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A network perspective to the measurement of Sense of Coherence (SOC): an exploratory graph analysis approach

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Abstract

The measurement of sense of coherence (SOC) has received attention for more than three decades. Despite the extensive use of the SOC-13, there is still a long debate regarding its psychometric properties. Recently, there was an increasing use of network modeling as a valid alternative to latent-variable modeling. This study proposes an exploratory approach to the structure of the SOC-13 by adopting a network perspective. Network structure was estimated with Gaussian Graphical Model and Exploratory Graph Analysis (EGA) was used for inspecting network dimensionality. We fit and compared unidimensional, first and second-order confirmatory factor analysis (CFA), Bifactor-CFA, and structure derived from EGA.

Our results showed unacceptable fit values for CFA models, suggesting that SOC is not unidimensional, and that comprehensibility, manageability, and meaningfulness could not be extracted from data. The inspection of the estimated network suggested that the SOC-13 items emerged as a dynamic system of mutually interacting nodes that clustered in three distinct communities that are not those defined in the literature. EGA identified three communities of items where the first community was characterized by comprehensibility and manageability items, the second community was characterized by comprehensibility and manageability items, and the third dimension was characterized by all the meaningfulness items and one comprehensibility item.

Our study presented a novel perspective in investigating the SOC-13's structure that strengthens the assumption that SOC should be conceptualized as a complex system of cognitive (comprehensibility), behavioral (manageability) and motivational dimensions (meaningfulness) that are deeply linked and not necessarily distinct.

Background

Since its theorization and development, the concept of sense of coherence (SOC) and its measurement have continued to receive attention in the field of salutogenesis (WHO, 2021). Antonovsky (1987, 1993) defined SOC as “a global orientation that expresses the extent to which one has a pervasive, enduring though dynamic feeling of confidence that (1) the stimuli from one’s internal and external environments in the course of living are structured, predictable, and explicable; (2) the resources are available to one to meet the demands posed by these stimuli; and (3) these demands are challenges, worthy of investment and engagement” (p. 19). Accordingly, to this definition, Antonovsky (1987, 1993) developed the self-report Orientation to Life Questionnaire (OLQ) composed of 29 items (SOC-29) and a shorter version with 13 items (SOC-13).

For developing the OLQ, Antonovsky adopted the facet theory (FT) developed by Guttman (1959). At the basis of the FT approach there is the construction of the mapping sentence for the formulation of items in the form of verbal statements with the purpose of facilitating theory construction (Guttman and Greenbaum, 1994; Guttman and Greenbaum, 1998; Levy, 2005). In this sense, it consists of two main sections: the facets and the sentences linking the facets together (Shye, 1978). Essentially, the mapping sentence should help researchers to define a priori the three basic elements (facets) of the investigated problem: the population of respondents being researched, the stimuli, and the range of the possible responses (Guttman and Greenbaum, 1998). Antonovsky (1987) built the OLQ defining five facets: (a) content facet of SOC as comprehensibility, manageability, and meaningfulness, (b) modality facet referred to individuals challenged with an instrumental, a cognitive, or an affective stimuli, (c) source facet referred to the “space” from which stimuli originate (internal and\or external), (d) demand facet referred to real, diffuse, or abstract demand(s), and (e) time facet referred to the time space (past, present, or future) (Hochwälder, 2019). Whereas Antonovsky (1987) described the genesis of the 29 items version, providing the list of items of each component, no information was provided concerning the SOC-13. The list of 13 items was just briefly introduced as the shorter version of the SOC questionnaire and no mention about the rationale behind the selection of these items (p.189). For both versions, Antonovsky (1993) highlighted that “in light of the facet-theoretical design of the measure, there is no basis for deriving distinguishable sub-scores for comprehensibility, manageability and meaningfulness” (p.731) – as only the first of the five above mentioned, broader facets (content, modality, source, demand, time) covered the three dimensions of comprehensibility, manageability and meaningfulness. In support of his hypothesis about a global measure of SOC, Antonovsky (1993) reported results from the (very limited number of) studies that tested for factor analysis of the SOC measures, concluding that “a single factor solution may be the most parsimonious explanation" and it is in line with his view as the three components should be considered as "inextricably intertwined" (Antonovsky, 1987; p.86).

Despite that fundamental theoretical rationale, in the last 35 years, researchers were systematically interested in investigating the interrelation between the SOC components, and their relationship with antecedents and outcomes of SOC. In the last three decades, the psychometric properties of the SOC scales have been widely investigated and there is a vast agreement in the literature that the factor structure of the SOC-13 is controversial and that it is multifactor rather than a one-factor construct (Eriksson and Lindström, 2005; Eriksson and Mittelmark, 2017; Eriksson and Contu, 2022). In the last two decades, the psychometric properties of the widely adopted SOC-13 were investigated by implementing the most popular model testing: Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Rash Models (Eriksson and Mittelmark, 2017; Eriksson and Contu, 2022). However, none of these techniques found a clear confirmation of the theoretically based structure of the SOC-13 items. Thus, researchers increasingly applied "confirmatory" studies aiming at to providing evidence for a global latent SOC construct comprised by three latent factors, following an a priori theoretical definition and not a data-driven approach. An important issue that has perhaps not received enough attention is the appropriateness of using a classical CFA approach to assess the factor structure underlying the SOC responses. For example, a factor analysis approach assumes independence among factors and items. These conditions are not in line with the intercorrelated nature of SOC as suggested by Antonovsky (1987; 1993). In this sense, it should be considered that items measuring SOC are not independent of each other and, therefore, a factor model may not be the appropriate approach.

Emerging new approach: network analysis

According to Fried and Epskamp (2016), in the decade there was an increasing use of network modeling as a valid alternative to latent-variable modeling in exploratory studies (Borsboom and Cramer, 2013; Schmittmann et al., 2013; Kossakowski et al., 2016; Glück et al., 2017; Briganti et al., 2019; Cosemans et al., 2021). Golino and Epskamp (2017) developed the network psychometrics approach to explore the dimensionality of psychological constructs adopting the network analysis perspective (Borsboom and Cramer, 2013).

From the network perspective, constructs such as SOC can be conceptualized as a network system of pairwise interactions among items where a change in one item can cause a change in the remaining items or in the whole network (Schmittmann et al., 2013; Fried and Cramer, 2017; Christensen et al., 2018). Adopting this approach in representing SOC as a network of interacting items may help to identify and disentangle important (neglected) features of the construct and how these features may group together. In this sense, items from questionnaires are the nodes that are connected by edges (links), which reflect the strength of the association (partial correlation coefficients) among the items (Epskamp and Fried, 2018). Absent edges indicate zero partial correlations (conditionally independent variables) whereas non-absent edges indicate the association that remains between two items after controlling for all other items (Epskamp et al., 2017; Epskamp and Fried, 2018).

A psychometric network model implies a structure of a fully connected network where factors emerge from data instead of testing the fit of a priori dimensionality. In this sense, network methodology offers a more comprehensive representation of how items are organized and how the dimensions are in multidimensional space to one another (Peralta et al., 2020). Recently, Oliver and Ebers (2015) suggested that combining facet theory with network analytical methods in analyzing complex constructs may “exploit the relative advantages each method offers”.

The current study

Given the increased use of the SOC-13 in research and practice, the primary aim of the present study was to expand the knowledge on psychometric characteristics of the measurement of SOC through application of network analysis. We implemented network methodology (Golino and Epskamp, 2017) to discover the dimensional structure of the SOC-13, comparing traditional factor analyses to the Exploratory Graph Analysis (EGA).

2. Method

2.1 Samples

This study is part of a larger study carried out in Italy between July 2020 and April 2021. The data were collected by administering a questionnaire via google forms to a convenience sample. The survey’s homepage reported information about the study purpose, a general description of the questionnaire, including information about risks and benefits of participation and privacy policy information.

2.2 Measure

The Italian version of the SOC-13 (Sardu et al., 2012) was used. The SOC-13 is composed of 13 items that measures three SOC components: comprehensibility (5 items), meaningfulness (4 items), and manageability (4 items) (see Table 1 for more details).

[insert table 1 here]

2.3 Data Analysis

As described by Kan and colleagues (2020), we compared psychometric factor and network models. Specifically, we fit and compared unidimensional, first and second-order confirmatory factor analysis (CFA), Bifactor-CFA, and network measurement models using the psychonetrics package (Epskamp, 2020) in R (R Core Team, 2018).

Factor models: we considered the most traditional factor structures of SOC (see figure 1 for more details): (1) a one factor CFA where all items define a unidimensional SOC; (b) a first order three-factor CFA where items define the three components of SOC as defined by Antonovsky (1987; 1990); (c) a second-order CFA, that reflects an overarching SOC with direct causal paths to the first-order factors Comprehensibility, Manageability, and Meaningfulness; (d) bifactor CFA, where items contribute to define a general component of SOC (G) and specific facets (comprehensibility, manageability, and meaningfulness) explaining the residual covariance not explained by G (Morin et al., 2016a; Bonifay et al., 2017; Sellbom and Tellegen, 2019).

Exploratory Graph Analysis. To investigate how the SOC-13's items were connected and the components that are extracted from the empirical data, we applied the EGA approach (Golino et al., 2020a; Golino and Epskamp, 2017). EGA estimates nodes, which represent items in our study, and edges defined as the partial correlation between two nodes, and the number of communities defined as clusters or sets of connected nodes in multivariate data using undirected network models (Epskamp et al., 2016).

We followed Golino and colleaagues' recommendations (2020a; in press) in estimating EGA applying both the Graphical Least Absolute Shrinkage Optimization (GLASSO) and the Triangular Maximally Filtered Graph (TMFG) methods. For both algorithms, analyses result is a network of n-node cliques (i.e., a set of connected nodes), which form the constituent elements of an emergent hierarchy in the network (Song et al., 2012). The total entropy fit index with Von Neumman entropy (TEFI.vn) is used to choose on the best solution in case GLASSO and TMFG solutions differed (Golino et al., 2021). Lower TEFI values indicate that a given dimensionality structure is more likely to represent the best organization of the variables.

Furthermore, potential redundancies between item pairs were evaluated using the Unique Variable Analysis (UVA; Chrisensen et al., 2020), which detects redundant variables in multivariate data. Item redundancy indicates strongly associated items which had overlapping nodes (topological overlap) in the network. Redundant items do not contribute to unique information in the network and can be source of overestimation of the number of dimensions in the network. We used the weighted topological overlaps (wTO; Gysi et al., 2018) to consider redundant pairs of items. Specifically, only items with both topological and conceptual overlap were combined and estimated as latent variables (Chrisensen et al., 2020).

Structural Consistency. We applied a Bootstrap Exploratory Graph Analysis (bootEGA; Christensen and Golino, 2021) to evaluate the stability and replicability of the communities of items previously identified by the EGA. Structural consistency is obtained by computing the proportion of times that each empirically derived community is exactly (i.e., identical item composition) recovered from the replicate bootstrap samples (n=1000). The range that structural consistency can take is from 0 to 1. Higher proportions of replicability indicate more reliable and stable results.

Furthermore, we considered item stability defined as the proportion of times that each item is identified in each empirically derived community across the replicate samples. As suggested by Christensen and colleagues (2020), as we were interested in investigating the hierarchical or "multi-level" structuring of factors, we considered the Louvain algorithm in community detection (Blondel et al., 2008). The Louvain algorithm was used to find how many dense subgraphs (communities) exist in the data (Blondel et al., 2008). According to Golino and Epskamp (2017), these communities are considered to be mathematically equivalent to latent variables.

We used the software R (version 4.1.1) and the following Packages: EGAnet version 1.0.0 (Golino et al., 2020) for dimensionality estimates; bootEGA (Christensen and Golino, 2021) function contained in EGAnet for the stability of the dimensionality estimates (1,000 bootstrap samples); UVA function of the EGAnet R package for assessing potential redundancies between item pairs (Christensen et al., 2020).

In assessing the fit of network and factor models, we considered the following fit indices (Schermelleh-Engel et al., 2003): root mean square error of approximation (RMSEA); the comparative fit index (CFI); and the Tucker Lewis index (TLI). RMSEA values ≤ 0.05 were considered to indicate a good absolute fit, RMSEA values between 0.05 and 0.08 as an adequate fit, and RMSEA values between 0.08 and 0.10 as mediocre. RMSEA values >0.10 were considered unacceptable. TLI and CFI values > 0.95 were considered acceptable.

3. Results.

The sample (n=5642) was randomly split into two: a derivation sample (n = 2,784) and a cross-validation sample (n = 2858).

Dimensionality

In the first step, we fit and compared a series of factor models of the SOC13 on the derivation sample (n = 2,784). Specifically, we tested five different factor structures using the psychonetrics package (Epskamp, 2019): (1) a one factor CFA, (2) a three-factor CFA, (3) a second-order CFA, (4) bifactor CFA, and (5) network models. As shown on table 2, results showed that the one-factor CFA, the theoretical three-factor CFA, and the second-order three factors model showed very poor fit, whereas the network model showed the better fit to the data (CFI = .99, TLI = .98, RMSEA = .029, 95% CI = 0.024–0.034). Finally, the bifactor CFA did not converge.

[insert table 2 here]

Exploratory Graph Analysis on the derivation sample (n = 2,784).

In the first step, as redundant items can cause an overestimation of the number of dimensions in the network, we explored potential redundancies between item pairs implementing the UVA. Out of the total 13 items, based on the wTO statistic, topological overlap between three pairs of items was identified: (1) CO1 and MA1 (wTO = 0.53), (2) CO2 and MA2 (wTO = 0.21), and CO4 and MA4 (wTO = 0.23).

Then, three sets of items were combined into latent factors: CO1-MA1, CO2-MA2, and CO4-MA4, and considered in our analyses, starting from zero redundancies up to three redundancies conditions.

Network estimation. In the second step (figure 1a), we applied EGA to estimate the SOC-13 network and item clustering (community of items) using both the GLASSO and TMFG methods. We firstly started considering zero redundancies. The GLASSO and TMFG methods produced different solutions in the number of dimensions and items assigned to each dimension. Specifically, the GLASSO method produced a three-community solution where each one reflects a mix of SOC items and a one-item community of items. This network does not offer further distinction among the comprehensibility, manageability, and meaningfulness. The TMFG method with zero redundancies produced a three-community solution. The first one was composed by three items: MA1, MA3, and CO1; the second by 6 items: CO3, CO5, ME1, ME2, ME3, and ME4; and the third was composed by four items: CO2, CO4, MA2, and MA4.

Next, in the third step, the evaluation of the bootstrap analyses showed that the three-dimensional structure was the most frequent in both GLASSO and TMFG methods, supporting for the occurrence of this structure in 98.2% and 100% of the bootstrap samples, respectively. For more details concerning communities to which each item belonged according to BOOTEGA and the proportion of times each item clustered with the same community, consider supplementary materials Figure S1b and S1c. For example, considering the GLASSO EGA, all items but items CO3 and CO5 clustered with the same community in 98% up to 100% of bootstrap samples. Specifically, items CO3 and CO5 clustered in the same community in 49% and 35% of all bootstrap samples, respectively. The low stability of these two items suggest that identified communities are frequently composed of a different set of items. Considering the TMFG EGA, all items showed very high stability, with 10 items showing values close to optimal 100% stability and three items (MA4, CO3, CO5) with lower stability ranging from 84% to 90%.

[insert figure 1 here]

Next, we investigated network loadings for both GLASSO and TMFG. Concerning the GLASSO method, there were three items with small network loadings (<.15): CO5, ME1, and ME3, whereas the remaining items showed moderate to high network loadings. Furthermore, the items CO3, ME4, and ME3 contributed to more than one dimension. Concerning the TMFG method, only the item CO5 showed small network loading (=.14), whereas the remaining items ranged from .24 to 0.52 suggesting moderate (ME1) and large network loadings. Furthermore, the items MA1, MA3, CO4, MA4, CO2, CO3, ME4, ME2 contributed to more than one community.

Therefore, in step fourth, we replicated steps two and three taking into account the redundancies. Specifically, the item pairs with the largest redundancies identified in step 1 were treated as latent variables, replacing the original items. Now, we have three new variables: CO1-MA1, CO2-MA2, CO4-MA4. Each analysis was performed progressively considering firstly CO1-MA1, then CO1-MA1 and CO2-MA2, and finally CO1-MA1, CO2-MA2, and CO4-MA4.

When the CO1-MA1 item pair was considered, the GLASSO and TMFG methods produced a 4-community and a two-community solution, respectively. In selecting the optimal solution, we computed the TEFI.vn finding support for the TMFG solution (=-5.64). Boot analyses supported a two-community solution finding that this structure was confirmed in the 61% of the bootstrap samples. Concerning item stability, items clustered with the same community in 83% up to 87% of all bootstrap samples.

Then, we considered one more redundancy adding the CO2-MA2 item pair to our analyses. Now, both the GLASSO and TMFG methods produced a 3-community solution. The TEFI.vn supported for the GLASSO solution (=-5.87) and boot analyses supported a three-community solution finding that this structure was confirmed in 47% of the bootstrap samples. Concerning item stability, items clustered with the same community in 59% up to 81% of all bootstrap samples.

Finally, we added one more redundancy considering the CO1-MA1, CO2-MA2, and CO4-MA4 item pair in our analyses. Again, both the GLASSO and TMFG methods produced a 3-community solution. Boot analyses supported a three-community solution for both methods finding that this structure was confirmed in 85% of the bootstrap samples for the GLASSO EGA and in 69% of the samples for the TMFG method. Concerning item stability, items clustered with the same community in 59% up to 81% of all bootstrap samples.

Considering those results, we decided not to consider any redundancies in our further EGA as the more stable and reliable solution was the first with zero redundancies. In this sense, all the items contribute to unique information in the network analysis.

EGA analysis with the cross-validation sample

EGA was conducted on the second half of the sample (n = 2858) for assessing the replicability of the EGA estimates from the first half of the sample. Specifically, we applied EGA to estimate the SOC-13 dimensionality and item clustering using both the GLASSO and TMFG methods considering zero redundancies and applying the Louvain algorithm for community identification (figure 2).

[insert figure 2 here]

In line with the results from the first half of the sample, the GLASSO method (figure 2) produced a three-community solution and, again, a single item (MA3) that formed a separate community, whereas the TMFG method produced a three-community solution. Whereas the GLASSO method showed a solution that is identical to the EGA from the first half of the sample, the TMFG method differed as item CO3 now belongs to another community. Next, the bootstrap analyses showed that the three-community structure was the most frequent in both GLASSO and TMFG methods supporting for the occurrence of this structure in 99.8% and 99.4% of the bootstrap samples, respectively. For more details concerning communities to which each item belonged according to BOOTEGA and the proportion of times each item clustered with the same community, consider supplementary materials Figure S2b and S2c. Considering the GLASSO EGA, all items but item CO3 clustered with the same dimension in 94% up to 100% of bootstrap samples. Specifically, item CO3 clustered in the same dimension in 72% of all bootstrap samples. Considering the TMFG EGA, all items showed very high stability, with 10 items showing values close to optimal 100% stability and three items (MA4, CO3, CO5) with lower stability ranging from 85% to 92%. Those results are in line with the EGA from the first half of the sample. In all, these results indicate that the network obtained with EGA for the first half of the sample cross-validated for the second half of our sample.

Next, we investigated network loadings for both GLASSO and TMFG. Concerning the GLASSO method, there were three items with small network loadings (<.15): CO5, ME1 and ME3, whereas the remaining items showed moderate to high network loadings. Furthermore, the items CO3, ME3, and ME4 contributed to more than one dimension showing moderate network loadings in two or three dimensions. Concerning the TMFG method, all items showed moderate (.24 to 0.52) to large (>0.52) network loadings. Furthermore, the items MA3, MA4, CO3, CO4, and ME4 contributed to more than one dimension (network loadings >.15).

It was not possible to compare the fit of the GLASSO and TMFG models using the TEFI due the fact the GLASSO method produced a network with one item (MA3) that did not belong to any community. Also, we considered the TMFG solution the more reliable network as it showed high replicability confirmed in the bootstrap analysis. As the TMFG (figure 2a) model covered all SOC-13 items and proved to be more reliable, we used it to identify the final dimensionality structure of the SOC-13.

According to EGA, SOC-13 had three communities (figure 2a) that are not aligned with the a priori theoretical structure as defined by Antonovsky (1987). Specifically, the first community was characterized by three comprehensibility and manageability items (CO1, MA1, MA3). The edge weights (strength of associations between nodes) among these items were strong (range 0.31-0.66).

The second community of five items was also characterized by comprehensibility and manageability items (CO2, CO4, CO5, MA2, MA4). Edge weights (strength of associations between nodes) among these items were zero for three pairs of nodes: CO4-CO5, CO5-MA2 and MA2-MA4, medium (range 0.24-0.26) for two pairs of nodes (CO2-CO5, and CO5-MA4), and strong (range 0.36-0.59) for the other edges.

Finally, the third dimension was characterized by five items, containing all the meaningfulness items (ME1, ME2, ME3, ME4) and finally one comprehensibility item (CO3). The edge weights among these items were zero for two pairs of nodes: ME1-ME2 and ME2-ME3, medium (range 0.25-0.29) for three pairs of nodes (ME1-ME3, ME1-ME4, and ME1-CO3), and strong (range 0.36-0.57) for the other edges.

Discussion

Despite the extensive use of the SOC-13, there is still a long debate regarding its psychometric properties. In this sense, the identification of latent factors of SOC and their respective items is of great importance and the new methodological developments coming from graphics models may help in finding a data driven model. To our knowledge, this is the first empirical study to investigate the factorial structure of the SOC-13 by adopting the network approach. Specifically, the main purpose of the present study was to expand the knowledge regarding the factor structure underlying the SOC13 by applying the EGA methodology. We compared different models: one-factor CFA solution, three-factor CFA solution as defined by Antonovsky (1987; 1990), and the three-factor solution derived from EGA. We estimated the dimensionality of the SOC-13, confirmed the stability of both dimensionality estimate and item assignments into the factors (communities), and assessed the impact of potential item redundancies on the dimensionality and structure of the SOC-13. Overall, our results confirmed the notion that the constructs measured by the SOC-13 are interrelated, making a simple structure confirmatory model inadequate for representing its structure. In fact, the results of our research showed unacceptable fit values for CFA models, suggesting that SOC is not unidimensional, and that Comprehensibility, Manageability, and Meaningfulness could not be extracted from data.

Although some authors found support for both unidimensional and three factor solution (Drageset and Haugan, 2016; Klepp et al., 2007; Rajesh et al., 2016; Spadoti Dantas et al., 2014), most of the research literature found dimensions that are not related to comprehensibility, manageability, and meaningfulness (Eriksson and Contu, 2022). In our study, the inspection of the estimated network suggested that the SOC-13 items emerged as clearly clustered in three distinct nodes communities that are not those defined by Antonovsky (1987). More interestingly, when we considered redundant items with the UVA, the network analyzed become more instable and not offered any stable solution. In this sense, all the 13 items significantly contributed to the emergence of the network and were considered in our analyses. The SOC-13 item network offered us the opportunity to shed light on the connectivity between items within the same domain and empirical derived domains of SOC. Considering the results from EGA, the first emerged community is a mix of three items from comprehensibility and manageability. Considering the development of the SOC-13, the main characteristics that link these items concern the mapping sentences of the facet design as all items share the same time reference facet: (into the) past (for more details, Antonovsky, 1988, p.189-194). Furthermore, item pair CO1 and MA1 showed high redundancy, suggesting that this pair share some similarity. Inspecting the SOC mapping sentences, we found that both items shared the same facets: instrumental stimulus (modality), external environment (source), diffuse demands (demand), and past (time). That suggests a kind of ability people have in understanding and managing past experiences where people negatively surprised them. EGA results are in line with Antonovsky's facet approach (1987) and our results confirmed previous research which highlighted the strong relationship between these items (2022).

The second community is also a mix of items from comprehensibility and manageability Considering the mapping sentences from the facet design, we found that these items share the same time facet: all but one item (CO5) refers to the present. Another interesting point is that items CO5, and MA2, share the same modality (instrumental) and source facets (external), whereas items CO4, MA2, and MA4 share the same demands facet (diffuse). In this sense, this community of items suggests a kind of person's ability in understanding and managing his\her own actual experiences that originated from the external and that poses diffuse demands. If we look at the root of the first definition of SOC proposed by Antonovsky (1979), we find that comprehensibility and manageability were the core dimensions as meaningfulness was defined only in 1987 (Vinje et al., 2022). In this sense, both dimensions were conceptualized as strongly linked, as dealing with a stressor (manageability) requires a clear understanding (comprehensibility) of the problem (Vinje et al., 2022). This community could be considered as a core dimension of items that are linked to the essence concept of SOC.

Finally, the third community is composed of all items from meaningfulness and one item from comprehensibility. What is interesting about this community is that it is the only one characterized by all item from the a priori dimension as defined in the SOC. Considering the mapping sentences of the facet design, we found that all but one item (ME2) share the same time facet with the CO3 item, referring to the present experiences. What emerged from the EGA is that meaningfulness was also empirically identified. Antonovsky (1990) defined Meaningfulness “as a way of looking at life as worth living, providing the motivational force which leads one to seek to order the world and to transform resources from potential to actuality” (p. 36; Vinje et al., 2022). The comprehensibility item CO3 entails a clear understanding of internal stimuli (here feelings and ideas). Apparently, this item, does not share anything with the Meaningfulness dimension. and future studies should consider replicating our results.

In general, our results support Antonovsky’s view (1987) about SOC being composed by “three dimensions continually interacting with each other and together to form a collective, overarching factor” (p.81; Eriksson and Contu, 2022). Although a unidimensional structure does not clearly emerge, the results from EGA are in line with the assumption that comprehensibility and manageability are deeply linked and are not necessarily distinct. In this sense, it confirms that “what one comprehends is easier to manage” (p.81; Eriksson and Contu, 2022) and then both dimensions should be considered strongly related, whereas meaningfulness empirically emerged a second dimension in the network analysis.

The present study has several limitations. First, our results are based on a large Italian adult sample, but it is crucial to test the network model across life span and in different cultures. Second, the cross-sectional nature of our study did not permit any inferences about the direction of influence constraining network analysis to undirected networks. Future research should address this concern by employing longitudinal data collection. Third, we did not investigate whether the dimensionality structure of the SOC-13 emerged in EGA is invariant for different sub-populations. Future work should address this limitation by considering, for example, whether network changes when gender, age groups, or employment are considered. Fourth, a main limitation of the community detection algorithm of EGA is that items may belong to only one community. In future, other algorithms, such as clique percolation method could be implemented allowing items to belong to multiple communities at the same time.

Conclusion

Beyond the emergence of three dimensions of the SOC-13 scale, the EGA highlights that dimensions and items in the network are linked in a way that reminds of complex systems. In this sense, the network perspective offered us a new interpretation of SOC as a dynamic system of mutually interacting nodes that, combined, form a complex system. Thus, SOC could be defined as a complex system structurally composed by a cognitive dimension (comprehensibility), a behavioral dimension (manageability) and a motivational dimension (meaningfulness). However, according to Laszlo and Krippner (1998), “structurally, a system is a divisible whole, but functionally it is an indivisible unity with emergent properties. An emergent property is marked by the appearance of novel characteristics exhibited on the level of the whole ensemble, but not by the components in isolation” (p. 53). Network approach offered us the possibility to find these emergent properties in a way never conceived before. We invite other researchers to replicate our study using different samples.

Our study has some important practical implications. As SOC-13 is neither unidimensional nor composed by three distinct dimensions, future research should consider the bias in using aggregate scores as a measure of whole SOC or for each SOC dimension. In fact, EGA showed us that in a large sample there is not a clear distinction of a whole SOC or the empirical confirmation of emergent dimensions of comprehensibility, manageability and meaningfulness, but other important properties emerged. Those properties should not be neglected as they may help in understanding the real properties of the SOC-13 and, eventually, opening new perspectives in the measurement of the SOC. For the future, we recommend discarding the SOC-13 and to use the SOC-29 for developing a shorter version. In fact, as Antonovsky (1987) did not provide any rationale in selecting 13 items from the 29-item version, it would be better using it as a new starting point, possibly using the network analysis. Returning to the SOC-29 might allow to fix some incongruences such as that the SOC-13 does not consider the future option of the facet time for which Antonovsky did not provide any explanation. For the SOC-13, the results of our study suggest formulating a core measure of SOC considering both communities two and three.

Ethics declarations

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

Ethical approval and consent to participate

The procedures performed in our study involved human participants and received formal approval from the local Institutional Research Committee (Prot. n. 0148446 - 16/07/2020). All participants were informed about the goal, procedures, risks, benefits, anonymity of data on the first page of the questionnaire. The study was carried out on a voluntary basis and participants were free to stop filling out the questionnaire at any time and had the opportunity to contact the research team with questions. Participants were informed that voluntary participation in the survey was taken as implied consent.

Data Availability

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Table 1. Sense of Coherence 13-item measure.

	Facets	SOC-13 Item	**Dimension**
CO1	A1, B2, C2, D1	Has it happened in the past that you were surprised by the behaviour of people whom you thought you knew well? (1=Never happened to 7=Always happened)	CO
CO2	A2, B2, C3, D2	Do you have the feeling that you are in an unfamiliar situation and don't know what to do? (1=Very often to 7=Very seldom or never)	
CO3	A2, B1, C2, D2	Do you have very mixed-up feelings and ideas? (1=Very often to 7=Very seldom or never)	
CO4	A3, B1, C2, D2	Does it happen that you have feelings inside you would rather not feel? (1=Very often to 7=Very seldom or never)	
CO5	A1, B2, C1, D1	When something happened, have you generally found that: (1=You overestimated or underestimated its importance to 7=You saw things in the right proportion)	
ME1	A1, B2, C2, D2	Do you have the feeling that you don't really care about what goes on around you? (1=Very seldom or never to 7=Very often)	ME
ME2	A2, B3, C3, D1	Until now your life has had: (1=No clear goals or purpose at all to 7=Very clear goals and purpose)	
ME3	A1, B3, C1, D2	Doing the things, you do every day is: (1=A source of deep pleasure and satisfaction to 7=A source of pain and boredom)	
ME4	A1, B2, C1, D2	How often do you have the feeling that there's little meaning in the things you do in your daily life? (1=Very often to 7=Very seldom or never)	
MA1	A1, B2, C2, D1	Has it happened that people whom you counted on disappointed you? (1=Never happened to 7=Always happened)	MA
MA2	A1, B2, C2, D2	Do you have the feeling that you're being treated unfairly? (1=Very often to 7=Very seldom or never)	
MA3	A3, B1, C3, D1	Many people – even those with a strong character – sometimes feel like sad sacks (losers) in certain situations. How often have you felt this way in the past? (1=Never to 7=Very often)	
MA4	A3, B1, C2, D2	How often do you have feelings that you're not sure you can keep under control? (1=Very often to 7=Very seldom or never)	

Note: CO=comprehensibility; MA=manageability; ME=meaningfulness; **A= Modality; A1= Instrumental, A2=Cognitive, A3=Affective; B=Source; B1=Internal, B2=External, B3=Both; C=Demand; C1=Concrete, C2=Diffuse, C3=Abstract; D=Time; D1=Past, D2=Present.**

Table 2. Goodness of fit statistics of the Italian version of SOC-13.

Model	χ2	df	CFI (> 0.95)	TLI (> 0.95)	RMSEA (90% CI)
One-factor CFA	1234.87	65	0.52	0.43	0.080 (0.077-0.083)
3-factor CFA	1086.02	62	0.58	0.48	0.077 (0.073-0.081)
Second-order 3-factor CFA	1101.96	62	0.58	0.47	0.078 (0.074-0.082)
Bifactor-CFA	*n.i.*	*n.i.*	*n.i.*	*n.i.*	*n.i.*
Network Model	147.32	45	0.99	0.98	0.029 (0.024-0.034)

Note: n = 2784; χ2 = Satorra-Bentler scaled chi-square, CFA = Confirmatory Factor Analysis; df = Degrees of freedom; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation, 90% CI = 90% confidence interval for RMSEA; TLI and CFI values > 0.95, RMSEA values ≤ 0.05 indicate good fit of the model. n.i.= not identified.