Chapter

Psychometric Networks and Their Implications for the Treatment and Diagnosis of Psychopathologies

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Abstract

In this chapter, we present the main methodological principles of psychological networks as a way of conceptualizing mental disorders. In the network approach, mental disorders are conceptualized as the consequence of direct interactions between symptoms, which may involve biological, psychological, and social mechanisms. If these cause-and-effect relationships are strong enough, symptoms can generate a degree of feedback to sustain them. It is discussed how such an approach contrasts with the traditional psychometric approach, known as the Latent Variable Theory, which assumes that disorders are constructs that exist but are not directly observable. Furthermore, it is also discussed how new neuropsychological hypotheses have been derived in the network approach and how such hypotheses generate direct implications for the understanding of diagnosis and treatment of psychological disorders. Finally, the recentness of the network approach in psychology and how future studies can establish its robustness are discussed.

Keywords: graph theory, network analysis, psychometrics, neuropsychology, clinical measurement

1. Introduction

Network psychometrics is a new approach to the study of latent variables (i.e., psychological constructs) that contrasts with the traditional psychometric approach. In the traditional approach, responses to items on a psychological instrument (e.g., responses to questions such as "Do you sleep poorly?") are analyzed as evidence of an underlying characteristic (or psychopathology) that the researcher or clinician wishes to measure [1]. This idea is formalized in analytic methods, such as Factor Analysis, Item Response Theory, Latent Class Analysis, and Mixture Modeling, among others, which are the main ways to validate psychological and psychiatric instruments [2].

In theoretical terms, the traditional psychometric approach, known as Latent Variable Theory [3], suppose that the observed behavior (e.g., responses to items on a psychological questionnaire or scale) is the effect of a common cause (in the clinical context, usually assumed to be psychiatric disorders). This approach is used in different ways in psychology and psychiatry (see the study by Demjaha et al. [4]). Whereas in psychology metric models (i.e., those that assume that psychiatric disorders are quantitative variables) are more commonly used, in psychiatry categorical models (i.e., those that assume that a disorder is or is not present) are more common. These theoretical differences translate into differences in how to diagnose, classify, and even clinically act on psychiatric disorders [4].

Network psychometrics has the main feature in relation to the traditional psychometric approach that it does not necessarily assume that psychological constructs exist [5]. More specifically, network models of psychopathology assume that symptoms form complex cause-and-effect relationships with each other, dynamically reinforcing each other and giving rise to psychiatric disorders [6–8]. However, there are alternative network models that allow different interpretations. Some are even compatible with the Latent Variable Theory. The aim of the present study is to analyze critically the main distinctions between Latent Variables Theory and Network Psychometrics in the context of psychopathologies. As specific objectives, we will critically evaluate Latent Variable Theory in the causal perspective of Pearl [9], present the theoretical foundations of Network Psychometrics, and discuss the theoretical and practical implications for clinical study and action in the context of psychopathology.

2. Latent variables in psychology

Latent Variable Theory, in its various implementations in statistical models, is formally indistinguishable from the so-called common cause model [9]. The models of this theory assume that when the latent variable is tested, the correlations between observable behaviors should disappear. This property is known as "local independence," which is normatively imposed in traditional psychometric models [10]. This implication derives from the fact that correlations between effects with a common cause are suppressed whenever there is no direct causal relationship between these effects and the relationship between the two variables is controlled by the common cause [9].

Thus, the psychometric model and the causal interpretation affirm that the psychological (or psychopathological) construct naturally causes the behaviors. This relationship is certainly not a coincidence: the standard psychometric model is based on the notion that different indicators measure the same thing because they depend on the same property and no other [11]. Another consequence of Latent Variable Theory is that item response can be described in terms of a functional relationship between a single property of individuals and items [1]. Thus, in the case of unidimensional tests (i.e., based primarily on a single construct or disorder), it is assumed that all psychopathology test items are statistically interchangeable [12]. From a pragmatic point of view, Item Response Theory models, such as the Two-Parameter Logistic Model [2], can demonstrate which items are most closely related to the central construct being measured (so-called item discrimination), as well as the sensitivity of items to the magnitude of the construct (so-called item difficulty). However, it cannot be said that there are items that play a more central role in the identification of the construct, and as long as their difficulties and discriminations are adjusted, all items are equivalent. Such implication contrasts with clinical practice, where it is identified that there are more characteristic or more influential symptoms in each psychopathological disorder [4].

Regarding the development of instruments for the measurement, identification, or screening of psychopathological disorders, the common cause model provides psychometrics and psychiatry with a standard approach to test construction and analysis [13]. This approach is implemented with the following steps:

1. create a set of items as a measure of the same construct;

2. collect data and apply a statistical model that formalizes this common causal dependence;

3. eliminate or modify items that do not fit the model, and

4. repeat steps 1 through 3 until the model fits the data adequately.

Following these steps, provided we are changed from the recommended order it is possible to measure virtually any construct [1], although there is criticism as to whether such an approach actually produces a true measure [14, 15]. Such an approach will not be accurate if there is no common factor across items, which some researchers in psychopathology suggest is the case (see the study by Fried et al. [16]).

For example, in one of the most influential works in psychometric history in the clinical and psychiatric context, Krueger [17] defined the two main higher-order factors of his model in terms of two central psychopathological processes: internalizing and externalizing. These latent variables of the measurement model (i.e., the statistical factors) refer to two intrinsically significant psychological mechanisms that, in principle, could be easily observable in the expression of a picture of even heterogeneous behaviors. According to this author, internalization can lead to depression or anxiety, whereas externalization can lead to antisocial or aggressive behaviors. Although the behaviors are very different, these differences would reflect basic processes in the way psychopathology manifests itself.

In Krueger's original approach [17], the underlying causal homogeneity is psychological in nature, but more recent studies propose that the underlying causal homogeneity is neurological or genetic. Overall, there is a growth in studies that seek to reveal the "underlying brain mechanisms" of psychopathology [18]. In essence, however, all of these approaches boil down to the same explanatory model: there is some "deeper" cause of the symptomatology (e.g., a psychological variable, a brain abnormality, a genetic mutation, among others) that explains why people show the observed symptomatology. Certainly, there are many advances in this area (see the study by Rose [19]). However, it is also known that there are a number of socioeconomic influences on the mental health of individuals, which are not considered in the identification, classification, and treatment of disorders (see the study by Silva et al. [20]).

3. The network psychometry approach and psychopathology

The network psychometrics approach assumes that the lack of stronger evidence for the latent origins (whether psychological, neurological, genetic, or otherwise) of psychopathological disorders cannot be a matter of measurement problems or a limited understanding of genetics and the brain. The alternative proposed by the network approach is that this lack of evidence may be the result of an erroneous way of thinking about or assessing the relationship between symptoms and disorders [21].

More specifically, in the network approach to psychopathology, it is assumed that disorders emerge when, over time, specific symptoms become more strongly connected [8]. From a pragmatic point of view, psychopathology is identifiable when the probability of observing a symptom is higher than "normal" (additionally another symptom has been observed).

It is important to specify that many diagnostic systems, such as the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) [22], do not make any explicit assumptions about the origins of the symptoms. No explanatory mechanisms of the disorder are presented, but only the main symptoms and clinical criteria. Traditionally in psychopathology, no direct attribution of relationships between symptoms of disorders and the common effect of a latent variable is made directly. The relationships between symptoms in their various contexts are established as criteria (see the study by Ramos Vera; Cramer et al.; Borsboom; and Spitzer et al. [23–26]). For example, a person who often has panic attacks in public places (symptom 1) is likely to be afraid that the attacks will recur (symptom 2) and, consequently, will avoid public places frequently (symptom 3). In another example, a person who cannot sleep (symptom 1) will end up tired and unable to concentrate (symptoms 2 and 3), which may cause him or her to feel guilty about poor performance at school or work (symptom 4). Evidence of this type of relationship between symptoms is common and makes it clear that local independence and equivalence between symptoms are not real for several disorders and their indicators.

It should be noted that, despite not explicitly assuming causal symptom structure, diagnostic systems, such as DSM-5, include such structures at least implicitly [24]. For example, a person who sleeps poorly does not show symptoms of depression if the lack of sleep is attributed to a newborn child, just as a person who frequently washes his or her hands only shows a symptom of obsessive-compulsive disorder, hand washing occurs in response to an excessive obsession with hygiene. From this point of view, it can be argued that diagnostic systems, such as the DSM-5, are not purely empirical or theoretically neutral as is often claimed. It is clear that at least as far as hegemonic diagnostic practice in psychopathology is concerned, common cause models are rejected [25, 26]. Such conceptual positioning may be better elaborated under the network approach, especially in cases where a certain event external to symptoms may activate relationships between symptoms of some disorder for a long time, even in the subsequent absence of such an external event [25, 26].

Another advantage of the network approach is the method by which comorbidities can be identified and classified. Ideally, symptoms should be sufficient and necessary conditions for identifying a disorder. However, in the general clinical context, this is rarely the case (even for some disorders or diseases that are clearly biological in origin). It is more common to state that symptoms nominated as "characteristic" of a psychiatric disorder are simply those more frequent in one group of individuals than in others [21, 25]. The traditional psychometric approach, by favoring symptoms that would be more "characteristic" (i.e., occur together more frequently and thus would be more correlated), would not identify idiosyncrasies derived from an individual's specific symptoms. Consequently, some authors [27] suggest that diagnostic comorbidity could be a consequence of spurious associations and, for this reason, could be reduced by retaining distinctive symptoms, but eliminating nonspecific symptoms, in psychopathological assessments.

In the network approach, symptoms are assessed in relation to their "importance" for the stability of the symptom network as a totality [25, 28]. For example, centrality measures indicate the degree of interconnectedness of a symptom with the other symptoms in the network. As there are different ways in which one symptom can connect to another, different centrality metrics can demonstrate different degrees of "importance" of the assessed symptom [29]. Thus, for the assessment of comorbidities, using an idiographic network analysis paradigm, it is possible to identify, for each individual and for groups of individuals, which symptoms appear most relevant in the set of networks and which expression of symptom interdependencies allows certain comorbidities to occur in some individuals [24, 30–32].

4. Analytical methods for network psychometry

The models used in network psychometry are derived from the graph theory of mathematics [33]. Graphs (also called networks) are mathematical objects in which nodes represent various elements (such as other mathematical objects, e.g., sets and variables, or even real objects, e.g., individuals and organizations) and edges represent relationships between nodes. In the statistical derivation of graph theory, known as probabilistic graph models [34], nodes are used to represent variables (in the case of psychopathology networks, the variables are usually the possible symptoms) and edges are used to represent the dependency relationships between the nodes. Dependency relationships usually involve correlations or partial correlations, but may also involve nonlinear dependency measures [35]. It is also common to use clustering methods to identify which variables are most strongly connected [36, 37].

Unlike social networks, in which nodes (people) and the relationships between them can be directly observed [38], psychological networks are based on probabilistic graphs [20, 39]. There are three main types of probabilistic graphs, which are given below [34]:

i. nondirectional graphs (in which the relationships between variables are symmetric);

ii. directional graphs (in which the relationships between variables are asymmetric); and.

iii. chain graphs (sometimes also called mixed graphs in which there are both symmetric and asymmetric relationships).

In the study of psychological networks, the use of nondirectional graphs where edges represent partial correlations is the most common [21, 27, 40, 41]. This preference is mainly because nondirectional graphs allow us to derive hypotheses about causal relationships without the need to make explicit assumptions about which variables are cause and which are effect.

Among the nondirectional graph models used in the study of psychological networks, three of them have received special attention in the literature, which are as follows:

i. correlation networks;

ii. partial correlation networks; and.

iii. directional graphs (directed acyclic graphs, DAG).

The first of these is the correlation network [34]. This type of model uses correlations as measures of dependence between variables and is used when one wants to know if there is a direct dependence between variables. These models have two main limitations. First, these models do not allow inferences to be made about causal relationships since, according to the theory of causal calculus [9], these can only be derived from conditional dependencies. The second limitation of this type of model is that, being based on correlations, the dependencies are not affected by the other variables in the network.

The second type of network model, probably the most widely used, is the partial correlations network model (also known as concentration networks) [42]. This type of model uses partial correlations to measure the strength of the linear relationship between variables. There are two main ways to estimate partial correlation network models [41]. The first is to simply calculate the partial correlations of all the variables in the model and remove the edges of the correlations that are not significant. However, this type of practice is sensitive to false positives. For this reason, it has been more common to use regularized partial correlation networks [42]. which minimizes the probability of maintaining spurious relationships. The use of partial correlations is particularly interesting, as such measures can be interpreted as causal relationships between variables [9, 34]. However, care must be taken not to interpret them as mutualistic causal relationships (which is the case in some important references in the literature) [42]. In fact, partial correlation network models can also be referred to as "visual graphs," which are the non-directional representations of DAGs [43]. This means that causal directions, in some cases, can be determined.

The third type of model is known as DAG [9]. Directional graphs of the DAG type imply all the expected causal relationships between the collected variables. DAGs allow one to appreciate the existence of cycles in the network. For example, it is possible that a variable A causes a variable B, which in turn causes a variable C, and that this in turn causes variable A. This condition is used to avoid breaking the basic assumptions of causality, such as localism and realism of natural phenomena, as well as the transitivity of causal relationships. However, working with longitudinal data, it is possible to identify cycles that are valid (i.e., when the transitivity of causal relationships at the same moment in time is respected) [44]. For example, inattention at a time point $t = 1$ can be the cause of inattention at the same time point $t = 1$. If this relationship is true, it is only causally valid to say that inattention is also the cause of inattention if inattention at time point $t = 1$ is the cause of inattention at time point $t \geq 2$. DAGs have not been widely used in psychology given that they require explicit assumptions about which relationships are causal or not; however, few causal theories in psychology or psychopathology have the robustness to be used in this way [30, 42].

4.1 The use of network models in the context of psychopathology

It is important to emphasize that the use of network models not only allows us to address the complexity of the relationships between variables but is in fact a different approach to thinking about theories in psychopathology. Network analyses have been fundamental for researchers to work with more diverse data sources (e.g., genetic, neurological, physiological, behavioral, and other data) and to seek more comprehensive ways of theorizing. In this context, network analyses have been complemented by what is known as conjoint modeling [45]. Joint modeling is a statistical approach similar to structural equation modeling, but which allows the use of any alternative model as a measurement model (i.e., "for example, see [46]"). These models are used, for example, to develop psychological or psychopathological models sensitive to neurophysiological limitations.

The proposal of the mental health-related symptom network model has promoted the application of different types of variables from different levels of psychobiological development to explore new systemic theories that may include cognitive, biological, and social aspects [47–49], as well as risk and protective factors for mental health [50]. This explanation is of great importance in the current context, for example, a network review study reported the first 18 months since the pandemic, symptomatological variables of fear, distress, and stress were used to a greater extent by COVID-19 [28].

These symptoms allow us to understand the etiological mechanisms of the psychological impact of a stressful event, such as the current pandemic. Protective factors, such as resilience or psychological well-being, and psychosocial measures, such as alcohol and drug abuse, were also included [28]. The studies reviewed by Ramos-Vera et al. [28] refer to the use of different clinical variables related to COVID-19, such as preventive behaviors; emergency personnel communication measures, atypical reactions to pandemic stress, anti-mask attitudes; components of COVID-19 dreams and nightmares, insomnia and work fatigue. One of the studies considered variables consequent to the pandemic, such as perceived present and future infection risk, loss of income, and financial worry [51], while another research conducted in Italy by Invito et al. [52] took into account psychological distress and viral contagion beliefs, and added epidemiological characteristics, such as COVID-19 diagnosis, sex status and number of COVID-19 infected and deaths according to the participant's region. Symptom interaction network theory research has spurred several papers seeking to explore the interconnections of the most recurrent physical and psychological symptoms in certain chronic conditions, such as cancer [53], HIV [54], schizophrenia [55], stroke [56], chronic pain [57] chronic bowel disease [58], multiple sclerosis [59], arterial hypertension [7], obesity [60], and COVID-19 [61].

4.2 The use of psychological network models in the context of neuropsychology

Network neuropsychology can be useful in understanding cognitive adaptation and maladaptation in neurological disorders. Since cognitive functions are not isolated from each other, despite being framed in different domains they can be represented as a cognitive network system, additionally, the successful performance of most neuropsychological tasks is based on the interdependence of several cognitive domains [62, 63]. One of the properties of this network variant is the representation of several networks where measurable differences in neuropsychological profiles between distinct groups can be identified. Two previous studies report that differences are identified in the way neuropsychological tasks are associated in the network between those with neurological diagnoses (cognitive impairment and Alzheimer's disease) relative to control groups [64, 65]. Specifically, regroupings of memory, language and semantic variables and executive or attention, working memory and processing speed variables are evidenced in the network system belonging to participants with Alzheimer's disease relative to healthy control models. This feature allows for new explorations of the cognitive network reorganization that may occur throughout the stages of aging, as referred to in the cognitive dedifferentiation hypothesis. It is very likely that aging has an impact on network composition and there is a need to identify topological deviations that may be indicative of age-related neuropathology [66].

Cognitive impairment can be considered as a transdiagnostic dimension of psychopathology [67, 68], therefore, it is possible to consider the study and use of psychopathological symptoms and cognitive performance in network models. An Italian research in patients with a psychiatric diagnosis of schizophrenia included in the network system psychopathological symptoms of disorganization and avolition, positive and negative symptoms related to schizophrenia, in addition to the expressive deficit, akathisia, dystonia, parkinsonism and dyskinesia, and cognitive performance according to six domains: thought processing, attention/vigilance, working memory, verbal learning, visual learning, reasoning and problem solving, and social cognition, [69]. This work found a greater positive relationship of cognitive performance with social cognition and a negative with parkinsonism (this factor was more connected with psychopathological and cognitive measures) and disorganization.

Networks in neuropsychology may also aim to gain insight into changing associative patterns between cognitive constructs following brain damage [70]. For example, research by Iverson et al. [71] estimated the network structure of physical, cognitive, and emotional symptoms associated with attention deficit hyperactivity disorder following concussion. A total of 3074 student athletes were included who reported increased levels of difficulty concentrating and emotional symptoms. Most of the relationships between symptoms were positive, and the most influential symptoms in the network were dizziness and intensity of emotional symptoms. The relationships with the highest magnitude were emotional intensity and psychological distress, as well as forgetfulness and visual problems. There was a structural difference in the network according to sex, with a higher frequency of symptoms in women [71]. These findings demonstrate that similar studies should be encouraged in clinical participants given that from a systems neuroscience perspective, damage to one area of the brain is considered to affect the functioning of other areas adaptively (e.g., compensation, neuronal reserve, degeneration) or maladaptively (e.g., diaschisis, transneuronal degeneration, and dedifferentiation) [72].

Researchers can make supplementary assumptions, such as specifying hierarchical and/or directional relationships between cognitive functions or support other neuropsychological approaches, such as cognitive neuropsychology to create network models. Network theory can also be used to model relationships between tasks, which offers the advantage of conditioning (multivariate control) on all variables in the model, without making any assumptions about the underlying relationships between cognitive functions. In the following, certain studies are detailed with the aim of illustrating findings that would probably not be found using traditional methods of psychometric analysis.

One of the most important contributions to the field of neuropsychology, in the context of network analysis, is the study by Tosi et al. [65]. In this study, differences in networks of neuropsychological variables were evaluated in patients with and without clinical conditions, composed of 165 healthy elderly, 191 patients with Alzheimer's disease (AD), and 129 patients with vascular encephalopathy (VE). These networks included neuropsychological measures in the domains of memory, language, executive functions, attention, and abstract reasoning, in addition to the covariates of age, sex, and years of schooling. Patients with VS obtained better results (greater connection of cognitive abilities) than those with AD even when controlling for covariates, also, two groups of variables focused on memory and frontal-executive functions were identified in these networks.

Another study evaluated the network configuration of neurocognitive measures in adults using four serial assessments approximately one year apart [73].

The sample consisted of two groups of 432 elderly who obtained, at baseline, a cognitive assessment at normal levels. However, after subsequent assessment steps, the first group retained the same cognitive diagnosis, whereas participants in the second group developed mild cognitive impairment or AD dementia. Differences in network structures (connectivity and centrality) were identified between the groups even before AD was diagnosed, with such differences increasing over time.

Ferguson [64] estimated three network structures in adults according to his neuropsychological assessment:

i. cognitive normality;

ii. amnestic mild cognitive impairment; and

iii. AD (Alzheimer's disease).

In these structures, the networks were composed of cognitive variables linked to the domains of attention, working memory, episodic memory, language, fluency, visuospatial ability, and sociodemographic variables (such as age and education). The centrality of episodic memory in the network structure of people with cognitive impairment was higher, whereas processing speed and fluency were more central in the network of people with AD. In addition, two groups of variables were identified in the three networks, the first focused on semantic memory and language, while the second was composed of attention, processing speed, and working memory.

The research by Foret et al. [74] composed of adults with no neurological or psychiatric history aimed to compare two simultaneous networks in men and women that included biomarkers of cognitive impairment risk, components of the metabolic syndrome (obesity, hypertension, dyslipidemia, and hyperglycemia), neuroimaging-based brain age minus chronological age, ratio of white matter hyperintensities to total brain volume, resting-state brain connectivity based on default mode network seed analysis, and ratios of N-acetyl aspartate, glutamate, and myo-inositol to creatine, which were measured by proton magnetic resonance spectroscopy [74]. Differences were found in the connectivity of both networks where women report lower relationships between cardiometabolic risk variables and brain functioning, furthermore, the most influential measures are shown to be apolipoprotein status and waist circumference.

An investigation in Scottish patients with multiple sclerosis evaluated two networks with a difference of a 12-month follow-up period where psychological aspects more prevalent in this clinical condition, such as fatigue, sleep quality, anxiety, and depression, were evaluated [59]. Measures of physical disability, upper extremity dexterity, gait speed, body mass index, and cognitive performance based on the domains of information processing speed, auditory information processing, working memory, and attention span, as well as neuroanatomical variables related to intracranial volume in the natural space were also considered. The results report that fatigue was related to most variables with the exception of brain measures and depression was the most central element in both networks, respectively [59].

The most recent study by Rotstein et al. [75] evaluated psychometric networks of cognitive impairment in more than 1000 American patients with Alzheimer's disease assessed by the cognitive subscale of the Alzheimer's Disease Assessment Scale composed of seven domains: temporal and spatial orientation, attention, learning, memory, abstract thinking, verbal fluency, and naming. Several network systems were represented between two groups that received treatment with donepezil and placebo at 24 weeks of follow-up, the results showed a statistically significant difference in the global strength of the network integrated by the patients who received medication, evidencing a lower cognitive deterioration in this group.

Also, other network variants that assess dimensionality have been implemented, such as Exploratory Graphical Analysis (EGA; [36]). EGA employs a network algorithm to detect Walktrap communities [76]. Therefore, EGA estimates the dimensionality of multivariate data by combining network analysis with a community detection algorithm, where a community represents a latent variable reported in a factor technique ([36, 37]). Consequently, it is a method to detect dimensions in networks, and additionally reports factor loadings of network variables with their respective communities. In addition to using the EBICglasso estimator for regularized partial correlation networks, this variant of the psychometric network can also group the variables in a graphical model composed of a zero-order correlation matrix using the Maximally Filtered Triangulated Graph Method (TMFG; [77]). This method allows regularizing the relationships and selecting the most parsimonious network structure.

The use of the Bootstrap Exploratory Bootstrap Graphical Analysis (bootEGA) module is recommended, to evaluate the structural consistency of an estimated dimensional structure. Structural consistency is understood as the extent to which a dimension is interrelated (internal consistency) and homogeneous in the presence of other related dimensions [78, 79], such a measure provides an alternative but complementary approach to internal consistency measures in the factor analytic framework. In bootEGA estimation, two metrics are required for structural consistency. The first consists of investigating the solidity of the structure of the dimensionality and the second in the robustness of the location of each element within these dimensions. Three steps have been described for this purpose: (1) estimating a network using EGA, (2) then generating new replicate data from a multivariate normal distribution (with the same number of cases as the original distribution), (3) then applying EGA to the replicate data sets, continuing interactively until the desired number of samples (e.g., 500 participants; [80]) is achieved. Therefore, there are two reasons for employing the parametric bootstrap: resampling smaller samples increase the influences that outlier cases may have on the estimated sampling distribution, and (2) its higher accuracy is the detection of the correct dimensionality structure in the simulated populations [80].

Finally, the need for more studies with multilayer networks (network of networks) is highlighted since they allow better statistical accuracy of the joint use of neurophysiological and psychological data [81, 82]. This may be important in the current pandemic context, as COVID-19 can affect the central nervous system and cause neuropsychiatric disorders [83]. Naturally, this clinical condition has a complex etiology, composed of associative networks of inflammatory biomarkers that can be represented in a network system [84], together with other physical and mental health risk phenotypes [84, 85] and neuroanatomical measures [59, 81, 86]. In this sense, network assessment of variables at different psychobiological levels related to COVID-19 can add to findings reported widely in the literature [87–93].

5. Conclusions

The main objective of this research was to critically analyze the main distinctions between Latent Variables Theory and Network Psychometrics in the context of psychopathologies. To achieve this goal, relevant implications of the common cause model have been presented which, in contrast to the discussion on Network Psychometrics, do not seem to correctly represent some of the empirical evidence. It is important to note that research in using network analysis is still being refined and specific theories are still scarce [94]. However, the observed results have been promising and consolidation of the field will show how important this new line of research can be [24, 41]. On the other hand, although the network approach is not, after all, the most suitable for the study of psychopathology and psychological constructs in general, the exemplified applications, especially those involving variables external to psychological symptoms, are important for the promotion of new hypotheses in the neuropsychological field [95–97], in the face of the inclusion of new network centrality metrics that allow the identification of different structural features following the systemic grouping of transdiagnostic variables in network models [98–100], including longitudinal data to assess how the network is organized over time [101].

In this perspective, network analysis has the potential to change the field of psychopathology, and even neuropsychology, given its tools that allow combining evidence from different contexts and backgrounds in a way that was not previously used, this is essential in the complex assessment of psychosocial and public health risk factors (e.g., addictions and suicidal behavior, see the study by Anderson et al.; Penzel et al.; Hirota et al.; Sanchez-Garcia et al.; and Calati et al. [101–105]). Therefore, future studies that combine data and evidence from different levels of analysis and from different sources may lead to a better understanding of transdiagnostic factors [106–109], cognitive deficits [67], and especially of the integration of neural, behavioral, and symptomatic systems [110–113].

Finally, it is recognized that the understanding and study of psychological variables is a complex task, involving a multitude of variables at multiple levels of analysis (biological, cognitive, and social), which are related to each other in a complex way [114]. However, network analysis may lead to a change in the current epistemological and methodological approach to psychological phenomena so that this complexity can be effectively assessed [115, 116]. Network analysis is unlikely to be one of the best innovations in the field of studying psychological phenomena and problems remain to be solved [28, 96, 117–122], but we believe that the presented discussion highlights positive expectations for the future.

Conflict of interest

The authors have no conflict of interest.

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