complete version of the HEXACO-PI (K. Lee & Ashton, 2004), which includes four facets, each assessed with eight items: Prudence ($\alpha_{sample1} = .77$ and $\alpha_{sample2} = .72$), diligence ($\alpha_{sample1} = .76$ and $\alpha_{sample2} = .74$), organization ($\alpha_{sample1} = .83$ and $\alpha_{sample2} = .80$), and perfectionism ($\alpha_{sample1} = .69$ and $\alpha_{sample2} = .68$). Participants responded on a 5-points scale, from 1 (*strongly disagree*) to 5 (*strongly agree*), a sample item is "I plan ahead and organize things, to avoid scrambling at the last minute".

IPIP – conscientiousness (Goldberg, 1999; Goldberg et al., 2006). We administered the 60-items scale of the IPIP that assess conscientiousness (C-ipip, $\alpha_{sample1}$ = .91 and $\alpha_{sample2}$ = .92) and the six facets of conscientiousness corresponding to those included in the NEO model (Costa et al., 1991), 10 items by facets: cautiousness ($\alpha_{sample1}$ = .77 and $\alpha_{sample2}$ = .77), achievement striving ($\alpha_{sample1}$ = .75 and $\alpha_{sample2}$ = .79), self-efficacy ($\alpha_{sample1}$ = .67 and $\alpha_{sample2}$ = .72), self-discipline ($\alpha_{sample1}$ = .80 and $\alpha_{sample2}$ = .81), orderliness ($\alpha_{sample1}$ = .86 and $\alpha_{sample2}$ = .85), and dutifulness ($\alpha_{sample1}$ = .73 and $\alpha_{sample2}$ = .72). Participants were instructed to indicate the extent to which each statement was an accurate description of themselves on a 5-points scale from 1 (*very inaccurate*) to 5 (*very accurate*). A sample item is "Love order and regularity".

Adjective checklist of conscientiousness. We developed this measure of conscientiousness' facets by means of a preliminary study. An initial list of 64 markers of conscientiousness was assembled from adjectives that had been identified in previous studies (Caprara & Perugini, 1994; Perugini & Gallucci, 1997; Roberts et al., 2004). One-hundred-eighty-one participants (76 women, mean age=22.6, SD=3.0) were administered the list and indicated how each adjective described them on a scale from 1 (*it does not describe me at all*) to 5 (*it describes me completely*). After an iterative procedure of PCA and of exclusion of the worst adjectives (those that did not load univocally on a component), four components were identified, with ten adjectives loading on each component, five on the positive pole and five on the negative pole. These forty items are reported in the Appendix Table 1 and were administered in this study. The items assessed four facets: Industriousness ($\alpha_{sample1}$ = .71 and $\alpha_{sample2}$ = .77), impulse-control ($\alpha_{sample1}$ = .81 and $\alpha_{sample2}$ = .83), orderliness ($\alpha_{sample1}$ = .87 and $\alpha_{sample2}$ = .88), and responsibility ($\alpha_{sample1}$ = .78 and $\alpha_{sample2}$ = .79).

Self-control scale (SCS, $\alpha_{sample1} = .74$ and $\alpha_{sample2} = .78$; Tangney, Baumeister, & Boone, 2004). Participants were instructed to rate how much each of 13 statements described them on a scale from 1 ([it does not describe me] *at all*) to 5 ([it describes me] *completely*). A sample item is “I am good at resisting temptation”.

Regulatory Focus. Several instruments have been developed aimed at assessing stable individual differences in regulatory focus (Greifeneder & Keller, 2012; Higgins et al., 2001; Lockwood, Jordan, & Kunda, 2002). Summerville and Rose (2008) pointed out that different measures may tap into different aspects of regulatory focus: for instance the Regulatory Focus Questionnaire (RFQ, Higgins et al., 2001) seems to emphasize mainly aspects connected to the self-guides, while General Regulatory Focus Measure (GRFM, Lockwood et al., 2002) emphasizes the gain versus losses aspect of regulatory focus. Haws and colleagues (Haws, Dholakia, & Bearden, 2010) analyzed psychometric properties of several measures of regulatory focus: although the different measures presented low convergence, the RFQ had the highest predictive validity. They also proposed composite scales of promotion and prevention focus aimed at encompassing all the key aspects of regulatory focus, that are not included in any of the analyzed scales when used individually. We decided to administer three widely used questionnaires: the RFQ, the GRFM and the Regulatory Concerns Questionnaire (RCQ; Greifeneder & Keller, 2011). The RFQ (RFQ, Higgins et al., 2001) includes eleven items, six for promotion focus and five for prevention focus, and participants rated each sentence on a 5-points scale (labels of each point varied across questions). A sample item is: “Compared to most people, are you typically unable to get what you want out of life? 1 = never or seldom / 5 = very often”. The GRFM (Lockwood et al., 2002) included 18 items, nine for promotion and nine for prevention focus. Participants indicated whether each sentence applied to them, on a scale from 1 (*Not at all true of me*) to 9 (*Very true of me*). A sample item is “I frequently imagine how I will achieve my hopes and aspirations”. The RCQ (Greifeneder &

Keller, 2012) includes 10 items, five for promotion and five for prevention focus. Participant indicated whether each sentence applied to them on a scale from 1 (*does not apply*) to 9 (*strongly applies*). A sample item is “My life is often shaped by fear of failure and negative events”. From these three instruments, we computed two scores, one for promotion focus (PRO, α = .80) and one for prevention focus (PRE, α = .83), by averaging all the standardized items of promotion and of prevention focus respectively.

BIS/BAS scales (Carver & White, 1994; L. Leone et al., 2002). Participants were instructed to indicate the extent to which 20 sentences described them on a scale from 1 (*it does not describe me at all*) to 5 (*it describes me completely*). Seven items assessed the behavioral inhibition system (BIS, α = .78), while thirteen items assessed three BAS dimensions: reward-responsiveness (REW, 5 items, α = .57), drive (DRI, 4 items, α = .58) and fun-seeking (FUN, 5 items, α = .68). A sample item is “When I see an opportunity for something I like, I get excited right away”.

Start and stop control scales (De Boer et al., 2011). Participants were instructed to indicate the extent to which each of 18 statements described them on a scale from 1 ([it does not describe me] *at all*) to 5 ([it describes me] *completely*). Two facets of self-control were assessed, with 9 items each: start-control (START, α = .65) is the proactive component of self-control, connected to initiating behavior, while the stop-control is the inhibitory component of self-control, connected to inhibiting behavior (STOP, α = .69). A sample item is “I’m still able to concentrate when things around me are very hectic”.

Positive Orientation (PO, α = .78; Caprara et al., 2012). Positive Orientation was assessed with the 8-items Positivity Scale. Participants provided their ratings on a 5-point scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). A sample item is “Others are generally here for me when I need them”.

Emotional checklist. We assembled a list of 62 emotions by including the items from Shah and Higgins (2001; cheerfulness/dejection and quiescence/agitation), from Leone, Perugini and Bagozzi (2005; satisfaction/dissatisfaction and relaxation/agitation, conceptually overlapping to Shah & Higgins' scales), from Tracy and Robins (2007; authentic pride and hubristic pride) and from the PANAS-X subscales Guilt, Self-assurance, Positive affect and negative affect (Watson & Clark, 1999). When items were common among the different scales, they were administered only once. Two more items, "gioioso" (joyful) e "contento" (synonym of happy) were included. The instructions were the same as the PANAS-X to assess the general emotional experience (Watson & Clark, 1999, p. 3): participants indicated to what extent they felt each emotion "in general, that is, on the average", on a scale from 1 (*very slightly or nota t all*) to 5 (*extremely*). The items were presented in alphabetic order.

Surprise (SUR). To our knowledge, a valid and reliable scale to assess the emotion of surprise is not available in the literature. The Panas-X (Watson & Clark, 1999) includes only three items of surprise (amazed, surprised and astonished) and this scale is indicated as one of the less valid; furthermore, this emotion is not well represented in the language: "with regard to surprise, the data suggest that these scales could be improved through the inclusion of additional marker terms. Unfortunately, the English language contains few suitable terms in these content domains and we have not been able to identify additional markers for these scales (Watson & Clark, 1999, p. 13)". Scherer (2005) categorized several emotions that are encoded in the language, even though on a subjective basis, and identified several roots tapping into surprise, some of which are not directly translatable in Italian (e.g., thunderstruck). We generated a surprise scale by means of a pretest. Nineteen PhD students of the department of psychology, including the author, were instructed to generate words that tapped into emotions similar to those expressed by the surprise scale of the PANAS-X (i.e., stupito = amazed, sorpreso = surprised, and sbalordito = astonished). Each of them generated 5.21 items on average (SD = 2.10, min = 2, max = 9). With this procedure, 30 words were generated. Six words were excluded (e.g., "unusual") because they could not be used as descriptors of the person (i.e., they would not have made sense in completing the sentence "I feel…"). The remaining 23 items were administered, together with the three PANAS-X items, to 111 participants (79 females, Mean age = 27.92, SD=11.04). A PCA on the 26 items was performed: five eigenvalues were higher than zero (the first six eigenvalues were 9.77, 2.53, 1.86, 1.50, 1.18 and 0.95). Although parallel analysis indicated that three eigenvalues were higher than those extracted from random data (the first four random eigenvalues were 2.03, 1.85, 1.72 and 1.62), we considered a single factor solution as indicated by the scree-test and in line with our goal to measure a general factor of surprise. Only one item had an unsatisfactory loading on the first component (contrariato, $\lambda = .31$), therefore we removed that item. After removing this item, the first factor explained 39% of variance and the factor loadings ranged between .42 and .77. We decided to retain all remaining 25 items. The final list of items was: allibito (stunned), ammaliato (dazed), attonito (astonished), basito (perplexed), colpito (thunderstruck), confuso (confused), disorientato (disoriented), esterrefatto (astounded), impressionato (struck), incantato (bewitched), incredulo (incredulous), interdetto (speechless), meravigliato (amazed), perplesso (perplexed), preso alla sprovvista (taken aback), sbigottito (dismayed), scioccato (shocked), sconcertato (bewildered), sconvolto (shocked), senza parole (dumbfounded), spiazzato (dismayed), stupefatto (startled), stupito (amazed), sorpreso (surprised), sbalordito (astonished). This final list was administered to the participants ($\alpha = .93$).

Self-esteem (SEST, $\alpha = .94$). Self-esteem was assessed comprehensively with the Revised Janis and Field Scale (Fleming & Courtney, 1984), which includes 36 items. Participants responded on 7 points scales, whose labels varied according to the items. A sample item is "How confident are you that others see you as being physically appealing?"

Consideration of Future Consequences (CFC, α = .79; Strathman et al., 1994). Participants were instructed to indicate how each of 12 statements characterized them, on a scale from 1 (*extremely uncharacteristic*) to 5 (*extremely characteristic*). A sample item is "My behavior is only influenced by the immediate (i.e., a matter of days or weeks) outcomes of my actions" (reverse scored).

Zimbardo Time Perspective Inventory (ZTPI; Laghi, Baiocco, Liga, Guarino, & Baumgartner, 2013; Zimbardo & Boyd, 1999). The ZTPI includes five subscales: positive past, negative past, hedonistic present, fatalistic present, and future. We administered the Italian short version of the scale (Laghi et al., 2013). Participants indicated how each of 15 statements were true for them (five items by subscale), on a scale from 1 (*absolutely false for me*) to 5 (*absolutely true for me*). Since the different orientations toward past were not expected to have any relationship with conscientiousness, we decided to include only three scales: fatalistic present (PF, α = .62), hedonistic present (PH, α = .58), and future (FU, α = .69). A sample item is "I'm able to resist temptations when I know that there is a work to be done".

Perfectionism. Two facets of perfectionism were assessed by means of the multidimensional perfectionism scale (Hewitt & Flett, 1991): the self-oriented perfectionism (PEse, 15 items, α = .89) and the socially prescribed perfectionism (PEso, 15 items, α = .69). Participants indicated their agreement on each item on a scale from 1 (*strongly disagree*) to 7 (*strongly agree*). A sample item is "It makes me uneasy to see an error in my work".

Need For Closure (NFC; Roets & Van Hiel, 2007). The original need for closure scale (Kruglanski & Webster, 1996; Webster & Kruglanski, 1994) has been recently revised by modifying the items that tapped into ability (Roets & Van Hiel, 2007, 2011), and includes five subscales: preference for order (10 items), preference for predictability (8 items), decisiveness (6 items), discomfort with ambiguity (10 items), and closed mindedness (8 items). Participants indicated how much they agreed on each of 41 statements, on a scale from 1 (*totally disagree*) to 5 (*totally agree*). We computed the composite NFC score (α = .79) after removing the closed-mindedness scale, as suggested by Roets and Van Hiel (2007), and the preference for order subscale, since some of its items overlapped in content with the conscientiousness facet orderliness (e.g., "My personal space is usually messy and disorganized"). A sample item is "I dislike unpredictable situations".

Alcohol Use Disorders Identification Test (AUDIT, α = .87; Babor, Higgins-Biddle, Saunders, & Monteiro, 2001; Saunders, Aasland, Babor, De la Fuente, & Grant, 1993). Participants answered to a 10 items questionnaire that investigated their use of alcoholics. A sample item is "How often do you have a drink containing alcohol?" (0 = Never, 4 = four or more times a week). The response scales varied for each item.

Fagerström Test for Nicotine Dependence (FTND, α = .67; Heatherton, Kozlowski, Frecker, & Fagerström, 1991). Participants indicated whether they were smokers or not. Those that indicated that they smoked, were administered the FTND scale, which included six items. A sample item is "How many cigarettes/day do you smoke?". The response scales varied for each item. One item ("Which cigarette would you hate most to give up?" 1 = *the first one in the morning*, 0 = *all others*) had a reverse correlation with the other items and lowered substantially the reliability of the scale, therefore it was dropped. The scale score was computed as the sum of the remaining items scores. A score of zero was assigned to the nonsmokers.

Procedure

The first sample was administered two batteries of questionnaires, with the second battery that was administered approximately four months after the first one. The first battery included the following measures in this order: the RFQ, the GRFM, the RCQ, the BIS/BAS scales, the conscientiousness scale from HEXACO, the adjective checklist of conscientiousness, the IPIP-conscientiousness, the HEXACO-60, the SCS, the start/stop control scales, and the positivity scale. The second battery included the emotions connected to conscientiousness and the RJFS. The second sample was administered one battery, which included the following measures in this order: the conscientiousness scale from HEXACO, the adjective scale of conscientiousness, the conscientiousness facets scale from IPIP, the HEXACO-60, the SCS, the CFC, the ZTPI, the MPS, the NFCL, the surprise scale, the AUDIT, and the FTND. The grade point average (GPA) for all participants was also assessed at the end of the school year. Table 6 summarizes the measures administered to each sample.

Table 6. The questionnaires administered in each battery and the corresponding nodes in the networks.

Questionnaire	Nodes
Sample 1 – battery 1	
Regulatory Focus Questionnaire General Regulatory Focus Measure Regulatory Concerns Questionnaire	Promotion Focus (PRO) Prevention focus (PRE)
Behavioral Inhibition and Behavioral Activation Scales	Behavioral Inhibition (BIS) Reward-responsiveness (REW) Drive (DRI) Fun-seeking (FUN)
HEXACO-PI conscientiousness Adjective Checklist of Conscientiousness IPIP - conscientiousness	Industriousness (IND) Impulse-control (IMC) Orderliness (ORD)
HEXACO-60	Honesty-Humility (H) Emotionality (E) Extraversion (X) Agreeableness vs. anger (A) Openness to experience (O)
Self-control Scale	Self-control (SCS)
Start and stop control scales	Start control (START) Stop control (STOP)
Positivity Scale	Positivity (PO)
Sample 1 – battery 2	
Emotional Checklist	Authentic Pride (APR) Hubristic Pride (HPR) Cheerfulness (CHE) Guilt / Dejection (GUI) Agitation (AGI)
Revised Janis-Field Scale	Self-esteem (SEST)
	Grade point average (GPA)
Sample 2 – battery 1	
HEXACO-PI conscientiousness Adjective Checklist of Conscientiousness IPIP - conscientiousness	Industriousness (IND) Impulse-control (IMC) Orderliness (ORD)
HEXACO-60	Honesty-Humility (H) Emotionality (E) Extraversion (X) Agreeableness vs. anger (A) Openness to experience (O)
Self-control Scale	Self-control (SCS)
Consideration of future consequences scale	Consideration of future consequences (CFC)
Zimbardo Time Perspective Inventory	Future (FU) Fatalistic Present (PF) Hedonistic Present (PH)
Multidimensional Perfectionism Scale	Self-oriented perfectionism (PEse) Socially-prescribed perfectionism (PEso)
Need for closure scale	Need for closure (NFCL)
Surprise scale	SUR
Alcohol use disorder identification test	AUDIT
Fagerströrm Test for Nicotine Dependence	FTND
	Grade point average (GPA)

Analyses plan

Since the conscientiousness measures were the same in both samples, we firstly analyzed the structure of the conscientiousness facets in the overall sample and established measurement invariance in the two samples. Since the 64 emotions that we administered to the first sample included several scales with overlapping items, we performed a PCA to identify which emotions could be distinguished in our sample.

We computed and analyzed two networks using the adaptive lasso method defined in Chapter 1: one network included the measures that were administered to the first sample, while the second network included the measures administered to the second sample. We first analyzed the properties of both networks, then discussed the mechanisms that were shared by one or more facets and finally discussed those that characterized differently the facets.

Results and discussion

The structure of conscientiousness facets

We tested whether the facets of conscientiousness that we measured using the HEXACO-PI, the IPIP, and the Adjective checklist of conscientiousness had a comparable structure between the two samples. The Steiger test (Steiger, 1980), as implemented in the R package *psych* (Revelle, 2014), showed that the differences between the correlation matrices of the conscientiousness facets measured in the two samples were non-significant, $\chi2$ (91) = 67.31, p = .97. Therefore, we pooled the data from the two samples and inspected the dimensionality of the conscientiousness facets with PCA. Three eigenvalues were larger than one (the first four eigenvalues were 6.61, 1.87, 1.50, and 0.79) and the scree-test (*Figure 15*) showed a clear break after the third component. Parallel analysis indicated that three components explained more variance than those extracted by random data (the first four eigenvalues extracted from random data were 1.31, 1.24, 1.18, and 1.13) and the MAP criterion (Velicer, 1976) indicated also three factors. Three components explained 71% of variance. After oblimin rotation, the three components could be easily interpreted as order, industriousness and impulse-control. The loadings are reported in Table 7 (see the column Solution 1). Three scales did not load clearly on a single component and were perfectionism from the HEXACO-PI, responsibility from the adjective checklist and dutifulness from the IPIP. Furthermore, the facet self-discipline (IPIP) had a secondary loading on the component order. We excluded these scales one by one and inspected, after each exclusion, whether the pattern of loadings improved. A slight improvement was obtained for scale self-discipline (IPIP), after removing the other problematic scales: the first loading amounted to .68 and the secondary loading to .32, however given that we had two more scales in the industriousness domain than in the other two domains, we decided to drop self-discipline for the sake of a cleaner solution. The factor loadings after the exclusion of these scales is reported in Table 7 (Solution 2). In this solution, the scale self-efficacy showed the largest secondary loading and the highest uniqueness, therefore we decided to drop it. This left three indicators by component, one by each measurement instrument. The final solution is reported in Table 1 (Solution 3). The final three components explained 84% of the total variance.

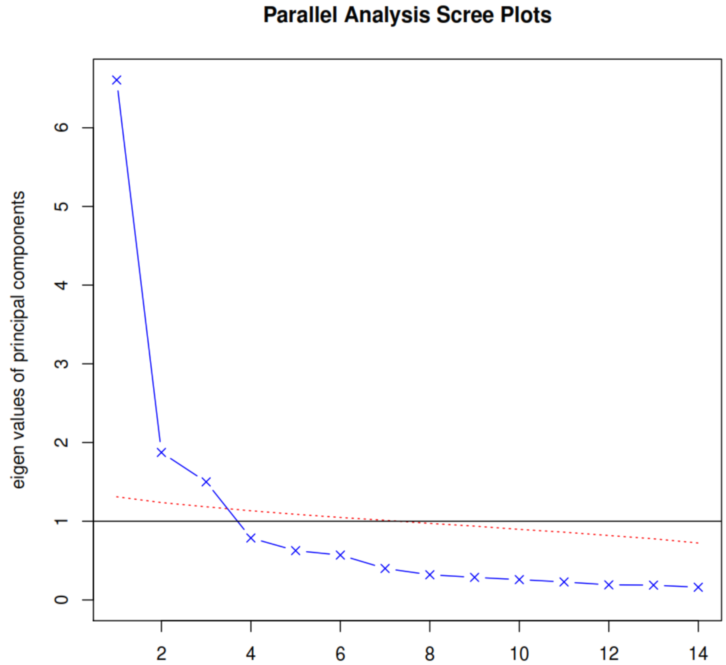

Figure 15. *Scree test and parallel analysis of the conscientiousness facets.*

The blue line represents the eigenvalues, while the red dotted line represents the mean eigenvalues extracted from random data.

Table 7. Component loadings and uniqueness for the three factor solutions.

	Component loadings											
	Solution 1				Solution 2				Solution 3			
	IND	IMC	ORD	u^2	IND	IMC	ORD	u^2	IND	IMC	ORD	u^2
HEXACO												
Diligence	**.83**	-.06	.15	.23	**.84**	-.04	.14	.21	**.91**	-.01	.04	.15
Prudence	-.10	**.85**	.09	.27	-.02	**.94**	-.04	.17	-.04	**.94**	-.04	.17
Orderliness	.01	.06	**.89**	.16	-.02	.01	**.93**	.13	-.04	-.02	**.97**	.12
Perfectionism	**.38**	**.22**	**.34**	.49	-	-	-	-	-	-	-	-
IPIP												
Achievement striving	**.92**	-.06	.01	.19	**.92**	-.05	.02	.17	**.95**	-.03	-.06	.17
Cautiousness	.04	**.84**	.09	.21	.09	**.88**	.01	.17	.09	**.89**	-.02	.16
Orderliness	.03	.05	**.89**	.15	.00	.00	**.93**	.13	-.02	-.03	**.96**	.12
Dutifulness	**.49**	**.57**	**-.21**	.36	-	-	-	-	-	-	-	-
Self-efficacy	**.71**	.09	-.19	.52	**.77**	.15	**-.26**	.42	-	-	-	-
Self-discipline	**.67**	-.08	**.35**	.32	-	-	-	-	-	-	-	-
Adjective checklist												
Industriousness	**.77**	.03	.14	.29	**.76**	.03	.16	.28	**.83**	.05	.06	.23
Impulse-control	-.11	**.87**	.14	.19	-.08	**.86**	.12	.20	-.05	**.87**	.08	.20
Orderliness	.17	.15	**.76**	.18	.16	.13	**.77**	.17	.16	.11	**.77**	.17
Responsibility	**.46**	**.51**	-.18	.46	-	-	-	-	-	-	-	-
	Correlations among components											
	IND	IMC	ORD		IND	IMC	ORD		IND	IMC	ORD	
IND	1				1				1			
IMC	.35	1			.32	1			.33	1		
ORD	.36	.37	1		.38	.43	1		.44	.47	1	

Note. u^2 = uniqueness, IND = industriousness, ORD = orderliness; IMC = impulse-control. Loadings lager than .20 are represented in **bold**.

We tested the measurement invariance of the three factors (Table 7, Solution 3) in the two samples using SEM, as implemented the R package *lavaan* (Rosseel, 2012). We specified a CFA model that mirrored the solution recovered in the PCA (three correlated latent variables with three indicators each) and tested the measurement invariance using the R package *semTools* (Pornprasertmanit, Miller, Schoemann, & Rosseel, 2014). Table 8 reports the results of the tests: measurement invariance was confirmed at all levels according to the criterion ΔCFI < .01 (Hirschfeld & von Brachel, 2014), and also according to the criteria proposed by Chen (Chen, 2007). We constrained factor loadings and intercepts to be equal across groups (see Table 8, Strong invariance, and Figure 16), the model fitted data well according to the values of CFI and srmr, and reasonably well according to RMSEA (L. Hu & Bentler, 1999). The latent variable's score for each participant was used as input for the subsequent analyses.

Table 8. Measurement invariance of conscientiousness facets.

Model	$\chi 2$	Df	p value	cfi	rmsea	srmr	BIC
1. Configural inv.	113.31	48	<.001	.976	.079	.047	5768
2. Weak inv.	132.81	54	<.001	.971	.081	.056	5751
Δ 2-1	19.50	6	.003	-.005	.003	.009	-17
3. Strong inv.	141.90	60	<.001	.970	.079	.057	5724
Δ 3-2	9.08	6	.169	-.001	-.003	.001	-27
4. Latent means	150.15	63	<.001	.968	.079	.065	5714
Δ 4-3	8.251	3	.041	-.002	<.001	.008	-10

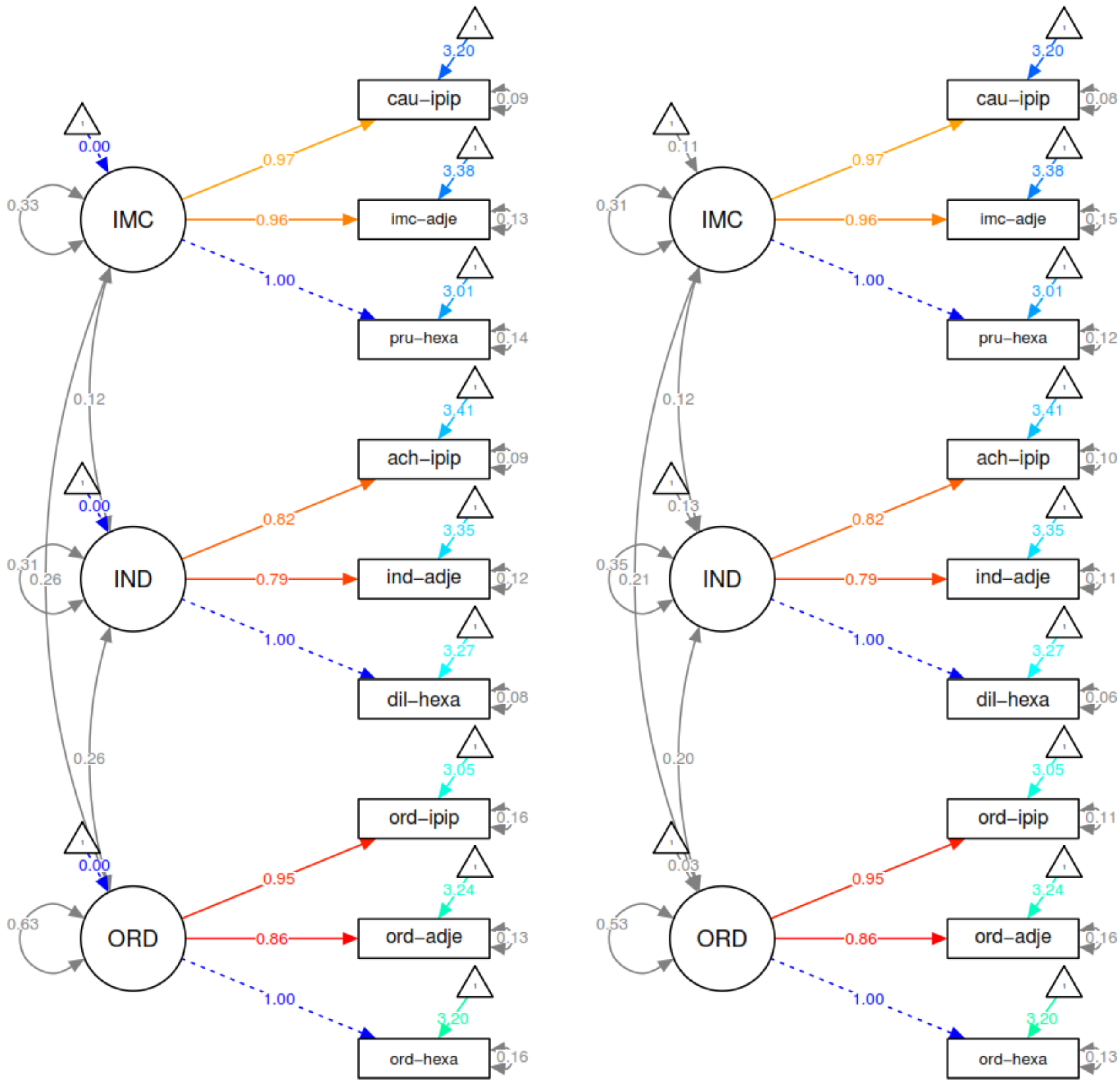

Figure 16. CFA model of the conscientiousness facets.

Edges of the same color are constrained to be equal. The plot was obtained with the R package *semPlot* (Epskamp, 2014). IMC = impulse control; IND = industriousness; ORD = orderliness; cau-ipip = cautiousness scale from IPIP; imc-adje = impulse-control scale from the ajective checklist; pru-hexa = prudence scale from HEXACO-PI; ach-ipip = achievement-striving scale from IPIP; ind-adje = industriousness scale form the Adjective checklist; dil-hexa = diligence scale from the HEXACO-PI; ord-ipip, ord-adje, ord-hexa are the orderliness scales from the IPIP, the Adjective checklist and he HEXACO-PI respectively.

The structure of the emotional checklist

We performed a PCA on the 64 emotions that were administered to the first sample. Thirteen factors had eigenvalues larger than 1 (the first 14 eigenvalues were 12.88, 8.79, 3.54, 2.53, 2.39, 2.03, 1.66, 1.49, 1.34, 1.21, 1.18, 1.12, 1.05, 0.99). Parallel analysis indicated that six components explained more variance than random (the first seven eigenvalues extracted from random data were 2.27, 2.15, 2.06, 1.98, 1.92, 1.86, 1.80). The MAP criterion achieved a minimum with 8 factors. The scree plot (Figure 17) indicated a drop after the fifth component. We inspected alternative solutions using the procedure described by Goldberg (Goldberg, 2006): we performed PCAs extracting from one to six oblique components, computed the component scores and correlated each solution with the subsequent (Figure 18). In the four-components solution, the agitation and guilt/dejection were not distinguished from each other and constituted a general negative affect component; in the six components solution, a component quiescence emerged, that included only three items, quieto (quiet), calmo (calm) and rilassato (relaxed); one of the items (rilassato) had a large secondary loading on cheerfulness. Since the number of items that loaded on this sixth component was not sufficient to compute a meaningful scale score, we preferred the five components solution. The five components were interpreted as agitation (AGI), guilt / dejection (GUI), cheerfulness (CHE), authentic pride (APR) and hubristic pride (HPR).

We iteratively removed the worst items (those that did not clearly loaded on a component) and repeated the PCA at each step: 20 items were removed with this procedure. The final solution is reported in *Table 9*. In the final solution, five factors explained 53% of variance. The correlations among the five components ranged between r = -.25 and r = .47 and can be found in the Appendix Table 2. We saved the five component scores to be used in further analyses.

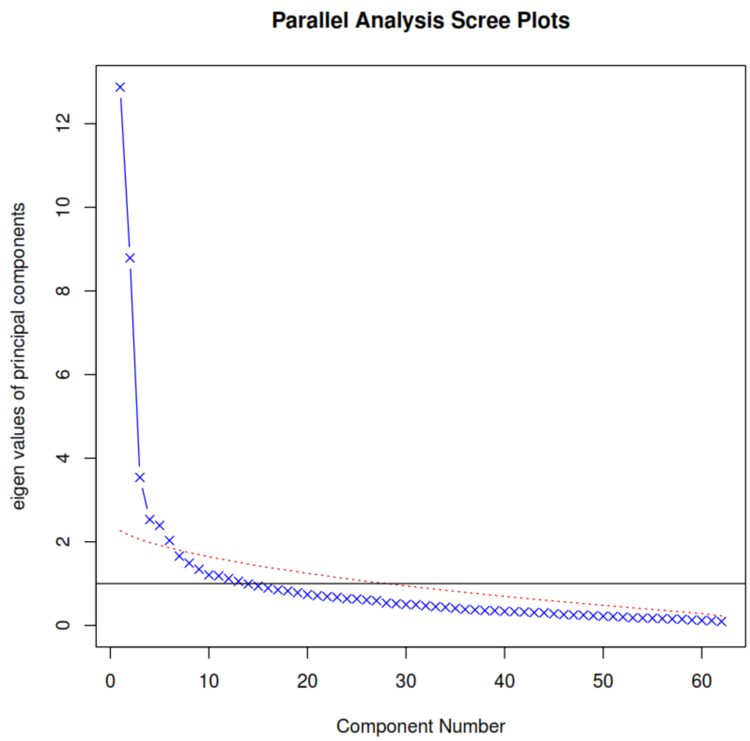

Figure 17. Scree plot of emotional checklist.

The blue line represents the eigenvalues, while the red dotted line represents the mean eigenvalues extracted from random data.

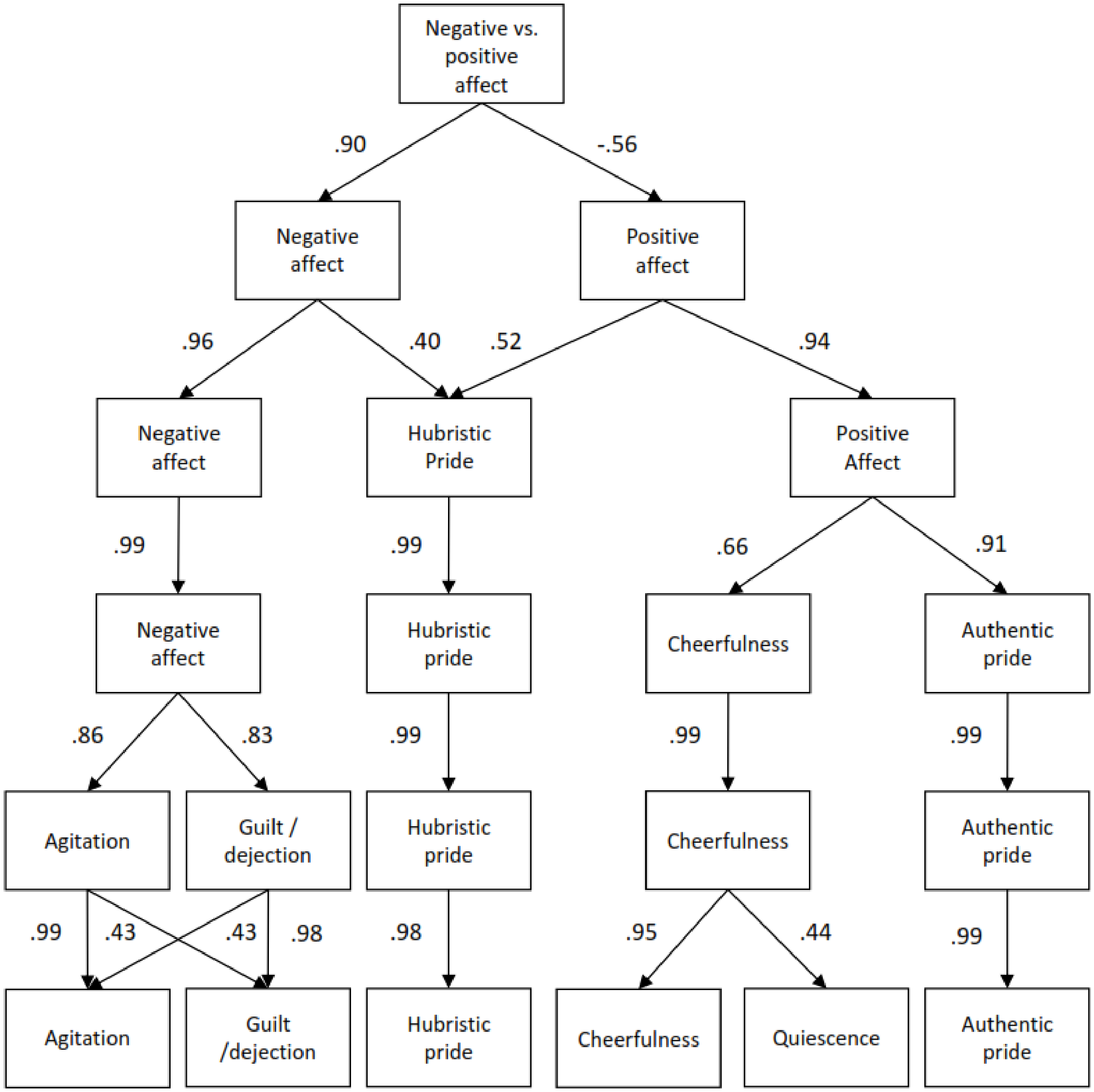

Figure 18. *Hierarchical structure of the emotional checklist.*

Table 9. Component loadings of the emotional items.

Loadings higher than .30 are in **bold**.

Item (English)	Original scales				Component loadings				
	PANAS	Shah	Leone	Tracy	AGI	APR	HPR	GUI	CHE
1. Teso (tense)		x			**.82**	.02	-.02	-.05	-.10
2. Agitato (jittery)	x				**.82**	-.03	.05	-.13	.13
3. Timoroso (afraid)	x				**.80**	-.11	.01	.08	.07
4. Preoccupato (uneasy)		x			**.74**	-.04	.00	.07	-.07
5. Ansioso (anxious)			x		**.72**	.17	-.08	.01	-.07
6. Spaventato (relieved)			x		**.72**	-.15	-.01	.12	.05
7. Turbato (upset)	x				**.63**	.08	.06	.23	-.10
8. Stressato (anguished)			x		**.62**	.01	.04	.14	-.02
9. Determinato (determined)	x				-.12	**.71**	-.04	.00	.07
10. Meritevole (worthy)			x		.01	**.69**	.15	-.08	-.15
11. Produttivo (productive)				x	.07	**.68**	-.08	.07	.13
12. Audace (daring)	x				-.02	**.63**	-.01	.10	.11
13. Coraggioso (fearless)	x				-.20	**.62**	.04	.08	.13
14. Una persona che raggiunge i suoi obiettivi (achieving)				x	.04	**.62**	.07	-.18	.08
15. Attento (attentive)	x				-.01	**.62**	-.21	-.07	-.04
16. Attivo (active)	x				-.09	**.58**	-.12	.01	.13
17. Forte (strong)	x				-.10	**.55**	.12	-.05	.13
18. Vigile (lively)	x				.21	**.55**	.16	-.02	-.17
19. Ispirato (inspired)	x				.07	**.47**	.09	.16	.25
20. Presuntuoso (conceited)				x	.03	-.01	**.81**	-.02	-.01
21. Arrogante (arrogant)				x	.03	.06	**.79**	.03	-.14
22. Snob (snobbish)				x	-.06	-.22	**.77**	.01	.07
23. Egoista (egoistical)				x	.06	-.05	**.74**	-.04	.05
24. Sfrontato (bold)	x				-.07	.00	**.67**	.22	.09
25. Pieno di sé (stuck-up)				x	-.03	.12	**.65**	-.08	.18
26. Ostile (hostile)	x				.04	.22	**.57**	.18	-.18
27. Orgoglioso (proud)	x		x		-.06	.25	**.49**	-.09	.09
28. Tronfio (pompous)				x	.20	.11	**.44**	-.05	.02
29. Insoddisfatto di me stesso (dissatisfied with self)	x				-.06	-.03	-.01	**.88**	-.03
30. Arrabbiato con me stesso (angry at self)	x				.06	-.04	.01	**.79**	.10
31. Insoddisfatto (dissatisfied)			x		.02	-.03	-.01	**.69**	-.12
32. Disgustato da me stesso (disgusted with self)	x				.12	.02	.06	**.69**	.13
33. Avvilito (low)		x			.03	.06	.08	**.65**	-.02
34. Deluso (disappointed)		x			.09	.10	.07	**.57**	-.15
35. Triste (sad)	x	x	x		.28	.02	-.01	**.57**	-.16
36. Sollevato (relieved)		x	x		.08	-.04	.13	-.07	**.74**
37. Contento (glad)					-.15	.14	.06	-.08	**.69**
38. Entusiasta (enthusiastic)	x				-.04	.14	.01	.08	**.63**
39. Felice (happy)	x	x	x		-.03	.12	-.02	-.26	**.61**
40. Compiaciuto (smug)				x	-.03	.08	-.02	.21	**.61**
41. Appagato (fulfilled)				x	.23	.05	-.08	.03	**.58**
42. Rilassato (relaxed)	x	x	x		-.17	.00	.00	-.09	**.57**

Note. AGI = agitation; APR = authentic pride; HPR = hubristic pride; GUI = guilt / dejection; CHE = cheerfulness. PANAS = the item is included in the PANAS-X (Watson & Clark, 1999); Shah = the item was proposed by Shah & Higgins (2001); Leone = the item was proposed by Leone et al. (2005); Tracy = the item was proposed by Tracy & Robins (2007)

Definition of the networks

The correlations among all the measures are reported in the Appendix Table 2 for the first sample and in the Appendix Table 3 for the second sample. In both samples, the facets of conscientiousness showed non-negligible correlations with other major personality dimensions. Honesty-humility correlated with impulse-control in the first sample and with all of conscientiousness facets in the second sample, extraversion had a positive correlation with industriousness in both samples and a negative correlation with impulse control in the second sample, agreeableness correlated with impulse-control in both samples, openness to experience correlated with industriousness in both samples and with impulse-control in the second[25].

The correlations of conscientiousness and its facets with different personality factors can be explained from two different perspectives. From the perspective of hierarchical models, they have been considered as the effect of higher order personality factors (DeYoung, 2006; Musek, 2007) or as the effect of blended indicators (Ashton, Lee, Goldberg, & de Vries, 2009). From this perspective, to observe the network of conscientiousness one should first rule out that the effects are not due to other personality factors. However from the perspective of circumplex models, facets are distinguished by their secondary loadings on different factors (Hofstee et al., 1992): Within this framework the variance shared with other factors is considered part of the facet itself. To control for both possibilities, we computed two networks for each sample. The first network was obtained from the raw data using the adaptive LASSO procedure described in Chapter 1, while the second one was computed by applying the adaptive LASSO procedure after partialling out the other five major personality factors assessed with the HEXACO-60. A

[25] Correlations among different HEXACO scales emerged also in the validation samples of the HEXACO questionnaires (Ashton & Lee, 2009; K. Lee & Ashton, 2004).

visual comparison of the networks reveals that the relationships of the conscientiousness facets with the other constructs are mostly similar even after removing the other personality factors. We will discuss the results according to the first kind of networks (Figure 19A and D) and mention the second kind of networks (Figure 19B and E) when the differences between the two networks are relevant.

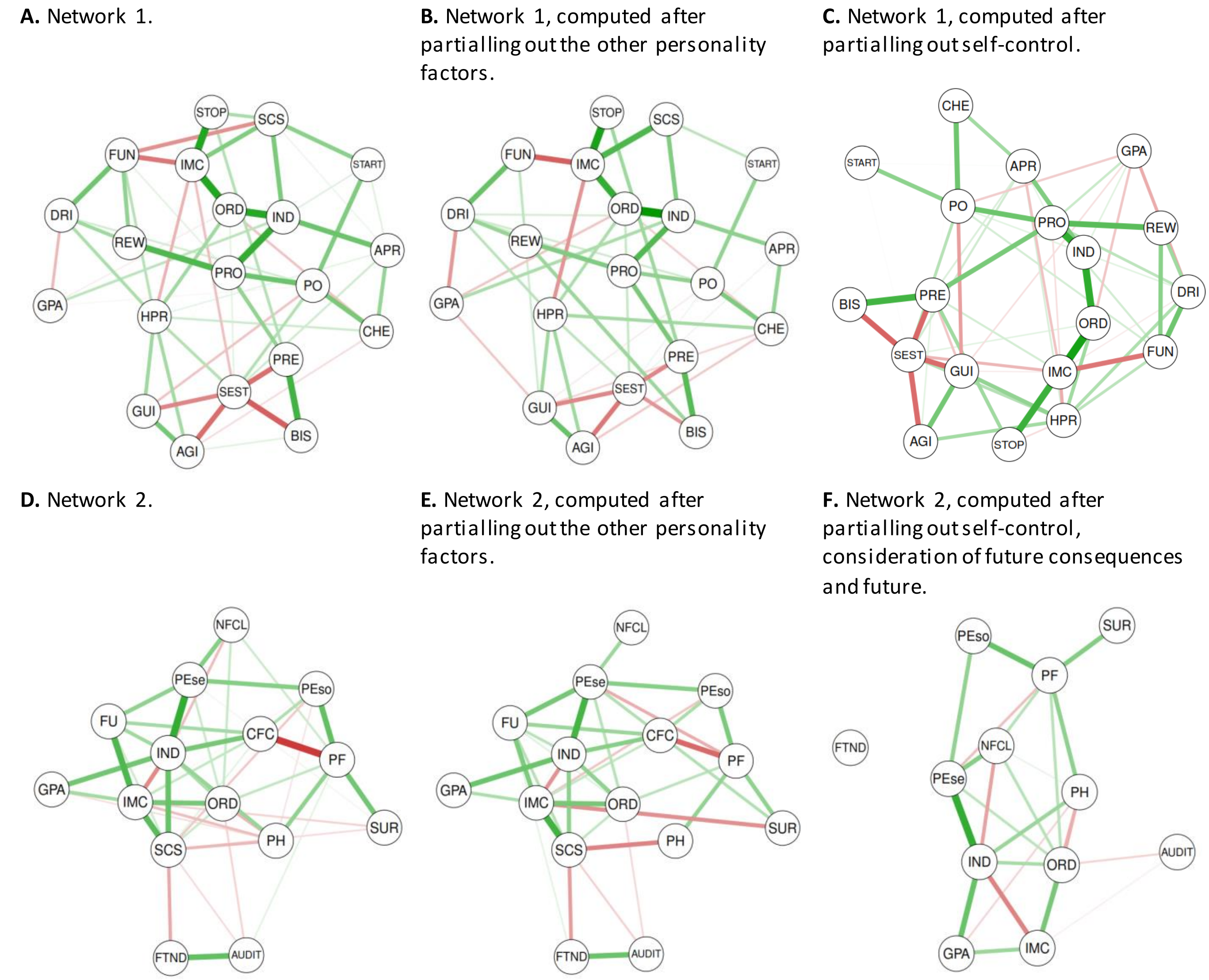

Figure 19. Networks of conscientiousness and of related measures.

The plots were obtained with the R package *qgraph* (Epskamp et al., 2014, 2012). To facilitate visualization, the position of the nodes in B is the same as in A and the position of the nodes in E is the same as in D. AGI = agitation, APR = authentic pride, AUDIT = alcohol use, BIS = behavioral inhibition, CFC = consideration of future consequences, CHE = cheerfulness, DRI = drive, FTND = nicotine dependence, FU = future orientation, FUN = fun-seeking, GPA = grade point average, GUI = guilt/dejection, HPR = hubristic pride, IMC = impulse-control, IND = industriousness, NFCL = need for closure, ORD = orderliness, PEse = self-oriented perfectionism, PEso = socially prescribed perfectionism, PF = fatalistic present, PH = hedonistic present, PO = positive orientation, PRE = prevention focus, PRO = promotion focus, REW = reward responsiveness, SCS = self-control, SEST = self-esteem, START = start-control, STOP = stop-control, SUR = surprise.

Network properties

The network computed on the first sample (Figure 19A) was sparser, having 54 nonzero edges out of 190 possible edges (28%): Of these 40 were positive and 14 were negative. The second network (Figure 19D) was denser, with 45 nonzero edges out of 105 possible edges (43%), of which 30 positive and 15 negative. In the first network (Figure 19A) the average absolute weight of positive edges was .18 (SD = .11), and that of negative edges was .16 (SD = .09), and positive and negative edges were not significantly different in weight, $t(52) = .76$, $p = .45$. In the second network (Figure 19D), the average weight of positive edges was .18 (SD = .09) while that of negative edge was .12 (SD = .08): in this network, the positive edges had a significantly stronger weight than negative edges $t(43) = 2.42$, $p = .02$. In both networks the small-worldness index (Humphries & Gurney, 2008) was close to unity, 1.20 for the first network and 0.93 for the second. An inspection of the values of transitivity and of average path length showed that they were not significantly different from those emerged from similar random networks, therefore neither networks showed a small-world topology.

We computed the same centrality indices considered in Chapter 1, plus the signed Zhang's signed clustering coefficients for both networks (see Chapter 2). In both networks, the centrality indices were strongly correlated with each other (Table 10), while the correlation of the centrality indices with clustering coefficients were nonsignificant (and they were generally lower in absolute value than those recovered for the HEXACO network discussed in Chapter 3). This means that being locally redundant in these network generally does not make a strong difference for the global role of the nodes in the whole network. This result is likely a byproduct of the low number of triangles in these networks. There were only 27 triangles in the first network (7 negative), while the connected triples (i.e., three nodes connected by two edges) were 1113. In the second network the triangles were 39 (18 negative), while the connected triples were 455. This means that there were generally few locally redundant nodes.

Table 10. Correlations among network indices.

	Betweenness	Closeness	Strength	Zhang
		Network 1		
Betweenness	1	.93***	.82***	-.41
Closeness	.89***	1	.71***	-.24
Strength	.78***	.79***	1	-.24
Zhang	-.38	-.25	-.21	1
		Network 2		
Betweenness	1	.68**	.70**	-.10
Closeness	.72**	1	.91***	.09
Strength	.77***	.88***	1	-.06
Zhang	.11	.09	.20	1

Note. *p<.05, **p<.01, ***p<.001. Pearson correlations are reported below the diagonal, Spearman correlations are above the diagonal. Zhang = Zhang's signed clustering coefficient (see Chapter 2).

Partialling out the remaining personality factors did not make a strong difference for centralities and clustering coefficients. The indices computed on the original networks and on the one obtained after partialling out the factors other than conscientiousness were strongly correlated. In the first network these correlations amounted to r = .90 ($p < .001$) for betweenness, r = .87 ($p < .001$) for closeness centrality, r =.81 ($p < .001$) for strength centrality and r = .81 ($p < .001$) for the clustering coefficient. In the second network, the correlations were r = .88 ($p < .001$) for betweenness, r = .91 ($p < .001$) for closeness, r = .90 ($p < .001$) for strength, and r = .81 ($p = .003$) for the clustering coefficient. This confirms that the conscientiousness network is not substantially affected by the other personality factors. The centralities and the clustering coefficient for each node are reported in *Figure 20* for the first network and in Figure 21 for the second network. Industriousness was always among the most central nodes in both networks. This is not surprising, since we intentionally included in the networks nodes that were supposed to be connected to the facets of conscientiousness. Among the facets of conscientiousness however orderliness was the lowest in strength and betweenness centrality in both networks. The nodes that we included in the two networks might be more relevant for industriousness and for impulse-control than they are for orderliness.

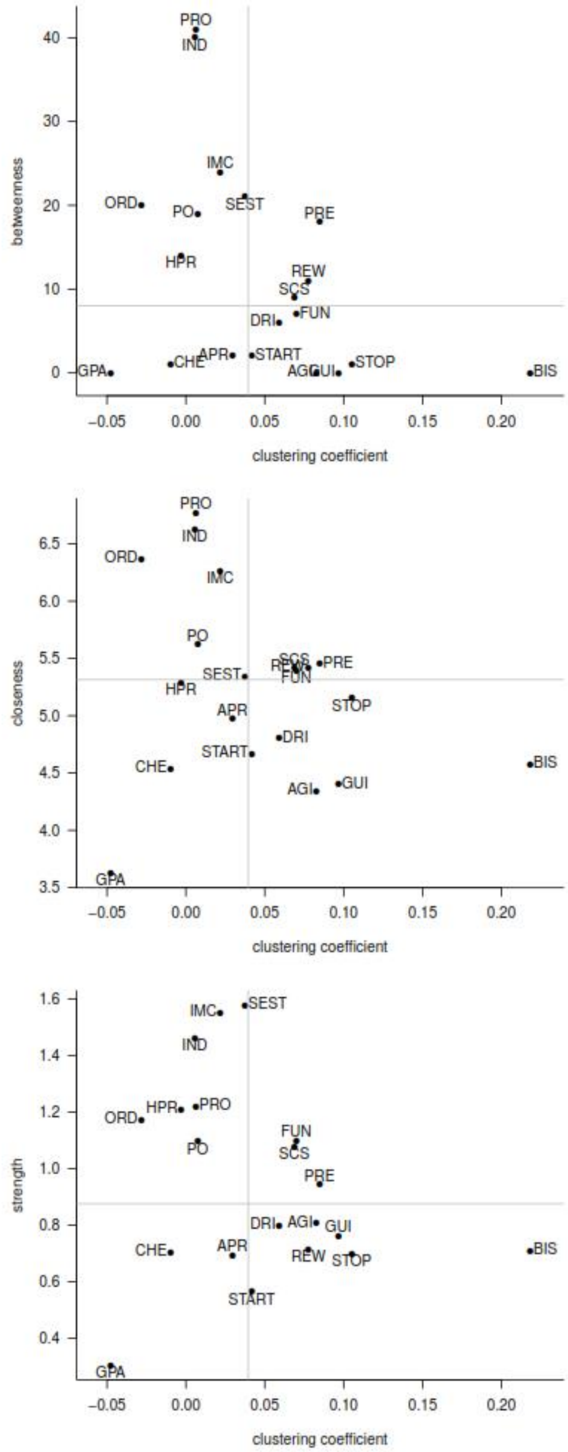

Figure 20. Centralities and Zhang's signed clustering coefficient computed on the first network (Figure 19A).

AGI = agitation, APR = authentic pride, BIS = behavioral inhibition, CHE = cheerfulness, DRI = drive, FUN = fun-seeking, GPA = grade point average, GUI = guilt/dejection, HPR = hubristic pride, IMC = impulse-control, IND = industriousness, ORD = orderliness, PO = positive orientation, PRE = prevention focus, PRO = promotion focus, REW = reward responsiveness, SCS = self-control, SEST = self-esteem, START = start-control, STOP = stop-control.

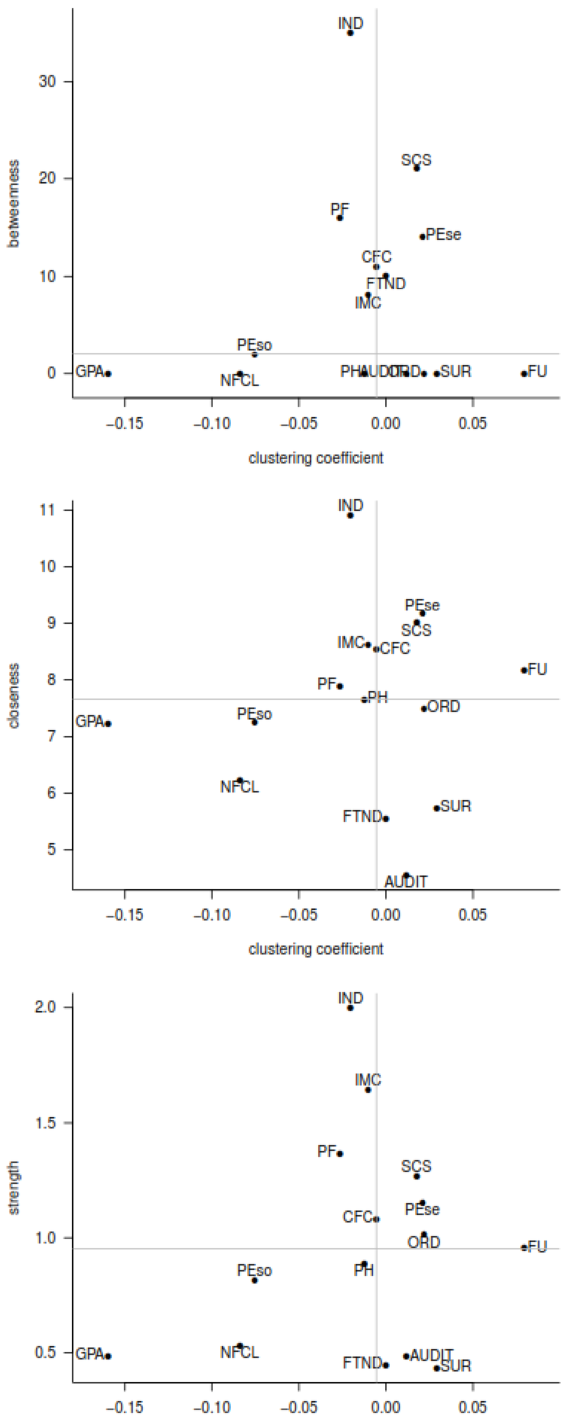

Figure 21. Centralities and Zhang's signed clustering coefficient computed on the second network (see Figure 19D).

CFC = consideration of future consequences, FTND = nicotine dependence, FU = future orientation, GPA = grade point average, GUI = guilt/dejection, IMC = impulse-control, IND = industriousness, NFCL = need for closure, ORD = orderliness, PEse = self-oriented perfectionism, PEso = socially prescribed perfectionism, PF = fatalistic present, PH = hedonistic present, SCS = self-control, SUR = surprise.

In the first network, promotion focus (PRO) was the most betweenness central node. The links involved in the shortest paths passing through node promotion focus are shown in Figure 22. Promotion focus occupies a very strategic position, by connecting several groups of nodes that, without promotion, would be connected by longer paths. In particular, promotion focus was responsible for connecting the facets of conscientiousness to other groups of nodes. It is unsurprising that the most betweenness central edges are all involved in this network. They are (in order of centrality) those between industriousness (IND) and promotion (PRO, 31 shortest paths), orderliness (ORD) and industriousness (IND, 27 shortest paths), promotion focus (PRO) and prevention focus (PRE, 27 shortest pahts), promotion focus (PRO) and reward-responsiveness (REW, 24 shortest paths), orderliness (ORD) and impulse-control (IMC, 20 shortest paths), and promotion focus (PRO) and positive orientation (PO, 19 shortest paths). Promotion focus was also the most closeness central node, meaning that from its position in the network it could quickly send influence to (and receive influence from) all other nodes. Promotion focus was not the highest in strength centrality: it was not the strength of its connections that made promotion focus central, but the specific position in the network. Conversely, self-esteem (SEST) was the most strength central and this was mostly because of its strong negative connections with negative emotions, with the behavioral inhibition system (BIS), and with prevention focus (PRE) nodes. The behavioral inhibition system (BIS) was particularly high in clustering coefficient, since it had only few connections, all with nodes that were already connected to each other in a congruent way (with edges that completed the connections forming a positive triangle, see Chapter 2), especially self-esteem (SEST) and prevention focus (PRE).

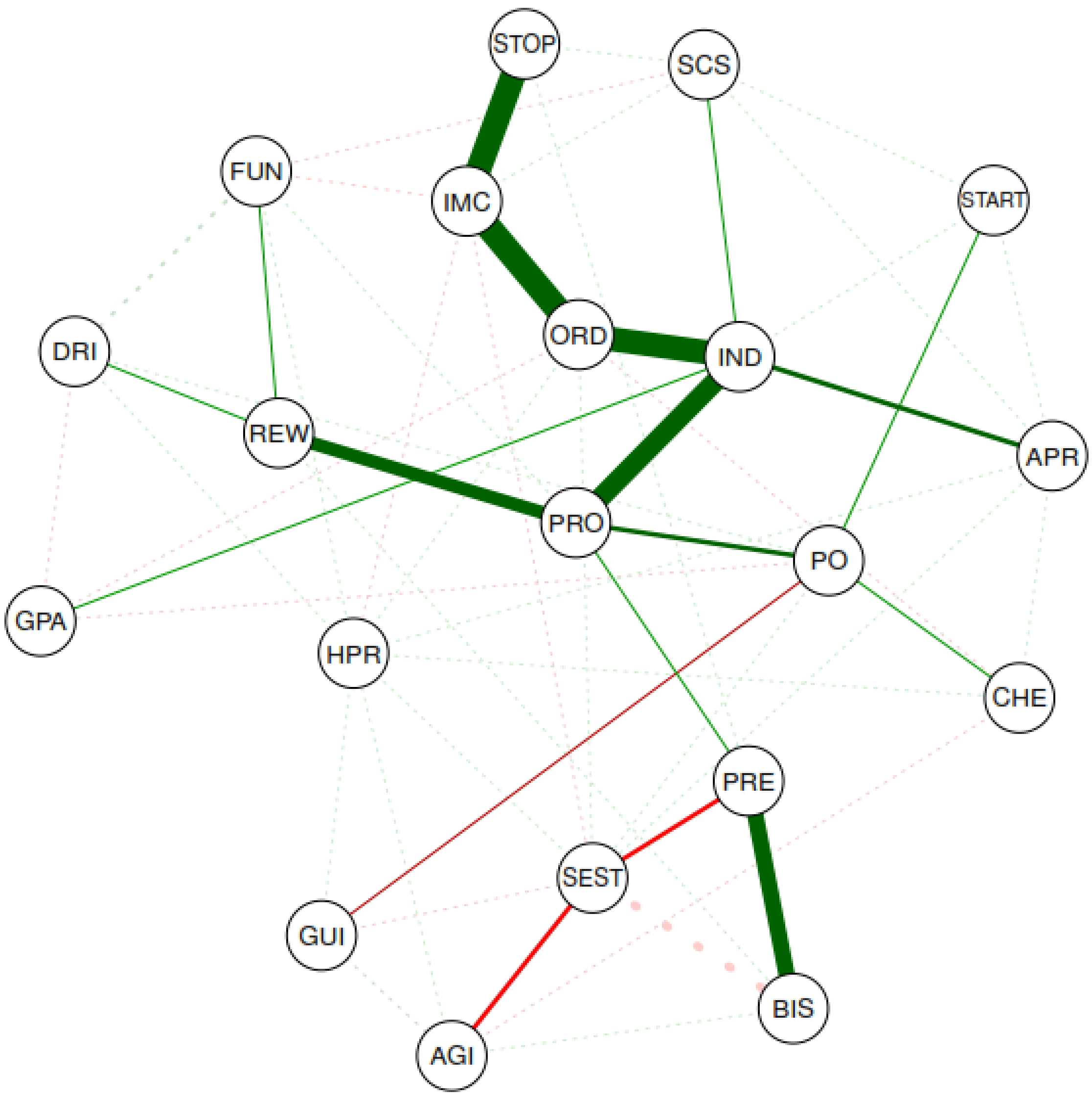

Figure 22. Shortest paths passing through promotion focus (PRO).

The edges belonging to the shortest-paths are full, while the other edges are dashed. AGI = agitation, APR = authentic pride, BIS = behavioral inhibition, CHE = cheerfulness, DRI = drive, FUN = fun-seeking, GPA = grade point average, GUI = guilt/dejection, HPR = hubristic pride, IMC = impulse-control, IND = industriousness, ORD = orderliness, PO = positive orientation, PRE = prevention focus, PRO = promotion focus, REW = reward responsiveness, SCS = self-control, SEST = self-esteem, START = start-control, STOP = stop-control.

In the second network, self-control (SCS) occupied a very betweenness-central position and this was due to its role in funneling the influence of other nodes towards nicotine dependence (FTND) and, through nicotine dependence, to alcohol use (AUDIT; see Figure 19D). Fatalistic present (PF) was the third highest node in betweenness centrality and it was also the first node in strength-centrality after two conscientiousness facets. Its centrality was mainly due to its role in transmitting the influence between the other nodes of the network and the emotion of surprise (SUR). Fatalistic present is defined as "a fatalistic, helpless, and hopeless attitude toward the future and life" (Zimbardo & Boyd, 1999, p. 1275), and is assessed by items such as "You can't really plan for the future because things change so much". It is possible that this systematic tendency of not engaging in the prediction of future events may lead fatalistic individuals to experience more surprise when confronted with the events that they did not (even attempt to) foresee.

The most closeness central node, after industriousness, was the self-oriented perfectionism (PEse), and this was due to its strong connection with industriousness (IND), that allowed the self-oriented perfectionism to influence and to be influenced by conscientiousness and its core mechanisms, but also thanks to its connections with socially-prescribed perfectionism (PEso), that allowed the self-oriented perfectionism to influence and be influenced also by nodes that farther away from the core of conscientiousness, such as fatalistic-present (PF) and surprise (SUR). Future orientation (FU) was the node highest in clustering coefficient, since it was mainly responsible for further connecting nodes that were already connected with each other in a congruent way (see Chapter 2), with the noticeable exception of industriousness (IND) and impulse-control (IMC), which were negatively connected with each other and had positive connections with future orientation (FU).

The most betweenness-central edges where those between self-control (SCS) and nicotine-dependence (FTND; 23 shortest paths), between industriousness (IND) and self-oriented perfectionism (PEse; 20 shortest paths), between industriousness (IND) and self-control (SCS; 19 shortest paths), between industriousness (IND) and the consideration of future consequences (CFC; 18 shortest paths), between the consideration of the future consequences (CFC) and the fatalistic present (PF; 15 shortest paths), and between the fatalistic present (PF) and surprise (SUR; 13 shortest paths). In the following paragraphs, we will elaborate on the implications that the results of network analysis have for the mechanisms of conscientiousness.

Shared mechanisms

One of the most interesting result that emerges from both networks is that, despite their positive correlation ($r = .40$ in the first sample and .42 in the second one, both *p*s < .001), industriousness (IND) and impulse-control (IMC) are not positively connected with each other. This means that they are substantially independent (or even negatively dependent, in the second network) given the other nodes (Chapter 1; Costantini et al., 2014). Their positive correlation is explained by the connections that they share in particular with orderliness and self-control in both networks, and also with the future orientation (FU) and the consideration of future consequences (CFC) in the second network. This pattern of connections supports the view of conscientiousness as having two distinguishable poles, industriousness (the proactive pole) and impulse-control (the inhibitive pole), which are nonetheless connected by shared mechanisms: the self-control, the orientation toward the future and the consideration of future consequences, although this last one seems to be shared to a lower degree, perhaps also because of its overlap with the construct of future-orientation.

We deepened the weight of these shared mechanisms by computing the partial correlation of industriousness and impulse-control after removing the effect of self-control in the first sample and also of future orientation and consideration of future consequences in the second sample. The partial correlation between industriousness and impulse-control after controlling for self-control was non-significant both in the first sample (partial $r = .07$, $p = .31$) and the second sample (partial $r = .0005$, $p > .99$). One could object that this result is due to the fact that the measures of self-control are to some extent overlapping with those of conscientiousness (e.g., Roberts et al., 2012). However, the partial correlations after removing self-control were much stronger between orderliness and impulse-control (partial $r = .42$, $p < .001$ in the first sample and partial $r = .33$, $p < .001$ in the second sample) and between orderliness and industriousness (partial $r = .47$, $p < .001$ in the first sample and partial $r = .25$, $p < .001$ in the second sample). Nonetheless, orderliness is considered as the closest facet to the core of conscientiousness (Hofstee et al., 1992).

In the second sample, after all the three shared mechanisms (self-control, future orientation, and the consideration of future consequences) were partialled out, the correlation among industriousness and impulse-control was negative (partial r = -.20, p = .002). The partial correlations between impulse-control and orderliness (partial r = .24, p < .001) and between industriousness and orderliness (partial r = .14, p = .03) were also reduced, but remained positive and significant. We further deepened this result by running a series of multiple regressions with conscientiousness and its facets as dependent variables and self-control, future orientation and the consideration of future consequences as predictors. These regressions were run on the second sample only, since it included all of these scales, and are reported in Table 12 (Step 1). When considered together, these three mechanisms explained more than 60% of overall conscientiousness' variance, being it assessed using the HEXACO or the IPIP. Moreover they explained more than 50% of variance for both facets industriousness and impulse-control, although the consideration of future consequences seemed to be an independent predictor only for industriousness. Two of these mechanisms, self-control and future orientation, also explained 36% of the variance of orderliness, with a negligible contribution from the consideration of future consequences.

Nonshared mechanisms

To inspect the mechanisms that are not shared by the different facets of conscientiousness, we redrew the network after partialling out the shared mechanisms, which were the self-control in the first network (Figure 19C) and self-control, future orientation and the consideration of future consequences in the second (Figure 19F). The layouts of the networks were allowed to differ from those of Figure 19A and Figure 19C because the nodes were different (self-control was removed from both networks, future orientation and the consideration of future consequences were removed from the second) and because the new layout emphasized the mechanisms that were not shared among the facets, especially for the first network.

After removing self-control from the first network (Figure 19C), the nodes could be roughly divided into two clusters, with few connections between each other. In the upper-right part of the plot there is a cluster including promotion focus (PRO), the BAS subscales (DRI, FUN, REW), start control (START), positive orientation (PO), the positive emotions authentic pride (APR) and cheerfulness (CHE), and the grade point average (GPA). In the lower-left part of the plot there are prevention focus (PRE), the behavioral inhibition (BIS), stop-control (STOP), self-esteem (SEST), the negative emotions guilt/dejection (GUI) and agitation (AGI), and the hubristic pride (HPR). Given the nodes that characterize them, we can call the first the “proactive / positive” cluster and the second the “inhibitive / negative” cluster. Industriousness is positioned in the proactive/positive cluster, to which is especially connected through promotion focus (PRO), but also by the authentic pride (APR). Impulse-control is positioned in the inhibitive/negative cluster, to which it is connected especially by stop-control (STOP), but also by negative connections with the hubristic pride (HPR) and self-esteem (SEST). Impulse control (IMC) has also negative connections with some of the nodes of the proactive cluster, and especially a negative connection with the fun-seeking subscale of BAS (FUN). Interestingly, orderliness (ORD) does not seem to be part of either clusters: most of the mechanisms that we considered seem to affect and to be affected by orderliness only indirectly, through industriousness (IND) and impulse-control (IMC) in this network. Most of the connections that are present in Figure 19C were also present in the original network (Figure 19A), but became more visible when after removing self-control, which was attracting the two clusters together.

We further explored how much additional variance of conscientiousness and of its facets could be explained by the addition of promotion and prevention focus, the behavioral inhibition and the subscales of the behavioral activation scale (reward responsiveness, fun-seeking, and drive), and by start and stop control. For the model selection in these regression, we did not use a lasso penalty (Krämer et al., 2009; Zou, 2006). Instead, we performed a series of BIC-based stepwise multiple regressions on conscientiousness and on its facets: self-control was always entered at the first step and the other predictors were allowed to enter in the second-step, according to the model fit (Table 11). In the prediction of overall conscientiousness, both proactive and inhibitory mechanisms were selected as predictors and explained a proportion of conscientiousness variance ranging between 54% and 63%, according to the scale used, HEXACO-PI or IPIP. In the prediction of industriousness, variables promotion focus and start-control were included, while in the prediction of impulse control, variables fun-seeking (with negative sign), prevention focus and stop-control were included. The inclusion of these variables increased substantially the variance of the facets explained by the mechanisms, which amounted to 57% for industriousness and to 65% for impulse-control. For orderliness, only one additional predictor was included in the stepwise process, and was prevention-focus, which increased the variance of orderliness of 3% above the sole self-control. Reward-responsiveness and drive never improved the model fit, most likely because of their strong correlation with other candidate mechanisms (such as fun-seeking and promotion focus).

Table 11. Stepwise multiple regression analysis predicting conscientiousness and its facets (sample 1).

	Dependent variable									
	Consc.(hexaco)		Consc. (ipip)		Industriousness		Impulse control		Orderliness	
Predictor	R^2	β	ΔR^2	β	ΔR^2	β	ΔR^2	β	ΔR^2	β
Step 1	.43***		.48***		.35***		.42***		.28***	
SCS		.65***		.69***		.59***		.64***		.53***
Step 2	.54*** Δ=.11***		.63*** Δ=.15***		.57*** Δ=.22***		.65*** Δ=.24***		.31*** Δ=.03**	
SCS		.50***		.48***		.40***		.34***		.51***
PRO		.34***		.34***		.46***				
START						.14**				
REW										
FUN		-.17**						-.26***		
DRI										
PRE								.21***		.19**
BIS		.13**								
STOP				.21***				.32***		

Note. *p<.05, **p<.01, ***p<.001. Consc. = conscientiousness, SCS = self control, PRO = promotion focus, START = start control, REW = reward-responsiveness, FUN = fun-seeking, DRI = drive, PRE = prevention focus, BIS = behavioral inhibition system, STOP = stop control. Self-control was always entered as a predictor. The remaining predictors were selected using a BIC-based stepwise multiple regression.

The two facets of pride seem to play a very different role in the network. The authentic pride (APR) appears to funnel the influence of industriousness towards cheerfulness, while hubristic pride

(HPR) occupies a particular position in the network (see also Figure 19A), being positively connected with both the proactive nodes of the proactive/positive cluster (fun-seeking, drive, and orderliness) and to the negative emotions of the inhibitive / negative cluster (agitation and guilt), and negatively connected to impulse-control. The hubristic pride therefore seems to be characterized both by proactivity and by negative emotionality. Somehow surprisingly, self-esteem (SEST) had most of its connections in the inhibitive cluster, being more connected to the negative than to the positive emotions. This pattern suggests that self-esteem might reduce (or be reduced by) negative emotions more than it might increase (or be increased by) positive emotions. Self-esteem was also strongly connected with the behavioral inhibition (BIS) and prevention focus (PRE): a lower self-esteem might be connected to an increased sensitivity to negative reinforcements and therefore to the consequent inhibition of behaviors that may lead to negative outcomes.

With the second network, we wanted to further inspect the mechanisms that could underlie orderliness. As we hypothesized, orderliness (ORD) was connected with the need for closure (NFCL, Figure 19D and F), although this connection was pulled out of the model when the other personality factors were controlled for (Figure 19E). Additionally, need for closure had a negative connection with industriousness (IND). Orderliness was also connected to self-control (SCS), self-oriented perfectionism (PEse), fatalistic-present (PF), hedonistic-present (PH), and had a small negative connection with alcohol use (AUDIT). Hedonistic present (PH) played an interesting role in the network: it was positively connected with industriousness (IND), but negatively with both orderliness (ORD) and impulse-control (IMC). After controlling for the other personality factors, the direct connections of the conscientiousness facets with hedonistic present waned (Figure 19E). Differently from what we had expected, orderliness (ORD) was not directly connected with surprise (SUR), but only indirectly, especially trough fatalistic present (PF). Another aim of the second network was to further inspect the role of perfectionism in relation to conscientiousness. Self-oriented perfectionism (PEse) was strongly connected with industriousness (IND) and, to a lower extent, with orderliness (ORD) and seemed to be part of the proactive pole of conscientiousness, while socially-prescribed perfectionism (PEso) did not have any relevant direct connection with the conscientiousness facets.

As we did for the first network, we further investigated the extent to which the non-shared mechanisms of the second network explained variance of conscientiousness and of its facets above and beyond the shared mechanisms (self-control, future orientation, and the consideration of future consequences). Therefore, we run a series of BIC-based stepwise multiple regressions, with conscientiousness and its facets as dependent variables (Table 12). Self-control, future-orientation and the consideration of future consequences were always entered in the first step, while need for closure, self-oriented perfectionism, socially-prescribed perfectionism, hedonistic present, and fatalistic present were allowed to enter in the second step if they improved the model fit. Self-oriented perfectionism explained additional variance of industriousness and, to a lower extent, of orderliness. The self-oriented perfectionism therefore seems to characterize especially the proactive pole of conscientiousness, being somehow in between orderliness and industriousness, and it might even be considered a facet of conscientiousness itself (e.g., Lee & Ashton, 2004). On the other hand, socially-prescribed perfectionism never entered the regressions. This result supports the idea that socially prescribed perfectionism is not directly involved in the mechanics of conscientiousness (Dunkley, 2012).

Need for closure was a negative predictor of industriousness and a positive predictor of orderliness. It is possible that need for closure is a mechanism responsible for distinguishing industriousness from orderliness: while individuals that are self-controlled and oriented towards the future (the shared mechanisms), but also high in need for closure, might spend their energies especially in organizing their environment and tasks, individuals that are similarly self-controlled and future-oriented, but lower in need for closure, might spend their energies for other goals, such as personal success. Notice for instance that the grade point average was connected to industriousness but not to orderliness.

Another interesting result is the fact that hedonistic present was a positive predictor of industriousness and a negative predictor of both impulse-control and orderliness. Hedonistic present has a three-fold definition, as it “reflects a hedonistic, risk-taking, «devil may care» attitude toward time and life” (Zimbardo & Boyd, 1999, p. 1275). Although our data do not allow to tear apart the three aspects of hedonistic present, we can hypothesize that the hedonistic component may positively characterize industriousness, since industrious individuals may work hard also in the pursuit of goals that entail hedonistic pleasure (e.g., success). On the other hand, the risk-taking component might negatively characterize impulse-control, and the «devil may care» component might negatively characterize orderliness. Further investigations are necessary to tear apart these components and especially to investigate the role that hedonism may play for the facets of conscientiousness.

Table 12. Stepwise multiple regression analysis predicting conscientiousness and its facets (sample 2).

	Dependent variable									
	Consc.(hexaco)		Consc. (ipip)		Industriousness		Impulse control		Orderliness	
Predictor	R^2	β	ΔR^2	β	ΔR^2	β	ΔR^2	β	ΔR^2	β
Step 1	.61***		.65***		.51***		.52***		.36***	
SCS		.33***		.42***		.27***		.44***		.32***
FU		.39***		.34***		.28***		.30***		.33***
CFC		.20***		.18***		.29***		.08		.02
Step 2	.66*** Δ=.04***		.70*** Δ=.05***		.62*** Δ=.11***		.55*** Δ=.03***		.42*** Δ=.06***	
SCS		.33***		.42***		.30***		.38***		.31***
FU		.27***		.21***		.14*		.31***		.21**
CFC		.16**		.14**		.24***		.08		-.02
NFCL						-.13**				.13*
PEse		.25***		.27***		.37***				.19**
PEso										
PH						.12**		-.18***		-.13*
PF										

Note. *p<.05, **p<.01, ***p<.001. Consc. = conscientiousness, SCS = self control, FU = future orientation, CFC = consideration of future consequences, NFCL = need for closure, PEse = self-oriented perfectionism, PEso = socially-prescribed perfectionism, PH = hedonistic present, PF = fatalistic present. SCS, FU and CFC were always entered as predictors. The remaining predictors were selected using a BIC-based stepwise multiple regression.

Conclusions

In this chapter our aims were to investigate the shared mechanisms of conscientiousness, that are responsible for conscientiousness facets to clump together into a single major dimension of personality, and those that are not shared among different facets of conscientiousness in the same way, and are responsible for those facets to be distinguishable. We collected data from 440 participants (plus 311 participants that contributed to the pretests of the adjective checklist of conscientiousness and of the surprise scale). The first shared mechanism that emerged consistently in two independent samples is self-control, which is responsible for the variance that is shared among the proactive pole (i.e., industriousness) and the inhibitive pole (i.e., impulse-control) of conscientiousness. Self-control however does not seem to be as much as an important mechanism for a third important facet of conscientiousness, namely orderliness.

Our data show that impulse-control and self-control cannot be reduced to each other, but one could ask how they differ and how can self-control characterize also facet industriousness. The first element to consider is that self-control has a proactive and an inhibitive components which have a different role for the two poles of conscientiousness (De Boer et al., 2011). The second element is that self-control does not seem to entail control over one's impulses or temptations as much as it entails selecting situations in which such inhibition is not necessary (Ent, Baumeister, & Tice, 2015). While self-control could be characterized especially by situation-selection strategies, impulse-control could be more characterized by the exertion of control over impulses and temptations. Furthermore, avoiding tempting situations, such as selecting a work environment without distractions (Ent et al., 2015), may be an important strategy also for the industrious individual. In the second sample, self-control was the node with the clearest connections with two unhealthy behaviors, smoke and alcohol use. It is possible that avoiding certain classes of situations, such as those in which one is lured by peers into drinking or smoking (self-control), might be a more effective strategy than getting into those situations and then actively trying to resist the temptation (impulse-control). Future research is needed to specifically investigate the different aspects of control, such as situation selection and resistance to temptation, but also other aspects of control (e.g., De Young, 2011) in the network of conscientiousness. Moreover, we think future research should also include in the network the role of situations that are relevant for conscientious behavior, using valid instruments such as the Riverside Situational Q-sort (Funder, 2006; Sherman et al., 2010), to inspect how situation selection shapes conscientious behavior.

A second important class of mechanisms that seems to be shared by all facets of conscientiousness is the orientation towards the future, including both future orientation (Zimbardo & Boyd, 1999) and the consideration of future consequences (Strathman et al., 1994). This is not surprising: the delay of gratification has been often considered a central component of conscientiousness (Roberts et al., 2012) and most behaviors that are central to conscientiousness require to give up the immediate enjoyment to pursue a later positive outcome or to avoid a later negative outcome (Jackson et al., 2010). The future orientation and self-control together explained more than 50% of the variance of industriousness and impulse control and the 36% of the variance of orderliness.

Several mechanisms emerged that characterized the different facets in a different way. Industriousness was especially defined by start-control, the proactive dimension of self-control, by promotion focus, which was also the most central mechanism in the first network, and by self-oriented perfectionism in the second network. Being industrious does not mean only to exert self-control and postpone gratification, but to do so in the pursuit of positive outcomes, by initiating and persisting in goal-directed behaviors and by requiring perfection from oneself. Conversely, impulse-control was especially defined by stop-control, the inhibitive part of self-control, by prevention focus and negatively by fun-seeking. Being impulse-controlled therefore entails to exert self-control and to postpone gratification mainly to prevent negative outcomes, by inhibiting potentially dangerous behaviors even at the expenses of immediate fun.

Although orderliness has been considered closer to the proactive pole of conscientiousness (Jackson et al., 2010; Roberts, Chernyshenko, et al., 2005) our results have shown that it shares aspects of both poles. Orderliness is strongly positively connected to both industriousness and impulse-control, above and beyond the variance accounted by the shared mechanisms of conscientiousness. Furthermore orderliness shared two additional mechanisms with impulse-control and not with orderliness: in the first sample prevention focus was the only predictor of orderliness that was selected in the BIC-based stepwise multiple regression, while in the second sample orderliness and impulsivity shared the hedonistic orientation towards present as a negative predictor, while industriousness was positively predicted by hedonistic-present. The need for closure further distinguished orderliness from industriousness, being positively connected with orderliness and negatively with industriousness.

The emotional correlates were also different for the different facets of conscientiousness. While industriousness was connected with positive emotionality and especially through the experience of authentic pride, impulse control had a negative connection with self-esteem and with the experience of hubristic pride, and the inhibitive cluster of the conscientiousness network was closely connected to negative emotionality. Differently from what we had hypothesized, surprise correlated with overall conscientiousness (see Appendix Table 3), but it was not specifically connected with orderliness.

In conclusion, the picture that emerges from our investigation is of a dimension constituted by a few common mechanisms and by a series of more specific mechanisms that are responsible for its different facets to emerge. In two studies, these mechanisms explained a large portion of the variance of conscientiousness and of its facets. Nevertheless the list of mechanisms underlying conscientiousness needs to be further extended: in particular, the mechanisms of orderliness seemed to be underrepresented in our networks compared to those underlying the other facets. The networks of conscientiousness are essentially based on correlational evidence and they do not allow to identify the direction of the relationships that we found. However they constitute a general map of the trait that may guide targeted experimental studies (e.g., Baumert et al., 2011) as well as longitudinal studies (Cramer et al., 2012a; van de Leemput et al., 2014) aimed at investigating more closely how the mechanisms of conscientiousness unfold in time.

Chapter 5. Conclusions and future developments

Highlights

- We summarize the concepts and the results presented in the previous chapters.
- We discuss potential extensions of our research that can help to overcome its limitations.
- We focus especially on the concept of topological overlap as a possible solution to one of the most challenging issues for future research.

In this work we showed how network analysis can be applied to model personality. In the first chapter, we presented the general concept of a network, discussed how networks can be defined from personality psychology data and introduced the most important network concepts. In the second chapter we argued in favor of the importance of considering edge signs when analyzing personality networks and introduced new indices of clustering coefficient for signed networks. In the third chapter we used network analysis to investigate the structure of a dataset based on a widespread personality psychology questionnaire, the HEXACO-60 (Ashton & Lee, 2009). In the fourth chapter, we used network analysis in conjunction with factor analysis to investigate the mechanisms underlying the dimensions of conscientiousness: we showed that each facet is both characterized by unique mechanisms and by mechanisms that underlie other facets as well and are responsible for different facets to aggregate into a single conscientiousness trait.

We consider the in-depth investigation of the mechanisms underlying personality as one of the most important task of personality research. This investigation can be easily extended to explore the mechanisms that are relevant for personality dimensions other than conscientiousness. Moreover, with due adaptations, it could be extended as well to many other topics within the psychological field. We think that psychological field may greatly benefit from considering network analysis both as a valuable theoretical perspective and as a versatile toolbox of techniques, as we hope to have shown in this work. The application of network analysis in psychology, including personality psychology, is in fact in its very infancy and, drawing a parallel with other scientific fields such as physics, genetics, computer science, and sociology, we think that this approach has a strong potential to contribute to the psychological field. As for any innovative approach, it is fair to recognize that there is still much room for improving it. In the following, we detail some of the most important potential directions of future research that we consider particularly promising for addressing issues that have yet to be fully solved.

Development of new network indices for signed and weighted networks

As noted in the first and second chapter, many network analytics were originally designed for unweighted and unsigned networks. Although some of the relevant analyses have now been extended to the weighted case (Barrat et al., 2004; Boccaletti, Latora, Moreno, Chavez, & Hwang, 2006; Costantini & Perugini, 2014; Opsahl et al., 2010; Saramäki et al., 2007), several other techniques still await such generalization. For instance, the determination of network structure, such as in terms of small-worlds (Humphries & Gurney, 2008), is based on unweighted networks. It would be highly useful if these notions, and the accompanying techniques, would be extended to the weighted network case.

Alternatives to the adaptive LASSO

In the studies presented in Chapters 3 and in Chapter 4, we used the adaptive LASSO to compute the networks. This technique has been profitably used to extract networks from data also in other fields (Krämer et al., 2009). However other promising techniques exist, such as the graphical lasso (J. Friedman et al., 2008), for which adaptations exist that take into account the presence of latent variables in the network (Chandrasekaran, Parrilo, & Willsky, 2012; Yuan, 2012). A systematic comparison of the performances of these and of other methods in the scenarios that are typically encountered in personality psychology is an important task for future studies.

It is important also to point out that only exploratory methods have been implemented so far in current research based on personality networks. A researcher could be interested in testing formal theories, each theory specifying in advance which edges in the network should be zeros and which edges should be allowed to vary. Theories could be compared based on how well they fit the data, with a similar logic to that of structural equation modelling (e.g., Kline, 2011). The development of confirmatory network analysis for personality research and a better integration with structural equation modelling are among the most important future developments of these techniques. Some of these extensions are currently being implemented and the preliminary results are promising (Sacha Epskamp, personal communication, November 14, 2014).

Extension to directed networks

In our work, we considered only undirected relationships among the nodes. Although it is possible that most of the connections among the nodes in the personality network do not have a specific direction, a researcher could be interested in testing hypotheses about the direction of specific edges. For example, in Chapter 4 a connection between industriousness and authentic pride emerged. Our data do not allow to determine whether the connection is present because pride is experienced as a consequence of being industrious (and of obtaining successes), or because the chronic experience of positive emotions increases work performance (see for instance Lyubomirsky et al., 2005), or because these possibilities are both true. The directionality of such relationships can be investigated in several ways. The first and simplest way is to ask participants to report how they perceive the causal relationships among different nodes in the network and to compute directed networks from such data (Frewen, Schmittmann, Bringmann, & Borsboom, 2013). Although the limits in the introspective abilities (e.g., Nisbett & Wilson, 1977) demand prudence in the interpretation of such connections as reflecting cause-effect relationships, they can still provide important information about how causal relationships are perceived (Frewen et al., 2013).

A second possibility is to perform experimental studies, by manipulating a node and inspecting the resulting effects on other nodes. Although it is not easy to envisage how to experimentally manipulate most personality characteristics in laboratory, a researcher could use different settings with an indirect approach. For instance, one could use experimental designs similar to those of impression formation studies (e.g., Asch, 1946). In such paradigms, the participants are asked to infer the characteristics of a hypothetical individual, based on a description provided by the researcher. The researcher can then manipulate specific characteristics of the hypothetical individual and inspect how certain manipulations impacts the participants' perceptions. This kind of settings would allow also to test the impact of central nodes in a network: Manipulating central nodes in the description should have a stronger impact than manipulating peripheral nodes.

Another way to investigate the direction of causal relationships is to collect intensive longitudinal data with experience sampling methods (Fleeson, 2001; Hamaker, Ceulemans, Grasman, & Tuerlinckx, in press), which have been already used to compute directed psychopathology networks (e.g., Bringmann et al., 2013; van de Leemput et al., 2014). Multilevel extensions of such methods have been proposed that allow to simultaneously account both for the general effects and for the individuals' random deviations from such effects (Bringmann et al., 2013; Hamaker et al., in press). Although such methods typically do not allow the breadth of content that can be obtained by means of cross-sectional studies, they have unique advantages and they could be employed for deeper investigations of specific patterns of relationships.

The definition of nodes and the concept of topological overlap

We recognize one of the most important issue as well as a very promising future directions of this research in the choice of the nodes. Although we consider facets as a very informative level of investigation, facets are computed as aggregates of items. One could argue that in some situations similar items (such as those that assess the same personality facet) give redundant information and therefore should be merged. However in other cases merging personality items could result in important information loss, in the same way as average scale scores may hide the effect of different symptoms in psychopathology networks (Fried, Nesse, Zivin, Guille, & Sen, 2014; Fried & Nesse, 2014).

Consider for instance two of the items that are included in the orderliness scale of the IPIP (Goldberg et al., 2006): “Often forget to put things back in their proper place” and “Leave a mess in my room”. These items reflect very similar behaviors and in many situations it is not interesting to consider them as distinct phenomena. In these cases, considering the two items as separate nodes in the network may have the detrimental effect of complicating the network with redundant information. Moreover the presence of redundant nodes may hamper the computation of centrality indices by inflating the centrality of such nodes, because of the strong connections among them. However one can also imagine contexts in which the distinction among the phenomena assessed by these items is relevant. In a hypothetical scenario in which a researcher is interested in the impact of cognitive impairment on orderliness, by considering the two items separately the researcher could find a specific connection between cognitive impairment and “forgetting to put things back in the proper place”, which could in turn convey the influence of cognitive impairment to the node “leave a mess in the room”. In this case merging the two nodes might obfuscate the presence of more complex different relationships with other nodes in the network. From this example, we can see that the decision of merging or separating two nodes in a network is often not trivial and that it does not depend only on the connection among the two nodes, but also on the context provided by the connections with the other nodes in the network.

A potentially viable solution to the problem of merging nodes according to their relationships with the other nodes could rely on an index that has been already developed in network analysis, namely the *topological overlap*. The topological overlap between two nodes in a network is defined as the ratio between the intersection of the neighbors shared between two nodes and the union of their neighborhoods (Fortunato, 2010) and it has been extended to weighted networks and to signed networks (Langfelder, 2012, 2013; Zhang & Horvath, 2005). Two nodes are highly topologically overlapped if they are not only connected with each other, but if they also share similar connections with the other nodes in the network. If two nodes have too similar connections with the other nodes, leaving them separate does not provide any more information than when they are aggregated, for instance by computing their average. Topological overlap is already used in other fields in conjunction with clustering techniques for similar purposes, such as identifying proteins that are part of the same biological module (Ravasz, Somera, Mongru, Oltvai, & Barabási, 2002) or identifying genes that are involved in the same functions in the human brain (Oldham et al., 2008).

Topological overlap can also provide a more systematic solution to another important issue in personality, namely the “jingle-jangle” fallacy identified by Ziegler and colleagues (2013). This fallacy is defined as the presence of scales with the same name that assess different constructs and scales with different names that assess the same construct. To know whether two scales assess the same construct, Ziegler and colleagues proposed to consider the scales in a broad personality correlation network, which is interpreted as a nomological network (Cronbach

& Meehl, 1955). Two scales that assess the same construct should have similar connections with the remaining nodes of the network, which means occupying a similar position in the network. For instance, facet perfectionism from the HEXACO-PI (K. Lee & Ashton, 2004) and facet perfectionism from the JPI (Paunonen & Jackson, 1996) showed a different pattern of connections with related scales and could not therefore be considered as assessing the same construct (Ziegler et al., 2013). This kind of analysis could be performed more systematically by computing a matrix of topological overlap among the pairs of scales and by using cluster analysis to identify which scales assess the same construct and which assess separate constructs.

The main goals of our work were to further develop network analysis for personality psychology and to show how this perspective can be used to answer substantive questions in the field: Such answers could not have been so easily conceived without assuming the network perspective. However, we do not see network analysis as a replacement of the methods that have been more frequently applied to the study of personality phenomena, such as factor analysis. These methods offer instead different perspectives that can be combined together to promote unique insights into the complex and multifaceted phenomenon of personality.

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Appendix

Appendix Table 1. items of the Adjective checklist of conscientiousness

Responsibility	
Affidabile (reliable)	Inaffidabile (unreliable)
Attendibile (dependable)	Inattendibile (undependable)
Rispettoso (respectful)	Sconsiderato (rash)
Responsabile (responsible)	Irresponsabile (unaccountable)
Fidato (trustworthy)	Indolente (sluggish)
Impulse control	
Cauto (cautious)	Spericolato (reckless)
Controllato (controlled)	Sregolato (profligate)
Disciplinato (disciplined)	Impulsivo (impulsive)
Prudente (prudent)	Istintivo (instinctive)
Riflessivo (reflective)	Imprudente (imprudent)
Orderliness	
Preciso (precise)	Disordinato (disordered)
Ordinato (ordered)	Disorganizzato (unorganized)
Organizzato (organized)	Caotico (chaotic)
Accurato (careful)	Approssimato (haphazard)
Pignolo (fussy)	Impreciso (imprecise)
Industriousness	
Laborioso (hard-working)	Pigro (lazy)
Tenace (tenacious)	Svogliato (unwilling)
Industrioso (industrious)	Sfaticato (workshy)
Diligente (diligent)	Negligente (negligent)
Efficace (effective)	Incostante (erratic)

Appendix Table 2. Correlation matrix of sample 1 (continues in the next page)

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. C (hexaco)													
2. C(ipip)	.83***												
3. ORD	.87***	.78***											
4. IND	.77***	.82***	.63***										
5. IMC	.75***	.71***	.61***	.42***									
6. SCS	.65***	.69***	.53***	.59***	.64***								
7. START	.32***	.38***	.27***	.41***	.23***	.44***							
8. STOP	.51***	.56***	.38***	.36***	.69***	.55***	.11						
9. PRO	.44***	.53***	.31***	.61***	.21**	.29***	.19**	.24***					
10. PRE	.29***	.29***	.25***	.17*	.39***	.12	-.07	.38***	.29***				
11. REW	.13	.17*	.08	.21**	.02	.02	.00	.01	.49***	.20**			
12. DRI	.02	.07	.01	.24***	-.23***	.00	.15*	-.21**	.41***	.00	.44***		
13. FUN	-.31***	-.25***	-.21**	-.10	-.54***	-.41***	-.06	-.40***	.21**	-.07	.38***	.51***	
14. BIS	.08	.02	.08	-.05	.18**	-.10	-.24***	.09	-.03	.56***	.17*	-.08	-.06
15. PO	.21**	.29***	.13	.33***	.04	.29***	.40***	.02	.44***	-.13	.16*	.34***	.17*
16. AGI	-.03	-.10	.02	-.13	.01	-.19**	-.25***	.08	-.02	.38***	.08	-.05	.08
17. APR	.30***	.42***	.26***	.51***	.06	.30***	.32***	.07	.43***	.07	.26***	.30***	.14*
18. HPR	-.19**	-.19**	-.05	-.05	-.41***	-.23***	.00	-.37***	.00	-.19**	.11	.33***	.41***
19. GUI	-.13	-.15*	-.09	-.11	-.12	-.17*	-.11	-.02	-.06	.11	.13	.03	.16*
20. CHE	.04	.09	-.04	.19**	-.06	.05	.16*	-.09	.21**	-.15*	.04	.18**	.14*
21. SEST	.05	.08	.05	.15*	-.15*	.16*	.29***	-.08	.12	-.51***	-.04	.14*	.07
22. GPA	.17*	.22**	.08	.25***	.20**	.16*	.07	.13	.19**	.14*	.05	-.13	-.11
23. H	.14*	.19**	.04	.12	.21**	.35***	.02	.34***	-.08	.07	-.22**	-.23***	-.40***
24. E	.03	-.05	.04	-.11	.11	-.19**	-.40***	.04	-.09	.39***	.03	-.14*	-.07
25. X	.12	.22**	.04	.29***	-.10	.09	.23***	-.06	.43***	-.18**	.30***	.31***	.30***
26. A	.16*	.17*	.12	.01	.31***	.28***	.13	.25***	-.05	.08	-.16*	-.17*	-.24***
27. O	.17*	.22**	.01	.30***	.12	.22**	.29***	.16*	.28***	.05	.18**	.05	-.04

A = agreeableness vs. anger, AGI = agitation, APR = authentic pride, BIS = behavioral inhibition, C (hexaco) = conscientiousness (from HEXACO-PI), C (ipip) = conscientiousness (from IPIP), CHE = cheerfulness, DRI = drive, E= emotionality, FUN = fun-seeking, GPA = grade point average, GUI = guilt/dejection, H = honesty-humility, HPR = hubristic pride, IMC = impulse-control, IND = industriousness, O = openness to experience, ORD = orderliness, PO = positive orientation, PRE = prevention focus, PRO = promotion focus, REW = reward responsiveness, SCS = self-control, SEST = self-esteem, START = start-control, STOP = stop-control, X = extraversion.

	14	15	16	17	18	19	20	21	22	23	24	25	26
1. C (hexaco)													
2. C(ipip)													
3. ORD													
4. IND													
5. IMC													
6. SCS													
7. START													
8. STOP													
9. PRO													
10. PRE													
11. REW													
12. DRI													
13. FUN													
14. BIS													
15. PO	-.30***												
16. AGI	.45***	-.25***											
17. APR	-.08	.28***	-.13										
18. HPR	-.18**	.08	.09	.16*									
19. GUI	.21**	-.30***	.47***	-.03	.20**								
20. CHE	-.17*	.41***	-.25***	.31***	.14*	-.23**							
21. SEST	-.60***	.42***	-.57***	.24***	.17*	-.42***	.28***						
22. GPA	.08	-.06	-.03	.09	-.07	-.10	-.06	-.03					
23. H	.14*	-.04	-.02	.04	-.45***	.00	.02	-.06	-.05				
24. E	.61***	-.24***	.44***	-.18*	-.20**	.16*	-.12	-.53***	-.01	.09			
25. X	-.32***	.53***	-.25***	.29***	.11	-.28***	.27***	.51***	-.05	-.17*	-.25***		
26. A	-.06	.12	-.06	-.15*	-.39***	-.09	.03	-.06	-.07	.30***	-.07	-.18*	
27. O	-.05	.07	-.09	.21**	-.06	.11	.07	.08	.17*	.21**	-.20**	.13	.08

Appendix Table 3. Correlation matrix of sample 2 (continues in the next page)

	1	2	3	4	5	6	7	8	9	10	11
1. C (hexaco)											
2. C (ipip)	.84***										
3. ORD	.83***	.74***									
4. IND	.73***	.81***	.49***								
5. IMC	.74***	.67***	.56***	.40***							
6. NFCL	.18**	.18**	.21**	.03	.12						
7. SCS	.67***	.72***	.54***	.60***	.67***	.00					
8. CFC	.61***	.61***	.39***	.60***	.50***	.11	.55***				
9. Fu	.70***	.70***	.54***	.61***	.61***	.18**	.60***	.59***			
10. PH	-.24***	-.17*	-.26***	-.06	-.37***	.07	-.33***	-.17**	-.17**		
11. PF	-.36***	-.42***	-.19**	-.38***	-.39***	.11	-.44***	-.52***	-.32***	.30***	
12. PEse	.59***	.60***	.45***	.61***	.32***	.27***	.35***	.42***	.55***	-.02	-.23***
13. PEso	.03	-.01	.05	.06	-.09	.16*	-.11	.08	.12	.03	.25***
14. SUR	-.26***	-.32***	-.16*	-.24***	-.32***	.05	-.34***	-.25***	-.20**	.16*	.40***
15. AUDIT	-.34***	-.32***	-.30***	-.25***	-.35***	-.10	-.36***	-.22***	-.23***	.14*	.23***
16. FTND	-.21**	-.20**	-.16*	-.15*	-.28***	-.05	-.34***	-.12	-.12	.18**	.14*
17. GPA	.40***	.41***	.25***	.44***	.38***	-.02	.37***	.30***	.29***	-.21**	-.27***
18. H	.37***	.39***	.25***	.34***	.38***	-.04	.44***	.48***	.37***	-.13	-.43***
19. E	.10	.02	.08	.05	.09	.28***	-.08	.05	.16*	.07	.08
20. X	.00	.20**	-.07	.24***	-.16*	-.08	.17**	.04	.04	.30***	-.12
21. A	.13*	.06	.02	.06	.31***	-.10	.17**	.04	.19**	-.10	-.07
22. O	.20**	.23***	.01	.28***	.15*	-.05	.20**	.33***	.15*	-.09	-.22***

A = agreeableness vs. anger, C (hexaco) = conscientiousness (from HEXACO-PI), C (ipip) = conscientiousness (from IPIP), CFC = consideration of future consequences, FTND = nicotine dependence, E = emotionality, FU = future orientation, GPA = grade point average, GUI = guilt/dejection, H = honesty-humility, IMC = impulse-control, IND = industriousness, NFCL = need for closure, O = openness to experience, ORD = orderliness, PEse = self-oriented perfectionism, PEso = socially prescribed perfectionism, PF = fatalistic present, PH = hedonistic present, SCS = self-control, SUR = surprise, X = extraversion.

	12	13	14	15	16	17	18	19	20	21
1. C (hexaco)										
2. C (ipip)										
3. ORD										
4. IND										
5. IMC										
6. NFCL										
7. SCS										
8. CFC										
9. Fu										
10. PH										
11. PF										
12. PEse										
13. PEso	.27***									
14. SUR	-.02	.18**								
15. AUDIT	-.13*	.09	.14*							
16. FTND	-.12	.07	.08	.38***						
17. GPA	.25***	-.05	-.13*	-.20**	-.15*					
18. H	.04	-.17*	-.23***	-.29***	-.14*	.19**				
19. E	.05	.13	.21**	-.20**	-.07	.08	.20**			
20. X	.18**	-.11	-.23***	.11	.03	-.07	-.11	-.31***		
21. A	-.10	-.06	-.04	-.14*	-.08	.00	.25***	.11	-.13*	
22. O	.17**	-.01	-.16*	-.11	-.08	.19**	.26***	-.10	.04	-.01