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The challenges in measuring symptoms of schizophrenia: An exploratory graph analysis of the Positive and Negative Syndrome Scale (PANSS)

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ABSTRACT

Background and hypothesis: The Positive and Negative Syndrome Scale (PANSS) is a widely used instrument for assessing symptom severity in schizophrenia. Significant concerns remain regarding its structural validity, with no consensus on a definitive model. Although the five-factor model (positive, negative, cognitive, hostility, and affective) is the most widely accepted, studies have demonstrated instability in item distribution across factors and difficulty in achieving adequate fit indices. This exploratory study aims to evaluate the structural validity of the PANSS, addressing these previously identified issues and contributing to the theoretical debate on the limited evidence supporting a robust model fit.

Study design: Data from five independent Brazilian samples ($N = 1262$) were analyzed. We conducted Exploratory Graph Analysis (EGA) and bootstrap analysis to assess the stability of the PANSS structure. We estimated network loadings and conducted the Loadings Comparison Test (LCT) to evaluate differences between structural frameworks.

Study results: The analysis identified a five-dimensional model consistent with prior literature. However, this model proved unstable, appearing in only 66.3 % of bootstrap samples. Several items exhibited low stability across dimensions, and the LCT algorithm indicated that a network framework provided a better fit for the data.

Conclusions: In line with previous research, this study found that the PANSS exhibits an unstable structure and item distribution. Moreover, the scale presents several validity limitations, and the difficulty in achieving a consolidated model may reflect both methodological gaps in its original construction and the inherently multidimensional nature of certain symptoms.

1. Introduction

Kay et al. (1987) developed the Positive and Negative Syndrome Scale (PANSS) as a clinical instrument to assess the severity of schizophrenia symptoms. Due to its widespread use in diagnostic assessments and randomized clinical trials (Dragioti et al., 2017), validity and reliability studies are crucial for indicating whether it effectively measures what it intends to measure. The scale was created in 1987 with three subscales based on a two-dimensional hypothesis (Kay et al., 1987): positive symptoms, negative symptoms, and general psychopathology. However, subsequent studies suggested additional dimensions, with a range varying between three and seven factors (Bell et al., 1994; Fresán et al., 2005; Stochl et al., 2014; van der Gaag et al., 2006b). The most accepted and consolidated model is the five-factor model, which includes positive symptoms, negative symptoms, cognitive/disorganization, depression-anxiety/affective, and excitability/hostility factors. Meta-analysis using exploratory methods corroborated the five-factor model; however, this evidence was limited by the heterogeneity in the distribution of scale items across factors in different studies analyzed (Lehoux et al., 2009; Lim et al., 2021; Shafer and Dazzi, 2019).

A recent systematic review and meta-analysis explicitly identified these issues, classifying the scale as sensitive to treatment trials but

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insufficient in terms of content and structural validity (Geck et al., 2025; Roithmeier et al., 2025). Studies with confirmatory factor analysis (CFA) showed difficulties achieving good fit indices. The study with the most acceptable model fit was designed by Wallwork et al. (2012), who used only 20 items from the original scale, resulting in a very restrictive model that excluded important symptoms, such as avolition and active social avoidance. For this reason, the three original subscales are still widely used (Demyttenaere et al., 2022b).

It is crucial to recognize that several key elements have been neglected in this debate, especially the fundamental goals of creating and validating scales for assessing psychiatric symptoms. These scales are vital for developing research and clinical tools that not only deepen our theoretical knowledge but also significantly improve clinical management. By prioritizing these objectives, we can work towards achieving greater confidence and accuracy in our approaches to psychiatric care (Clark and Watson, 2019; Rodebaugh et al., 2016). Using a scale without appropriate validity compromises the precision of study results, similar to using a thermometer that consistently provides incorrect temperature readings. It is vital to gather compelling evidence that demonstrates the validity and reliability of clinical instruments, as this significantly strengthens the credibility of research findings built upon them. Establishing a solid theoretical foundation for the investigation is a crucial first step in ensuring that our research is both rigorous and impactful.

The present study will consider the network theory of psychopathology, which explains symptom covariance through feedback loops and interdependent relationships among symptoms (Contreras et al., 2019). This approach contrasts with the latent variable theory, which attributes symptom covariance to the presence of an underlying latent construct (Borsboom et al., 2003). We will employ Exploratory Graph Analysis (EGA) to explore these perspectives. EGA produces results comparable to confirmatory factor analysis and has proven promising as a robust statistical model (Golino and Epskamp, 2017). This method assigns items to dimensions without requiring researcher intervention, thereby eliminating the need to select a rotation method and increasing analytical flexibility while reducing potential biases (Golino et al., 2020). Another advantage of EGA is its greater flexibility concerning sample size, even in cases where factor correlations are high, factor loadings are low, and the number of symptoms per factor varies (Golino et al., 2020; Golino and Epskamp, 2017). Additionally, bootstrap techniques enable the assessment of dimension stability, further enhancing the confidence in the findings (Christensen and Golino, 2021a). While some studies have applied this method in schizophrenia research, this is the first to use it specifically to assess the psychometric properties of the PANSS (Moura et al., 2021).

In this context, we aim to evaluate the PANSS, focusing on its content and structural validity to foster a theoretical debate and guide future research on this relevant scale for schizophrenia spectrum disorders. It is important to emphasize that this is an exploratory study, and our primary goal is to raise questions and generate hypotheses.

2. Methods

2.1. Participants

The present study analyzed existing data from five independent Brazilian samples comprising 1272 participants. All participants provided written informed consent, and local ethics committees approved the research protocols. The supplementary materials provide more details regarding the data sources, including project objectives, inclusion and exclusion criteria, and ethical considerations.

We excluded three participants during data analysis: two due to the absence of diagnostic evaluation and one due to a cerebral palsy diagnosis. We assessed missing data using the *naniar v.1.1.0* package in *R v.4.4.1,* which revealed 0.6 % missing values. No variable had more than 10 % of missing data. Following the guideline that all cases should have up to 10 % missing data (Hair et al., 2022), seven cases were excluded as they exceeded this threshold. After this step, the dataset showed <0.1 % of missing data. We imputed missing values in PANSS items using the mean, based on the nature of the data, which resulted in a dataset with no remaining missing values. The final sample consisted of 1262 participants.

2.2. Measures

The Positive and Negative Syndrome Scale (PANSS) is a 30-item instrument. It comprises three subscales: seven items for positive symptoms (P1-P7), seven items for negative symptoms (N1-N7), and sixteen items for general psychopathology (G1-G16). Each item is rated on a seven-point Likert scale, ranging from 1 (no symptoms) to 7 (extreme). This scale was adapted and translated into Brazilian Portuguese (Chaves and Shirakawa, 1998), but only a limited number of studies have examined the factor structure of this adaptation. Previous factor analyses in Brazilian samples indicate a five-factor model similar to those observed in other countries (Higuchi et al., 2014, 2022). However, one study applied the Wallwork model, which has several limitations concerning content validity (Higuchi et al., 2022), while the other had a small sample size and did not report goodness-of-fit indices (Higuchi et al., 2014).

2.3. Statistical analysis

To evaluate the dimensional structure of the PANSS, we conducted an EGA using the *EGAnet v.2.0.9* package in *R v.4.4.1* on February 01, 2025. We chose this statistical approach based on both methodological and theoretical reasons. According to simulation studies, EGA performs better than exploratory factor analysis in scenarios as expected in this study: a five-factor model with five items per factor (Golino et al., 2020; Golino and Epskamp, 2017; Haslbeck and van Bork, 2024). Furthermore, considering that EGA is statistically equivalent to factor models (Epskamp et al., 2017; van Bork et al., 2021), this method enables interpretations that align with both network and latent variable theories. EGA constructs a *Gaussian Graphical Model* (GGM), where edges represent partial correlations between nodes, controlled for all other nodes in the network (Epskamp et al., 2018). Then, a random walk community detection algorithm (*walktrap*) was applied to identify clusters of items. Additionally, the regularization *Graphical Least Absolute Shrinkage and Selection Operator* (GLASSO) was applied to shrink spurious correlations to zero with an *Extended Bayesian Information Criterion* (EBIC) estimation procedure with a hyperparameter $\gamma = 0.5$ (Golino et al., 2020; Golino and Epskamp, 2017; Tibshirani, 1996). By default, the *Fruchterman-Reingold* algorithms were applied (Jones et al., 2018). To assess the stability of the network structure, we performed a resampling bootstrap analysis with 1000 interactions (bootEGA), verifying the consistency of nodes within their respective community (Christensen and Golino, 2021a). The items were considered unstable when their values fell within 0.65–0.75 (Christensen and Golino, 2021a). Network loadings were estimated to determine each node's contribution to its respective communities, classified as small (0.0–0.2), moderate (0.21–0.35), or strong (0.36–0.50). For cross-loadings, the effects considered network loadings ≥ 0.25 (Christensen et al., 2024).

Regarding the different theoretical perspectives for analyzing data in psychopathological constructs - namely, latent variable theory and network theory - the Loadings Comparison Test (LCT) algorithm was applied, with 100 interactions (Christensen and Golino, 2021b). The purpose of this method is to support a theoretical framework for data analysis and enhance understanding of the underlying phenomenon. The LCT estimates a phi coefficient, which helps identify whether the data aligns more with a factor or network model. This is achieved by examining the characteristic behaviors of each model. In a factor model, high factor loadings are observed on one factor, with moderate or low loadings on others, and minimal cross-loadings. In contrast, the network

model is identified by detecting a small-world network structure (Borsboom et al., 2011), where symptoms are closely interconnected and separated by only a few intermediary symptoms.

3. Results

3.1. Participants characteristics

Table 1 presents the descriptive analysis. Table S1 in the supplementary materials provides further details. Almost all symptoms (e.g., PANSS items) exhibited a normal distribution, as indicated by skewness and kurtosis values, except for P5, P7, G1, G8, and G10, which had kurtosis >2, suggesting potential deviations from normality. *Grandiosity* (P5), *hostility* (P7), *somatic concern* (G1), *guilt* (G3), *uncooperativeness* (G8), and *disorientation* (G10) had mean scores below 2, indicating low variability in the data. This suggests that patients consistently scored low on these items or did not present these symptoms during the assessment.

3.2. Exploratory graph analysis

In line with previous studies, the EGA identified a five-dimensional model comprising positive symptoms, negative symptoms, cognitive/disorganization, affective/depression-anxiety, and hostility/excitement (Fig. 1). Considering the bootstrap results, the median number of dimensions was 5, with a 95 % bootstrap confidence interval ranging from 4 (Lower Quartile) to 7 (Upper Quartile). See Table S5 in the supplementary material for further information. The five-factor model emerged in 66.3 % of bootstrap interactions, highlighting the instability of the proposed factor structure. Supplementary Table S6 and Table S7 detail the frequency and consistency of each dimensional model. The positive, cognitive, hostility, and negative dimensions show instability. The affective dimension was stable (0.96), while the cognitive symptoms dimension was the least stable (0.29), likely due to the significant instability of items G5 and G7, as discussed below.

The bootstrap exploratory graph analysis yielded similar results (Fig. 1), identifying a five-dimensional model with comparable correlation patterns between symptoms. However, a notable difference emerged in the distribution of items across dimensions. Specifically, the EGA assigned *mannerism/posturing* (G5) and *motor retardation* (G7) to the cognitive dimension, while the bootEGA considered them part of the negative dimension.

The analysis identified six items with stability distributions below the 0.65–0.75 threshold, suggesting potential dimensional instability. The item m*annerisms and posturing* (G5) exhibit the lowest stability within its dimension (0.42). Three dimensions included unstable items: *lack of judgment and insight* (G12), *grandiosity* (P5), and *preoccupation* (G15) were unstable within the positive symptoms dimension; *mannerisms and posturing* (G5), and *motor retardation* (G7) were unstable within the cognitive dimension; *active social avoidance* (G16) was unstable within the negative symptoms dimension. All these items presented similar instability. For further results, see Fig. 2 and Tables S4 and S8 in the supplementary materials.

Table 1
Demographic and clinical data ($N = 1262$).

Variables	Mean (SD)
Demographic	
Age [mean (SD)]	32.80 (±10.68)
Sex [n, male/female/(missing)]	847/411 (4)
Clinical	
PANSS Positive [mean (SD)]	17.87 (±7.65)
PANSS Negative [mean (SD)]	20.69 (±7.94)
PANSS General [mean (SD)]	37.37 (±12.11)
PANSS Total [mean (SD)]	75.93 (±23.67)

Legend: PANSS - Positive and Negative Syndrome Scale; SD – standard deviation.

Table 2 and supplementary Table S9 present the results regarding network loadings. *Delusion* (P1) exhibited the highest loading (0.81). Most symptoms showed moderate or strong loadings. Additionally, the items *grandiosity* (P5), *motor retardation* (G7), *preoccupation* (G15), and *active social avoidance* (G16) showed similar loadings across multiple dimensions. No item reached the threshold for cross-loading. The item *lack of spontaneity* (N6) exhibited borderline cross-loadings in the negative (0.36) and cognitive (0.24) dimensions, with a stronger association in the negative dimension. Relative to the LCT results, both empirical and bootstrap analyses indicated that a network model better represented the data ($\varphi = 0.28$ for the factor model and $\varphi = 0.72$ for the network model).

4. Discussion

The present study aimed to investigate empirical instability observed in previous studies regarding the structural validity of PANSS. We found that most items were allocated as theoretically expected. However, some items, such as preoccupation, and mannerisms and posture, showed instability and low network loadings, reproducing the findings from previous literature (Lehoux et al., 2009; Lim et al., 2021; Shafer and Dazzi, 2019). As anticipated, the bootstrap analysis also did not find a stable model across boot samples. These results indicate that the dimensionality of the PANSS might be influenced by sample variation, which aligns with the inconsistent findings reported in previous studies (Lançon et al., 2000; Lehoux et al., 2009; Mohr et al., 2004). The cognitive dimension demonstrated the lowest stability, which is in line with previous findings (Geck et al., 2025; Roithmeier et al., 2025). Additionally, the LCT revealed that the PANSS items exhibited small-world network properties. This suggests that changes in any node or edge could influence other nodes or edges within just a few steps, raising important considerations about the potential underlying mechanisms of schizophrenia, which is consistent with previous studies (Moura et al., 2021).

Our study supports previous evidence suggesting that negative and positive symptoms are independent (Kay et al., 1987; Kay and Sevy, 1990). However, it is noteworthy that *active social avoidance* (G16) correlated with *suspiciousness and persecution* (P6), reinforcing the hypothesis that paranoia may contribute to social impairment in schizophrenia (Demyttenaere et al., 2022b). This finding suggests a potential dependence between these symptoms, and we can hypothesize that paranoia might play a causal role in active social avoidance. Another relevant connection of G16 is with the item *preoccupation* (G15), an association that may reflect their item content. In the PANSS, preoccupation is linked to impaired social interactions associated with autistic-like experiences, which may challenge evaluation given its overlap with both social impairment and autistic symptoms. These associations could explain why G16 exhibits similar loadings in both positive and negative dimensions. Nevertheless, G16 was also strongly connected with passive apathetic social withdrawal (N4), a negative symptom. These results underline that, as a negative symptom, G16 exhibited significant edges with positive symptoms, indicating a potential distinction between primary and secondary negative symptoms. These findings signal that active social avoidance (G16) may be alleviated through targeted treatment of positive symptoms.

A relevant difference between EGA and bootEGA concerns the distribution of the items *mannerisms and posturing* (G5) and *motor retardation* (G7), which were allocated to different dimensions: cognitive and negative domains, respectively. Interestingly, both symptoms are related to motor functions. Previous studies highlighted this instability, suggesting potential multidimensional characteristics (Lehoux et al., 2009; Lim et al., 2021; Shafer and Dazzi, 2019). Regarding network loadings, G5 exhibited a moderate loading on the cognitive dimension, while G7 presented similar loadings for both the cognitive and negative dimensions. Examining the edge weights of these symptoms (Table S3)

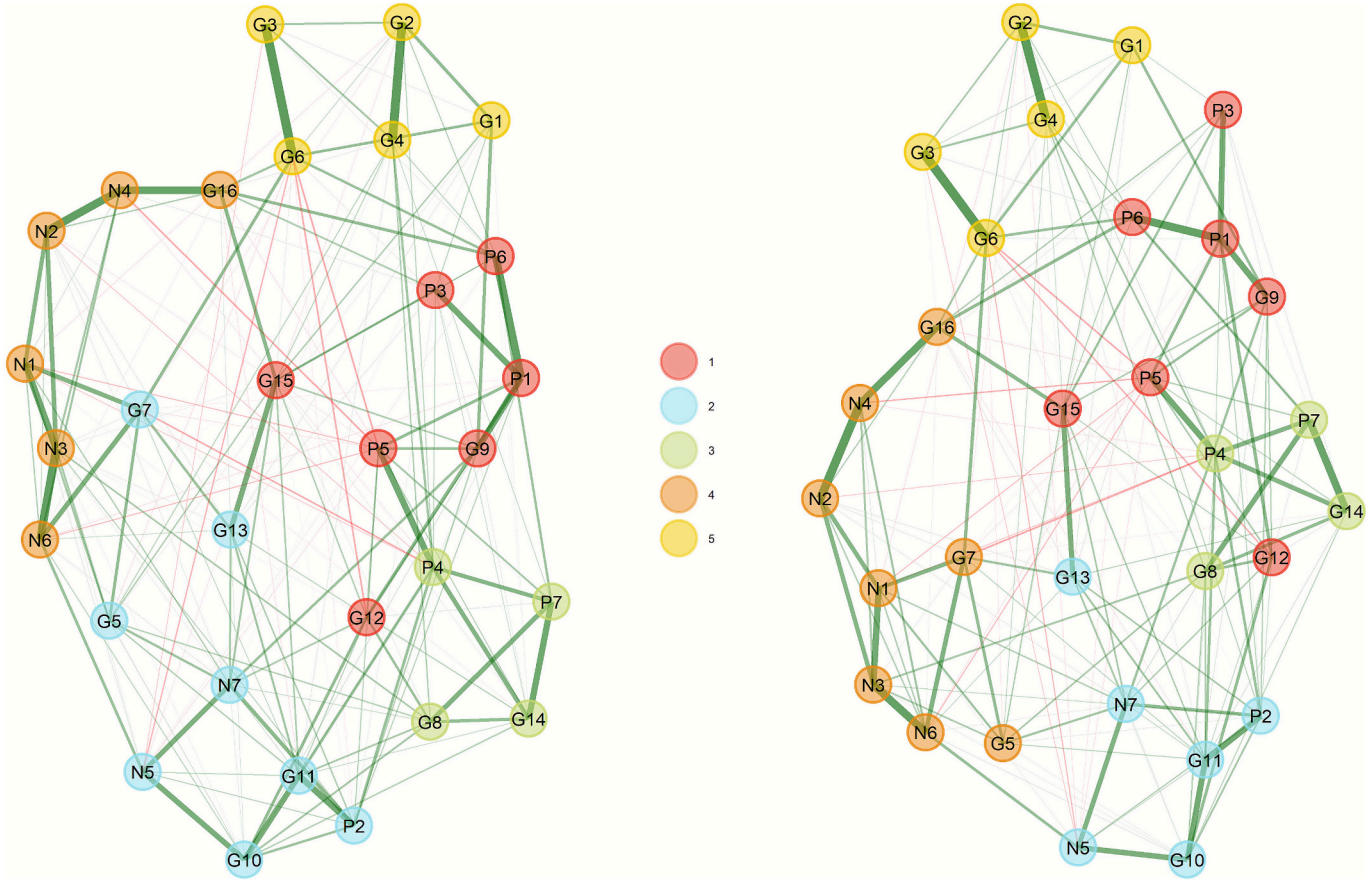

Fig. 1. EGA **(left)** and bootEGA **(right)** of Positive and Negative Syndrome Scale (PANSS). **Legend: 1 (Red) - Positive Symptoms:** P1 – Delusion; P3 – Hallucinatory behavior; P5 – Grandiosity; P6 – Suspiciousness and persecution; G9 – Unusual thought content; G12 – Lack of judgment and insight; G15 – Preoccupation. **2 (Blue) – Cognitive/Disorganization:** P2 – Conceptual disorganization; N5 – Difficulty in abstract thinking; N7 – Stereotype thinking; G5 – Mannerisms and posturing; G7 – Motor retardation; G10 – Disorientation; G11 – Poor attention; G13 – Disturbance of volition. **3 (Green) – Hostility:** P4 – Excitement; P7 – Hostility; G8 – Uncooperativeness; G14 – Poor impulse control. **4 (Orange) – Negative symptoms:** N1 – Blunted affect; N2 – Emotional withdrawal; N3 – Poor rapport; N4 – Passive apathetic social withdrawal; N6 – Lack of spontaneity; G16 – Active social avoidance**. 5 (Yellow) – Affective symptoms:** G1 – Somatic concern; G2 – Anxiety; G3 – Guilt; G4 –Tension; G6 – Depression. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

reveals that G5 is relatively isolated, showing only weak connections to stereotype thinking (N7) and G7. In contrast, G7 had stronger correlations with *blunted affect* (N1), *lack of spontaneity* (N6), G5, and *depression* (G6). These patterns are consistent with existing knowledge, as depressed mood is often associated with motor retardation (Bennabi et al., 2013). Different perspectives may explain the observed correlations with alogia and blunted affect. Blunted affect may contribute to motor retardation, although both phenomena could also arise from extrapyramidal side effects of antipsychotic medication (Lindgren et al., 2022). Alternatively, the relationship with alogia might be better understood by considering their underlying content similarities, both reflecting reduced activity levels. The instability of these items accounts for a substantial portion of the instability observed in the cognitive dimension.

The results of this study reinforce previous evidence on PANSS instability, as fitting robust models continues to be a challenge (Geck et al., 2025; Roithmeier et al., 2025; Smith et al., 1998; van der Gaag et al., 2006a; van der Gaag et al., 2006b). Furthermore, the debate over an empirically validated model of schizophrenia remains unresolved, as its characterization is inherently shaped by the assessments' instruments, statistical methodologies, descriptive biases, and methodological approaches (Peralta and Cuesta, 2001). This raises questions about potential underlying limitations of the PANSS: Are essential symptoms missing, thereby affecting the validity of its structure? Does the inclusion of specific symptoms misrepresent the core features of schizophrenia? For instance, a key negative symptom, anhedonia, was not included in the scale, limiting its comprehensiveness and clinical relevance (Demyttenaere et al., 2022a; Demyttenaere et al., 2022b; Geck et al., 2025; Marder and Galderisi, 2017). We recommend including this symptom in future instruments aimed at assessing global schizophrenia symptomatology.

Furthermore, it is key to note gaps in existing models in the literature. The Wallwork model (Wallwork et al., 2012), for instance, excludes several significant symptoms of the disorder solely to achieve acceptable fit indices. While this procedure may enhance the structural validity of the instrument, it sacrifices content validity by omitting clinically relevant aspects. Conversely, the study by van der Gaag et al. (2006b) adopted a robust theoretical and methodological framework, yielding good model fit and reinforcing the argument that theoretical assumptions are essential for improving the validity of an instrument. However, this study did not include important fit indices, and the proposed model has not been tested in other samples, limiting its generalizability. These contrasting approaches highlight the crucial need for theoretical rigor and rigorous validation when developing or revising instruments like the PANSS.

The scale's development process, given the period of its creation, presents methodological flaws that may contribute to the persistent challenges in establishing a robust model for schizophrenia (Geck et al., 2025; Roithmeier et al., 2025). The formulation of the items and the selection of symptoms likely hinder the attainment of structural validity, as the necessary methodological rigor for these decisions were not followed, according to the development process described by the authors

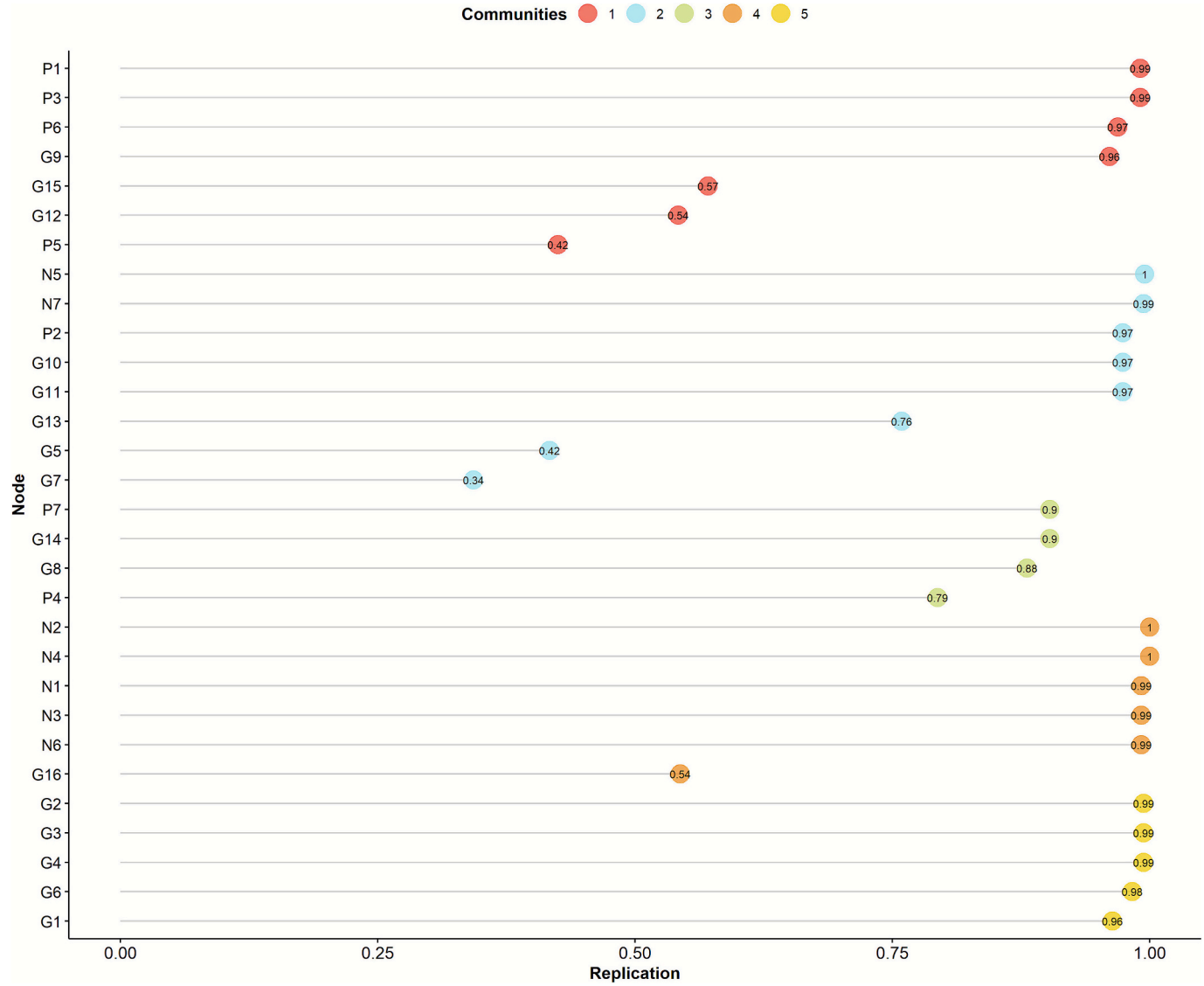

Fig. 2. Item stability of PANSS Items. **Legend: 1 (Red) - Positive Symptoms:** P1 – Delusion; P3 – Hallucinatory behavior; P6 – Suspiciousness and persecution; G9 – Unusual thought content; G15 – Preoccupation; G12 – Lack of judgment and insight; P5 – Grandiosity. **2 (Blue) – Cognitive/Disorganization:** N5 – Difficulty in abstract thinking; N7 – Stereotype thinking; P2 – Conceptual disorganization; G10 – Disorientation; G11 – Poor attention; G13 – Disturbance of volition; G5 – Mannerisms and posturing; G7 – Motor retardation. **3 (Green) – Hostility:** P7 – Hostility; G14 – Poor impulse control; G8 – Uncooperativeness; P4 – Excitement. **4 (Orange) – Negative symptoms:** N2 – Emotional withdrawal; N4 – Passive apathetic social withdrawal; N1 – Blunted affect; N3 – Poor rapport; N6 – Lack of spontaneity; G16 – Active social avoidance**. 5 (Yellow) – Affective symptoms:** G2 – Anxiety; G3 – Guilt; G4 –Tension; G6 – Depression; G1 – Somatic concern. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(Kay et al., 1987). This underscores the urgent need to develop a revised instrument to measure schizophrenia symptoms, considering new evidence and updated guidelines, such as those from COSMIN (Mokkink et al., 2010) or the Standards for Educational and Psychological Testing (AERA et al., 2014). When the initial development of a scale - including item construction and selection - does not follow a rigorous protocol, no statistical approach can fully fix these foundational issues in future structural validity assessments (Clark and Watson, 2019).

It is essential to emphasize that the validity of a measure refers to the extent to which all accumulated evidence supports the intended interpretation of test scores (AERA et al., 2014). Therefore, considering previous studies on the PANSS, particularly its widely used original model comprising negative symptoms, positive symptoms, and general psychopathology, it is not possible to assert that the scale effectively measures schizophrenia symptoms with sufficient reliability and precision. While this may seem like a psychometric technicality, it carries significant implications for research on schizophrenia that relies on the PANSS as an assessment tool. The absence of an empirically validated model allows researchers to select from the various models available in the literature, leading to inconsistencies in item allocation across factors and, consequently, divergent research findings. For instance, if one researcher classifies motor symptoms (G5 and G7) under the negative symptom dimension while another assigns them to the cognitive dimension, the resulting scores will differ, ultimately affecting study outcomes. In other words, using a scale that lacks a rigorous theoretical and methodological foundation compromises the replicability and reproducibility of research. This absence of a standardized and widely accepted model arises from insufficient evidence supporting a solid and robust factor structure.

Considering the methodological approaches used in this study, it was not possible to make conclusions in line with causality; however, considering the exploratory nature, we raised hypotheses related to the symptoms derived from the network to propose potential future studies that aim to construct a valid and reliable scale to capture the

Table 2
Network loadings.

Symptom item	Positive dimension	Cognitive dimension	Hostility dimension	Negative dimension	Affective dimension
P1	0.81				
G9	0.38				
P6	0.30				
P3	0.29				
P5	0.23		0.25		
G12	0.25				
G15	0.20	0.26			
G11		0.52			
N7		0.41			
P2		0.44			
N5		0.35			
G10		0.43			
G13		0.25			
P7			0.57		
G14			0.51		
G8			0.29		
P4			0.32		
N4				0.60	
N2				0.55	
N3				0.60	
N1		0.21		0.35	
N6		0.24		0.36	
G7		0.20		0.24	
G5		0.23			
G16	0.21			0.25	
G2					0.51
G3					0.44
G4					0.40
G6					0.44
G1					0.24

Legend: P1 - Delusions; G9 - Unusual thought content; P6 - Suspiciousness and persecution; P3 - Hallucinatory behavior; P5 - Grandiosity; G12 - Lack of judgment and insight; G15 - Preoccupation; G11 - Poor attention; N7 - Stereotype thinking; P2 - Conceptual disorganization; N5 - Difficulty in abstract thinking; G10 - Disorientation; G13 - Disturbance of volition; P7 - Hostility; G14 - Poor impulse control; G8 - Uncooperativeness; P4 - Excitement; N4 - Passive apathetic social withdrawal; N2 - Emotional withdrawal; N3 - Poor rapport; N1 - Blunted affect; N6 - Lack of spontaneity; G7 - Motor retardation; G5 - Mannerism/posturing; G16 - Active social avoidance; G2 - Anxiety; G3 - Guilt; G4 - Tension; G6 - Depression; G1 - Somatic concern.

complexities of schizophrenia fully. Despite the results of the LCT algorithm indicating that a network model better explained the loadings, it is important to note that the accuracy of this algorithm has only been tested in simulations involving three-factor models with continuous variables (Christensen and Golino, 2021b). Thus, no simulation was conducted with more factors or categorical variables, reducing the confidence in these results.

Despite these limitations, our findings advance the understanding of why establishing a robust explanatory model for the scale remains difficult, while contributing novel insights and hypotheses to this discussion. For instance, the item active social avoidance (G16) appears unstable due to its edge weights with symptoms from other dimensions, such as preoccupation (G15) and suspiciousness/persecution (P6). Likewise, motor symptoms, which previous studies consistently identified as unstable items (Lehoux et al., 2009; Lim et al., 2021; Shafer and Dazzi, 2019), may be explained by their overlapping content or correlations with negative and cognitive symptoms, reflecting a multidimensional nature.

These findings support the hypothesis that certain items may act as bridge symptoms, connecting different dimensions of schizophrenia. Excluding such symptoms due to their psychometric instability may result in the loss of clinically relevant information about the disorder. Bridge symptoms are particularly important because their activation may trigger a cascade effect, leading to the emergence of symptoms from other dimensions (Jones et al., 2021). This cascade can contribute to the activation and maintenance of a pathological network through hysteresis (Borsboom, 2017). Therefore, bridge symptoms could serve as key treatment targets, as highlighted by network theory (Jones et al., 2021). This perspective not only provides insights into why achieving a stable PANSS model has been so challenging but also deepens our understanding of how symptoms are interrelated in schizophrenia and how different dimensions may depend on each other. Thus, methodological shortcomings in its development, as well as the interrelatedness and multidimensional aspects of schizophrenia symptoms, may account for the challenges of the PANSS.

Second, we observed that the PANSS structure demonstrated a better fit under small-world network properties compared to latent models. This suggests that schizophrenia may be conceptualized within a network approach, in which symptoms are intrinsically interconnected and reinforce one another through feedback loops (Borsboom et al., 2021; Christensen and Golino, 2021a). Such a framework moves beyond traditional latent variable assumptions and supports the hypothesis that schizophrenia symptoms may exhibit causal relationships. Importantly, this is not a trivial contribution: expanding the theoretical perspectives used to understand schizophrenia can generate novel insights and research questions with direct implications for both theory and clinical practice.

Third, in line with recent calls for the broader inclusion of underrepresented populations in psychosis research (Burkhard et al., 2021; Alliende et al., 2022), a noteworthy strength of this study is the inclusion of a representative sample from the Global South. This feature is particularly relevant given that most psychosis research has been conducted within the northern global populations, a limitation that restricts the generalizability of findings.

Finally, while reinforcing prior evidence that the PANSS in its current form lacks a robust and generalizable structure, our study provides unique contributions to its validity evaluation. Our results highlight the need for a task force to develop an updated measure of schizophrenia symptoms (Geck et al., 2025). Future research should integrate preliminary evidence of the small-world network properties of schizophrenia (Moura et al., 2021), rather than relying exclusively on formative or reflective measurement frameworks. In addition, we recommend replacing the PANSS with measures of stronger validity. In line with previous recommendations, we emphasize that newer and more specific instruments, such as the *Brief Negative Symptom Scale* (BNSS) and the *Clinical Assessment Interview for Negative Symptoms* (CAINS) for negative symptoms (Strauss et al., 2018), as well as neuropsychological tests for cognitive aspects (Rodriguez-Jimenez et al., 2013), together with other measures, including the *Scale for the Assessment of Positive Symptoms* (SAPS) and the *Calgary Depression Scale for Schizophrenia* (CDSS), represent suitable alternatives to the PANSS in future research, given its structural and content validity limitations.

CRediT authorship contribution statement

Pedro Henrique Minotto Serafim: Writing – original draft, Formal analysis, Data curation, Conceptualization. **Ary Gadelha:** Writing – review & editing, Methodology. **Raffael Massuda:** Writing – review & editing, Methodology. **Mario Louzã:** Writing – review & editing. **Clarissa Severino Gama:** Writing – review & editing. **Luisa de Castro Ostoja Roguski:** Methodology, Investigation. **Pedro Henrique Pereira Alvim:** Methodology, Investigation. **Leticia Sanguinetti Czepielewski:** Writing – review & editing, Conceptualization.

Declaration of competing interest

Ary Gadelha has been a consultant and/or advisor to or has received honoraria from Aché, Daiichi-Sankyo, Teva, Lundbeck, Cristalia, Adium, EMS, and Janssen.

Raffael Massuda has been a consultant and/or advisor to or has received honoraria from Daiichi-Sankyo, Boehringer, Adium and Janssen.

Letícia Sanguinetti Czepielewski has been a consultant and/or advisor to or has received honoraria from Boehringer.

The other authors declare no competing interests.

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The authors have no acknowledgments to declare.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.schres.2025.11.010.

Data availability

We generated and analyzed an anonymized dataset during the current study; however, we cannot to share publicly due to institutional and ethical restrictions. Although all identifying information has been removed, the data remain subject to confidentiality agreements and restrictions imposed by the Institutional Review Board (IRB) and the terms of participant consent, which not permit open data sharing. Therefore, in accordance with Psychiatry Research's data policy (Option B), the dataset is not available in a public repository.

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