Title
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Authors
Carmo, Marwin
Morin, Charles M
Hasan, Rosa
et al.

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The network of dysfunctional beliefs about sleep: a structural re-analysis of the DBAS-16

Marwin Carmo[1,2], Charles M Morin[3], Rosa Hasan[4], Andrea Toscanini[4], and & Renatha El Rafihi-Ferreira[5]

[1] Department of Psychology

University of California - Davis

USA

[2] Department of Psychiatry

University of São Paulo

Brazil

[3] Department of Psychology

École de Psychologie

Université Laval

Canada

[4] Hospital das Clínicas

Faculty of Medicine

University of São Paulo

Brazil

[5] Department of Clinical Psychology

University of São Paulo

Brazil

Author Note

Correspondence concerning this article should be addressed to Marwin Carmo, University of California, Davis, 135 Young Hall, One Shields Avenue, Davis, CA 95616, USA. E-mail: marwinbr@gmail.com

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Abstract

Objectives: Insomnia is a common problem that affects a significant portion of the population. Dysfunctional beliefs and attitudes about sleep contribute to developing and maintaining insomnia. We developed a Brazilian-Portuguese version of the Dysfunctional Beliefs and Attitudes about Sleep Scale (DBAS-16) and conducted a comprehensive psychometric evaluation using latent variable and psychometric network frameworks. **Method:** Participants (N = 1,385) were between 18 and 59 years old, with and without insomnia complaints. We used Confirmatory Factor Analysis (CFA) with dynamic fit indices to evaluate the original DBAS-16 structure and tested longitudinal invariance (14 days) and invariance across good and bad sleepers. We applied Unique Variable Analysis (UVA) and Exploratory Graph Analysis (EGA) to a derivation subsample (n = 693), with the remaining half reserved for cross-validation. **Results:** The original structure was replicated with moderate fit. We found support for longitudinal but not cross-group metric invariance. UVA identified three redundant items for exclusion (1. *Need 8 hours of sleep*, 3. *Consequences of insomnia on health*, and 15. *Medication as a solution*). EGA identified two highly stable dimensions, replicated in the cross-validation subsample. **Conclusion:** The EGA model fit significantly better than the theoretical model, endorsing an alternative DBAS dimensionality. After excluding locally dependent variables, two dimensions may better represent dysfunctional beliefs and attitudes about sleep.

The network of dysfunctional beliefs about sleep: a structural re-analysis of the DBAS-16

Introduction

Insomnia is a disorder characterized by dissatisfaction with the duration or quality of sleep (American Psychiatric Association, 2013). Several cognitive and behavioral models emphasize the role of sleep-related thoughts in perpetuating insomnia (Espie et al., 2006; Harvey, 2002; Lundh, 2005; Morin et al., 1993; Ong et al., 2012; Perlis et al., 1997). Harvey (2002), for example, suggests that negative thoughts and behaviors related to sleep can trigger arousal and distress, leading to distorted perceptions of sleep and increased worry. These beliefs may also heighten cognitive activity and hinder the natural ability to correct sleep issues. Empirical evidence indicates that beliefs and attitudes about sleep contribute to the persistence of insomnia (Akram et al., 2020; Chow et al., 2018; Harvey et al., 2017; Lancee et al., 2019), though not all studies support this connection (Norell-Clarke et al., 2021).

Relatedly, the Microanalytic model (1993) argues that insomnia is maintained through a cyclic process involving arousal, dysfunctional cognitions, maladaptive habits, and consequences. Arousal can manifest as excessive emotional, cognitive, or physiological activity, which shapes core beliefs that guide information processing (Marques et al., 2015). The dysfunctional cognitions often include rigid beliefs about sleep requirements, unrealistic expectations, and heightened worry about the causes and consequences of sleep disturbances. As a result, individuals may adopt unhealthy sleep practices such as daytime napping, spending too much time in bed, or using sleep medication indiscriminately. The real or perceived consequences are ultimately linked to diminished performance during the day (Sullivan et al., 2022).

Individuals with higher insomnia symptoms are typically strong endorsers of dysfunctional beliefs about sleep (Carney & Edinger, 2006; Crönlein et al., 2014; Eidelman et al., 2016). Cognitive-behavioral treatments aim to modify unhelpful beliefs and habits about sleep, resulting in improvements in both objective and subjective sleep quality (Belanger et al., 2006; Harvey et al., 2014; Rafihi-Ferreira et al., 2024; Sánchez-Ortuño & Edinger, 2010). Building on this, Edinger et al. (2021) showed in their systematic review that multicomponent Cognitive Behavioral Therapy for Insomnia (CBT-I)—which integrates education about sleep regulation with cognitive strategies and behavioral components such as stimulus control and sleep restriction— significantly improves beliefs and attitudes about sleep compared to control conditions that included treatment as usual, waitlist, minimal intervention (e.g., sleep hygiene education), or placebo (behavioral or pharmacological), although the quality of this evidence was low.

Insomnia severity is also known as a risk factor for anxiety (Neckelmann et al., 2007) and depression (Blanken et al., 2020; Li et al., 2016), with some researchers suggesting that this relationship may be bidirectional (Chen et al., 2017; Jansson-Fröjmark & Lindblom, 2008). A connection between these conditions and dysfunctional beliefs about sleep is to be expected. For instance, Beck's (1979) cognitive model of depression highlights the role of inaccurate beliefs and maladaptive information processing. Similarly, unpleasant memories from negative experiences can cause anxiety (Brewin, 1996). Therefore, unrealistic expectations and perceptions about sleep can easily lead to anxiety-provoking thoughts. Dysfunctional beliefs about sleep have also been identified as an indirect link between insomnia and depression (Sadler et al., 2013).

Measurement of dysfunctional beliefs and attitudes about sleep

The Dysfunctional Beliefs and Attitudes About Sleep Scale (DBAS, Morin, 1993) is one of the earliest tools to evaluate sleep-related beliefs and attitudes. It is often used in research studies that examine sleep-related thoughts, particularly the 16-question version (Thakral et al., 2020). Originally a 30-item self-report measure rated on a 100-mm scale of agreement/disagreement, it was shortened to 16 items and rated on an 11-point scale ranging from 0 (strongly disagree) to 10 (strongly agree) (Morin et al., 2007). The 16 items were selected based on response distribution, item-total correlations, and exploratory oblique factor analysis.

Morin et al. (2007) proposed a four-factor structure for the DBAS-16: (a) consequences of insomnia, (b) worry about sleep, (c) sleep expectations, and (d) medication, along with a fifth higher-order general factor. While their confirmatory factor analysis yielded acceptable fit indices, they noted that items 10 ("sleep is unpredictable") and 13 ("insomnia resulting from chemical imbalance") were retained despite their very low item-total correlations and factor loadings, due to their clinical relevance. The DBAS-16 has since been translated and validated across various cultures, generally demonstrating good validity evidence (Boysan et al., 2010; Dhyani et al., 2013; Lang et al., 2017).

The DBAS-16 is not the only short version of the scale. Prior to its development, a 10-item version (DBAS-10) was created by Espie et al. (2000) based on items of the original DBAS that showed statistically significant change after cognitive-behavioral therapy for insomnia. A later replication study, however, failed to fully reproduce the DBAS-10's three-factor structure (Edinger & Wohlgemuth, 2001). This likely occurred because the DBAS-10 items had been selected for their sensitivity to treatment-related change rather than through factor-analytic criteria, leaving its dimensional structure unstable across samples. Furthermore, the DBAS-16 has been found to outperform both the 30-item and 10-item versions in reproducibility, internal consistency, concurrent validity, and sensitivity to change (Chung et al., 2016). In that comparison, only the DBAS-16 reproduced a factor structure consistent with previous studies, whereas the 30- and 10-item versions yielded solutions that diverged from prior work.

More recently, Castillo et al. (2023) analyzed the DBAS-16 using Item Response Theory (IRT) with university students. They discovered that the "Medication" and "Expectations" factors provided the lowest test information, while the "Worry/Helplessness" and "Consequences" factors were highly informative in measuring the latent construct. Based on these findings, the authors suggested removing items 10, 13, and 16 to improve the model's fit.

Another variant of a 16-item DBAS was proposed by Clemente et al. (2023). Their DBAS-SF-16 was obtained after refining the DBAS-30 items through sequential psychometric analysis, which included observing item discrimination between groups with different levels of sleep difficulty, item-total and inter-item correlations, face validity, and item correlations with insomnia severity. An Exploratory Factor Analysis of the DBAS-SF-16 revealed two factors: "Consequences and Helplessness" and "Medication and Hopelessness." Notably, four of the items from Morin et al. (2007)'s DBAS-16 were not included in this new version.

The Present Study

The present study has two primary aims. The first goal is to create a Brazilian-Portuguese adaptation of the Dysfunctional Beliefs and Attitudes about Sleep Scale (DBAS-16). Using latent variable modeling, we will analyze its factorial structure, reliability, and construct validity. A secondary goal is to conduct an exploratory analysis using a psychometric network perspective. This approach models psychopathology as a network of causal interactions among symptoms rather than originating from a root cause, such as latent variable models, and has gained popularity in psychiatry and psychology (Borsboom, 2008; Borsboom & Cramer, 2013; Bringmann et al., 2022). This exploratory analysis is motivated by the discrepancies among studies regarding the accuracy of DBAS items and factors in representing the underlying construct, indicating a need for additional psychometric research on this measurement tool.

Methods

Study design and setting

The current study is linked to a randomized controlled trial (RCT) of behavioral treatment for insomnia (Clinical trial: NCT04866914). The study was approved by the research ethics committee of the General Hospital of the University of São Paulo, School of Medicine (HC-FMUSP), São Paulo, Brazil (CAAE: 46284821.1.0000.0068).

All participants signed a consent form prior to their inclusion. Participants then completed an online survey using REDCap electronic data capture tools (Harris et al., 2019), which included the Brazilian-Portuguese version of the DBAS-16 and other auxiliary instruments. To assess temporal stability, the same participants were contacted via email and asked to complete the same measures again 14 days later. The R code and dataset used for this study are available at https://osf.io/qcbwn/?view_only=115971d9519c46f4b74c8e288d80dbc3.

Participants

Participants with and without insomnia were recruited through advertisements on social media of the Institute of Psychiatry at the University of São Paulo between March 2021 and July 2022. The first group consisted of individuals enrolled in a behavioral treatment for insomnia (Rafihi-Ferreira et al., 2024). To include participants without insomnia, we requested volunteers who believed they had no sleeping issues. Interested individuals accessed the REDCap database platform and completed an initial screening. The inclusion criteria were an age range of 18 to 59 years and the ability to read and write in Portuguese without reported difficulties. We deliberately sampled individuals enrolled in insomnia treatment and volunteers who considered themselves good sleepers to ensure sufficient endorsement of dysfunctional beliefs and adequate variability in sleep quality for the confirmatory, measurement-invariance, and network analyses, all of which require the construct to be well represented across the full range of responses.

Participants were classified as good sleepers if they met none of the DSM insomnia criteria (American Psychiatric Association, 2013) and scored below 8 on the Insomnia Severity Index (Bastien et al., 2001), a range indicating the absence of clinically significant insomnia. Participants who met at least one DSM insomnia criterion or scored 8 or higher on the Insomnia Severity Index were classified as bad sleepers.

After excluding individuals who did not complete at least one item on the DBAS-16 during the first administration, the final sample consisted of 1,385 participants, of whom 80.78% were female and 73.51% reported insomnia symptoms. The mean age of participants was 38.39 years (SD = 9.79, range: 18–59). Among those who reported their race, 71.78%

identified as White, 23.83% as Black, and 3.46% as Asian. Most participants held a university degree (77.75%) and were employed (76.96%). A total of 1,154 participants (83.3% of the initial sample) also completed the second assessment 14 days later. Table 1 reports descriptive statistics for the full sample and separately for good and bad sleepers.

Material

Dysfunctional Beliefs and Attitudes About Sleep Scale (DBAS-16)

We created a Brazilian-Portuguese version of the DBAS-16 following the steps of translation, backtranslation, and pre-testing (Beaton et al., 2000; Borsa et al., 2012). The original English version was translated by three independent translators: two who were familiar with the instrument's construct and one English teacher without a medical background. All three translators were bilingual and native speakers of Brazilian Portuguese. A committee comprised of two clinical psychologists, who are experts in insomnia, then synthesized the translated versions, documenting their decisions in a formal record. Then, two native speakers of the source language back-translated the synthesized version into English for review by the first author of the original questionnaire.

Afterwards, we conducted a cognitive debriefing with 15 participants from various regions of Brazil and educational backgrounds to assess the pre-final version. Debriefing was conducted through individual remote interviews. Participants completed the pre-final version using a structured form and, for each item, answered open-ended questions about their understanding of key terms. They were invited to suggest alternative wording and were also asked to evaluate the clarity of the instructions and response scale. Twelve of the participants were female, with a mean age of 43 years (ranging from 19 to 57). Overall, the participants understood the test items and instructions well, and only one term needed modification for improved readability in the target language. The final translation is available as supplementary material, and all intermediate versions can be accessed at https://osf.io/av45j/?view_only=b2a09050f5b84bf5afe10e944f0c01f0.

Additional measures

1. *Insomnia Severity Index* (ISI, Bastien et al., 2001; Morin et al., 2011) is a seven-item questionnaire that assesses the severity of insomnia and its impact on a person's life. The scale ranges from 0 (no problems) to 4 (very severe problem) and categorizes respondents as having no insomnia (0–7), mild insomnia (8–14), moderate insomnia (15–21), or severe insomnia (22–28). For our study, we used the Brazilian-Portuguese version (Castro, 2011). A Confirmatory Factor Analysis (CFA) of the single-factor model produced an acceptable fit to our sample: χ^2 (14) = 342.35, $p < 0.001$ RMSEA = 0.128 90% CI [0.117, 0.140], CFI = 0.996, SRMR = 0.047, and good internal consistency reliability: $\omega = 0.955$ [0.948, 0.962].

2. *The Hospital Anxiety and Depression Scale* (HADS, Zigmond & Snaith, 1983) assesses psychological distress in non-psychiatric patients through two factors with seven items each: Anxiety and Depression. The score ranges from 0 to 21 for each factor. Scores of 0 to 8 indicate no anxiety/depression, while scores of 9 and above indicate their presence. The Brazilian-Portuguese version created by Botega et al. (1995) was used. A two-factor model produced excellent CFA fit indices: χ^2 (76) = 572.01, RMSEA = 0.068 90% CI [0.063, 0.073], CFI = 0.993, SRMR = 0.047, and good internal consistency reliability for both factors: $\omega_{\text{depression}} = 0.882$ [0.874, 0.981], $\omega_{\text{anxiety}} = 0.914$ [0.905, 0.925].

Data analysis

Data screening and item evaluation

First, we examined response frequency and item statistics to assess item variation, distribution, and data entry. We also investigated inter-item correlations and searched for unusual response patterns by identifying multivariate outliers using Mahalanobis distance. Additionally, we used the generalized Cook's distance (gCD) with the R package `faoutlier` version 0.7.6 (Chalmers & Flora, 2015) to identify any points of influence.

Assessing the factor structure

We fitted the original DBAS-16 model (Morin et al., 2007) to our full sample using Confirmatory Factor Analysis (CFA) as a first test of structural validity. This model is a four-factor structure and a higher-order general factor. But because the DBAS-16 is often modeled with disregard for the higher-order factor (Boysan et al., 2010; Castillo et al., 2023; Clemente et al., 2023; Lang et al., 2017), we also tested a four-factor model allowing factors to covary and compared the fit of both models. We used normal theory maximum likelihood (ML) to estimate the structural model parameters (Rhemtulla et al., 2012). To account for the severe non-normality in our data, we applied maximum likelihood estimation with robust standard errors and a mean and variance-adjusted test statistic (MLMV) (Maydeu-Olivares, 2017). Our model fit evaluation relied on fit statistics including chi-squared (χ^2), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Squared Residual (SRMR). Obtaining confidence intervals (CI) for robust RMSEA and CFI involved computing the second-order corrected RMSEA CI based on the MLMV test statistic (Savalei, 2018). All the CFA analyses were conducted with the R packages `lavaan` version 0.6.12 (Rosseel, 2012) and `semTools` version 0.5-6 (Jorgensen et al., 2022).

Traditionally, CFA studies use cutoff values of SRMR ≤ 0.08, RMSEA ≤ 0.06, and CFI, TLI, and RNI ≥ 0.96 to evaluate model misspecification (Hu & Bentler, 1999). These values have limitations because they were derived from specific conditions, making generalizations to other models limited and unwarranted (Marsh et al., 2004). Therefore, another advantage of using an ML estimation method is the possibility of using dynamic fit index (DFI) cutoffs (McNeish & Wolf, 2021). In essence, DFI provides cutoff values that would have been derived had our model been used in simulations similar to the one conducted by Hu and Bentler (1999). DFI is calculated based on the number of factors in the model and assesses the severity of misspecification at sequential levels. The three DFI levels represent increasingly severe misspecification, defined by an increasing number and magnitude of omitted cross-loadings. For each level, the procedure simulates data under the corresponding degree of misspecification and determines the expected fit-index cutoffs. A model with fit worse than the Level-3 cutoffs indicates misspecification more severe than that produced by a substantial set of omitted cross-loadings. We used the Dynamic Model Fit R Shiny application, version 1.1.0 (Wolf & McNeish, 2020), to obtain the DFI for our models.

Measurement invariance

We examined whether the psychometric properties of our scale were equal across groups with and without insomnia symptoms and across time points, comparing baseline test scores to those from a second administration taken 14 days later. We tested invariance by restricting the measurement properties across groups and time in increasing levels of stringency. We tested a sequence of factor structure (configural invariance), factor loadings (metric invariance), items' intercepts (scalar invariance), and items' residual variances (strict invariance) (Flake & Luong, 2021). If a level of non-invariance was detected, no further tests were conducted. The criteria used to evaluate model fit were the chi-squared difference test for goodness of fit and differences in alternative fit indices, such as CFI, RMSEA, and SRMR (Putnick & Bornstein, 2016). While there are suggested cutoffs for alternative fit indices that indicate a lack of invariance (e.g., Chen, 2007; Cheung & Rensvold, 2002; Meade et al., 2008), these are still limited because different testing conditions may generate different criteria (Putnick & Bornstein, 2016). Thus, we used a global approach that tested differences in fit between the restricted and less-constrained models at each stage, also examining comparative fit indices such as the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) (Mackinnon et al., 2022). We gave greater weight to BIC results because it performs better in different simulation scenarios (Lin et al., 2017).

Reliability and validity

We used McDonald's omega (ω) to estimate internal consistency. This measure has advantages over Cronbach's α, as it does not assume tau equivalence (i.e., loadings are not assumed equal) or a perfect fit in CFA (Kelley & Pornprasertmanit, 2016). We calculated the point estimate and the bias-corrected and accelerated bootstrap confidence interval (1000 bootstrap samples) for the internal consistency indices using the R package `MBESS` version 4.9.2 (Kelley, 2022). We followed the traditional guideline of internal consistency indices $\geq$ 0.70 to evaluate reliability as acceptable (Kline, 1986).

To assess convergent validity, we estimated a structural equation model where the DBAS-16 factors, insomnia severity, and the HADS subscales of depression and anxiety were allowed to correlate. We expect all associations to be positive and moderate to strong. These associations were also explored in a network model, where variables' sum scores are the nodes, and their connections the weighted edges, representing their conditional associations (Borsboom et al., 2021). We used `bootnet` version 1.5 (Epskamp, Borsboom, & Fried, 2017) to estimate the network and `qgraph` version 1.9.4 (Epskamp et al., 2012) to create the plot. We assessed the importance of each node using strength centrality, defined as the sum of the absolute weights of the edges connected to a node. We focused on strength because it is generally the most stable and interpretable centrality index in cross-sectional psychometric networks, whereas betweenness and closeness were developed for information-transfer networks and tend to be unstable and difficult to interpret in this context (Bringmann et al., 2019; Epskamp, Borsboom, & Fried, 2017). Because strength disregards the sign of the edges, and our network contained a negative edge, we also inspected expected influence, which preserves edge sign (Robinaugh et al., 2016).

Exploratory Graph Analysis (EGA)

In psychometric networks, symptoms or observed behaviors, such as those measured by the DBAS-16, do not stem from a latent construct. Instead, the causal interactions between these symptoms help shape these unobserved cognitive representations (Borsboom, 2017). Despite their differing theoretical perspectives, network models and latent variable models are generally statistically equivalent; both aim to describe or explain the variance-covariance structure of observed variables (Christensen et al., 2020b; van Bork et al., 2021). More precisely, for continuous data a single common factor is statistically equivalent to a network model and can imply the same covariance matrix (Epskamp, Rhemtulla, & Borsboom, 2017), and for binary data the Ising network model is equivalent to a multidimensional item response model (Kruis & Maris, 2016; Marsman et al., 2018). When two models are equivalent in this way, they fit the data equally well, so model fit alone cannot establish whether the covariation among items arises from a common cause or from mutual interactions among the items themselves; adjudicating between these interpretations requires substantive theory rather than statistics (Kruis & Maris, 2016). This equivalence is not universal, however, as latent variable and network models can imply different, testable constraints and are in some cases statistically distinguishable (van Bork et al., 2021). For this reason, we use Exploratory Graph Analysis (EGA) to recover the number and composition of dimensions—whose communities correspond to the factors of a latent variable model and whose network loadings parallel factor loadings (Christensen & Golino, 2021a; Golino & Epskamp, 2017)—rather than as evidence that the DBAS-16 items form a causal network.

EGA was estimated via the R package `EGAnet` version 2.0.7 (Golino & Christensen, 2022). This method uses undirected network models to estimate the dimensionality of multivariate data. These dimensions are clusters of items that are more similar to one another than to items in other clusters. We opted for EGA because it has shown more promising results in estimating the number of dimensions than traditional factor analytic methods, such as Parallel Analysis, especially in structures with four or more factors (Golino et al., 2020). All network figures in this article were drawn using the Fruchterman–Reingold force-directed layout algorithm (Fruchterman & Reingold, 1991), as implemented in the `qgraph` package (Epskamp et al., 2012); in this layout, more strongly connected nodes are positioned closer together.

For this study, we randomly split our sample into two halves, stratified by sleeper group, and conducted derivation and confirmation analyses. Because the split was stratified, good and bad sleepers were distributed in the same proportion across both subsamples: the derivation subsample comprised 693 participants (510 bad and 183 good sleepers) and the confirmation subsample comprised 692 participants (509 bad and 183 good sleepers), each preserving the full-sample composition of approximately 74% bad and 26% good sleepers. The split was performed with the `rsample` package (Frick et al., 2024) using a fixed random seed for reproducibility. In the derivation step, our goal was to obtain an optimal network structure through redundancy search, dimensionality estimation, and internal structure analysis (Christensen et al., 2020a). In the confirmation step, we tested whether our obtained solution could be replicated and assessed its plausibility against the theoretical model using CFA.

The recommended first step in the EGA framework is to identify potential redundant items. When modeling psychological data as networks, redundant items can lead to unintended effects, such as biased parameter estimates (Christensen, Garrido, & Golino, 2023). When using latent variable modeling, item redundancy may violate the principle of local independence. Unique Variable Analysis (UVA, Christensen, Garrido, & Golino, 2023) can identify redundant items using network modeling and a graph theory measure called weighted topological overlap (wTO). UVA identifies locally dependent pairs of variables and uses the false discovery rate to assess the expected count of false positives. This algorithm first computes the association structure of the observed data, then uses a threshold or significance test to determine redundancy between pairs of variables. The redundant variables can be removed, leaving a single non-redundant indicator, or aggregated as latent variables. Redundant pairs of items are identified as those in which the wTO overlap exceeds the cutoff value of 0.25 (Christensen, Garrido, & Golino, 2023). We opted to remove redundant items, keeping the one with the lowest maximum wTO to all other items. When this criterion was inconclusive, we also considered factors such as item-test correlations, variances, and the representation of the attribute.

We estimated the network of the DBAS-16 items using EGA with the Graphical Least Absolute Shrinkage and Selection Operator (GLASSO, Friedman et al., 2008). EGA was conducted using the Walktrap algorithm for community detection, as it is popular in the psychometric network literature and effective at retrieving the correct number of dimensions (Christensen, Garrido, Guerra-Peña, & Golino, 2023; Golino et al., 2020). We also specified the Leading Eigenvalue as the method of unidimensionality check. This algorithm is applied to the correlation matrix, and undimensionality is determined if a single dimension is identified (Christensen, Garrido, Guerra-Peña, & Golino, 2023). Conversely, for multiple dimensions, the standard EGA procedure is followed.

To select the best solution in case of different suggested models, we employed the *total entropy fit index with Von Neumman entropy* (TEFI.vn, Golino et al., 2021). Structures with lower entropy better reflect the underlying latent factors (Golino et al., 2021). Spearman's rho correlation was used to compute the correlation matrix for the network estimation methods.

Computing internal consistency measures from a psychometric network perspective is not feasible due to the absence of common covariance among items in the model (Christensen et al., 2020a). To address this issue Christensen et al. (2020a) suggests examining "the extent to which items in a dimension are homogeneous and interrelated given the multidimensional structure of the questionnaire" (p. 8), which they refer to as *structural consistency*. This measure was estimated using Bootstrap Exploratory Graph Analysis (bootEGA, Christensen & Golino, 2021b), which generates a sampling distribution of EGA results from replicate data. It informs how often dimensions are exactly recovered (structural consistency) and how often each item is allocated in its respective empirical dimension (item stability). Structural consistency and item stability range from 0 to 1, and values above 0.75 are acceptable for both. The bootstrap results are summarized as median, standard error, 95% confidence intervals, and the frequency with which a given number of dimensions are replicated. Additionally, bootEGA provides a measure of the typical network structure of the sampling distribution. A single network is estimated by computing the median value for each edge across replicate networks and then applying the community detection algorithm.

We also investigated configural and metric invariance across groups of good and bad sleepers using EGA. Configural invariance is achieved when the same nodes are partitioned into the same communities across groups. The test for metric invariance employs permutation testing to verify whether network loadings are equivalent across groups (Jamison et al., 2024). Network loadings represent the unique contribution of each node to the emergence of a network dimension (Christensen & Golino, 2021a).

Results

Data screening

We used Mahalanobis distance (MD) to scan for multivariate outliers and found 27 respondents with D^2 values with probability values <.001 (df = 16). After examining the item statistics, we determined that all observations fell within the expected score range, eliminating the possibility of outliers due to data collection or entry errors. Therefore, no observations were excluded.

To identify leverage points in our sample, we used the generalized Cook's distance (gCD) statistic, which measures the amount of change in a group of parameter estimates when an observation is excluded (Pek & MacCallum, 2011). We calculated a gCD value for each observation in our sample and identified five highly influential observations using a box plot of gCD values (Flora et al., 2012). These observations were excluded from the sample to ensure the accuracy of our analysis.

Confirmatory Factor Analysis

After comparing the fit of a higher-order structure with a four-factor structure, we concluded that the latter was a better fit for our data: $\Delta\chi^2(2) = 269.10$, $p < 0.001$, ΔAIC = -296.86, ΔBIC = -286.40. The four-factor model fit indices were as follows: χ^2 (98) = 974.41, RMSEA = 0.094 90% CI [0.089, 0.100], CFI = 0.891, SRMR = 0.074. These indices were slightly worse than a Level-3 misspecification by DFI standards (SRMR = 0.051, RMSEA = 0.10, CFI = 0.922), indicating inconsistency even with large misspecification. This inconsistency represented an omission of standardized cross-loadings with magnitudes of

0.456, 0.443, and 0.464.

Further examination of the modification indices revealed that the model could be improved by freeing the correlations between the residual variances of items 3 and 4, and between items 6 and 15. After making these changes, the model fit indices improved and were more consistent with a Level-3 misspecification (SRMR = 0.051, RMSEA = 0.094, CFI = 0.936): χ^2 (96) = 686.176, RMSEA = 0.077 90% CI [0.072, 0.083], CFI = 0.928, SRMR = 0.060. Table 2 shows the factor loadings for each item.

Table 1

Sample characteristics by sleeper group.

Characteristic	Good sleepers	Bad sleepers	Total	p
Recruited (screened), n	387	1,192	1,579	
Analyzed, n	366	1,019	1,385	
Age, years	36.71 (8.93)	38.97 (10.01)	38.38 (9.78)	$<$ .001
Female	317 (86.6)	802 (78.7)	1,119 (80.8)	.001
Race				.759
White	270 (73.8)	723 (71.7)	993 (72.2)	
Black	81 (22.1)	250 (24.8)	331 (24.1)	
Asian	14 (3.8)	34 (3.4)	48 (3.5)	
Other	1 (0.3)	2 (0.2)	3 (0.2)	
University degree	319 (87.2)	759 (74.5)	1,078 (77.8)	$<$ .001
Employed / active	298 (81.4)	767 (75.3)	1,065 (76.9)	.020
Insomnia Severity Index	1.78 (1.71)	18.97 (4.27)	14.43 (8.46)	$<$ .001
HADS – Anxiety	5.03 (3.28)	11.47 (4.29)	9.77 (4.94)	$<$ .001
HADS – Depression	3.79 (2.99)	9.45 (4.33)	7.95 (4.73)	$<$ .001
DBAS-16 total	60.22 (25.02)	112.94 (25.54)	99.01 (34.43)	$<$ .001

Note. Recruited (screened) = eligible participants remaining after removing duplicate entries; Analyzed = participants with at least one DBAS-16 response, on whom all descriptive statistics below are computed. Continuous variables are reported as M (SD) and compared with Welch's t-test; categorical variables as counts and within-group percentages of non-missing responses, compared with χ^2 tests. Good sleepers met no DSM insomnia criterion and scored below 8 on the Insomnia Severity Index; all others were classified as bad sleepers. HADS = Hospital Anxiety and Depression Scale.

Table 2

Factor and Network loadings of the theoretical and EGA-derived models with the full sample.

	CFA - Theoretical model				CFA		EGA	
Item	Consequences	Worry	Expectations	Medication	F1	F2	F1	F2
5. Insomnia interferes with functioning	0.69				0.67		0.28	0.03
7. Mood disturbances due to insomnia	0.72				0.73		0.27	0.10
9. Cannot function without a good night of sleep	0.77				0.75		0.43	0.03
12. Lack of energy due to poor sleep	0.78				0.76		0.32	0.10
16. Cancel obligations after a poor night's sleep	0.63				0.64		0.18	0.14
3. Concerned about consequences of insomnia on health		0.80						
4. Worried about losing control of sleep		0.81				0.82	0.08	0.41
8. One poor night disturbs whole week		0.69			0.73		0.24	0.17
10. Sleep is unpredictable		0.62				0.62	0.01	0.27
11. Unable to manage consequences of disturbed sleep		0.65				0.66	0.08	0.25
14. Insomnia destroying life		0.86				0.86	0.20	0.36
1. Need 8 hours of sleep			0.64					
2. Need to catch up on sleep loss			0.68		0.32		0.12	-0.003
6. Insomnia destroying life				0.60		0.60	0.09	0.18
13. Insomnia resulting from chemical imbalance				0.62		0.62	0.07	0.18
15. Medication as the only solution				0.58				

Measurement Invariance

We analyzed measurement invariance in insomnia severity by comparing good and bad sleepers. First, we tested the configural invariance model to determine whether the number of latent factors and the items loaded onto them were equivalent across groups. This first model showed acceptable fit: χ^2 (164) = 496.260, RMSEA = 0.064 (90% CI [0.058, 0.071]), CFI = 0.921, SRMR = 0.047.

Next, we tested metric invariance to see if factor loadings were equivalent for both groups, but we found no support for it. As shown in Table 3, the significant difference in chi-square between the configural and metric invariant models, along with the AIC and BIC indices favoring the less restricted model, indicates that metric invariance was not achieved. Because of that, we did not test for stricter invariant models. These results suggest that the indicators may not relate to the latent variables in the same way for both groups.

Longitudinal measurement invariance of the DBAS-16 was tested in a similar manner. Table 3 shows that the configural invariant model had adequate fit, allowing further testing. The metric-invariant model showed no significant differences in the chi-squared test, indicating metric invariance across time. We then moved on to the scalar invariance model, which assessed the equality of item responses, constraining the intercepts. There was a slight worsening in comparative fit measures (ΔCFI = -0.003, ΔRMSEA = 0.0005); however, the change was considered negligible (Chen, 2007; Meade et al., 2008). The change in BIC was lower than 6, a value deemed evidence of model difference (Raftery, 1995). Despite the notable increase in the chi-squared statistic, we believe that any scalar non-invariance is minimal, if not negligible. However, we decided not to proceed with further testing out of caution.

Reliability and Validity

The internal consistencies of each of the four dimensions were good, with omega values ranging from 0.60 to 0.88. The DBAS-16 total score had an ω value of 0.890 95% CI [0.876, 0.902], indicating good internal consistency. It is important to note that the scale is

Table 3

Model fit differences for CFA measurement invariance tests.

Model	$\Delta\chi^2$	Δdf	p-value	ΔRMSEA	ΔCFI	ΔAIC	ΔBIC
Longitudinal invariance							
Configural	1430.40	416	<.001	0.0607	0.9364	164747	165474
Metric - Configural	20.24	12	0.03	-0.0007	0.0004	-1.24	-61.84
Scalar - Metric	64.12	12	<0.001	0.0005	-0.0029	65.19	-4.59
Strict - Scalar	143.17	16	<0.001	0.0024	-0.0081	208.11	127.31
Group invariance							
Configural	496.26	164	<0.001	0.0643	0.9211	96100	96654
Metric - Configural	57.43	11	<0.001	0.0042	-0.0168	91.2	33.7

not unidimensional, and it is inappropriate to interpret it as such. However, we report the internal consistency of the unidimensional scores because many studies interpret the total sum score to examine the level of dysfunctional beliefs and behaviors about sleep. Table 4 shows the full results of internal consistency coefficients.

DBAS-16's factors showed significant associations with depression, anxiety, and insomnia severity with moderate to strong strength, except for "Expectation" scores, as shown in Table 4. The network in Figure 1 represents a joint partial correlation structure of the DBAS-16 factors and these psychological variables. Each weighted edge in this network represents a conditional pairwise correlation between two nodes, controlling for all other variables. The absence of edges between nodes reflects weak partial correlations shrunk to zero due to penalization for model complexity. Notably, there were negligible relationships between depression and anxiety with any of the four DBAS-16 factors after accounting for insomnia severity and either of the two variables. Relations with insomnia severity were also low, except for the "Worry" factor, which was the node with the highest strength centrality. The network also showed a negative association between "Expectations" and insomnia severity.

Table 4

Latent correlations and internal consistency levels.

Variable	1	2	3	4	ω [95% CI]
1. Consequences	1.000				0.827 [0.811, 0.843]
2. Worry	0.693	1.000			0.882 [0.871, 0.893]
3. Expectations	0.569	0.101	1.000		0.600 [0.557, 0.644]
4. Medication	0.704	0.994	0.126	1.000	0.752 [0.730, 0.771]
5. ISI	0.508	0.937	-0.079	0.861	0.942 [0.937, 0.947]
6. Depression	0.433	0.682	0.051	0.662	0.876 [0.866, 0.886]
7. Anxiety	0.421	0.719	0.020	0.676	0.884 [0.874, 0.892]

Note. Off-diagonal values in columns 1–4 are latent correlations (r) among the numbered variables; ω denotes McDonald's omega with its 95% confidence interval.

Eploratory Graph Analysis

Derivation of the factor structure in the training sample

First, we investigated potential redundancies between item pairs using UVA. Based on weighted topological overlap (wTO) we found redundancies between items 1 (*Need 8 hours of sleep*) and 2 (*Need to catch up on sleep loss*) (wTO = 0.26), 3 (*Consequences of insomnia on health*) and 4 (*Worried about losing control of sleep*) (wTO = 0.32), and between items 6 (*Better taking sleeping pills*) and 15 (*Medication as a solution*) (wTO = 0.31).

Before addressing redundant items, we estimated the full dimensionality of the DBAS-16 using EGA. To do this, we utilized GLASSO with the Walktrap algorithm and Spearman correlation matrix. The EGA produced two dimensions, with a TEFI.vn index of -10.38. We then assessed structural consistency using the bootEGA with 1000 replicates. The two-dimensional structure was replicated with a 51.1% frequency across bootstrap samples.

We then repeated these steps, taking into account the redundancies identified prior to the EGA. We first dealt with the redundancy between items 6 and 15, keeping item 6 based on quantitative criteria and better generalization. Item 15 had a larger maximum wTO to all other items (0.112 vs. 0.083), a lower item-total correlation corrected for item overlap and scale reliability (0.56 vs. 0.61), and a lower standard deviation (3.53 vs. 3.81). The model without item 15 suggested three dimensions with a TEFI.vn index of -11.12. Dimensionality replication was still unsatisfactory, with a rate of 51.2%. Next, we dropped item 3 due to its higher maximum wTO, lower item-total correlation, and lower variance, and re-estimated the model. We found three dimensions, with the same community structure (except for item 3, which was removed), along with a small improvement in dimensionality replication of 63.1%, and a lower TEFI.vn of -9.77. As in the previous model, the cluster formed by items 1 and 2 showed poor replicability, with values ≤ 0.60 in both cases. Lastly, we excluded item 1 over item 2 due to its lower maximum wTO to all other items and higher variance. This time, two dimensions were found. The resulting network with two clusters, without nodes 1, 3, and 15, had the lowest TEFI.vn (-7.60) and a higher replication rate (76.3%), as well as more satisfying structural consistency, and better item stability into empirical dimensions, as shown in Table 5. Figure 2 shows the network plots obtained in each step of the analysis with the derivation sample. With no further redundancies to address, we evaluated these results with the confirmation sample.

Confirmation of the factor structure in the test sample

To determine if our results from the derivation sample were consistent, we repeated the same procedures with the second half of our split sample. UVA identified the same three redundancy pairs, prompting us to run the EGA with items 1, 3, and 15 dropped simultaneously. The resulting network returned two dimensions and replicated the item assignment from the last model fitted with the derivation sample. An even more satisfying dimensionality replication rate of 89.0% was found, with great structural consistency

(Dimension 1: 80.2%; Dimension 2: 95.6%). Overall, these results support the accuracy of the structure obtained with the derivation sample.

Modeling the final EGA structure in a confirmatory factor analysis yielded fit indices slightly worse than a Level-3 misspecification obtained through DFI (SRMR = 0.051, RMSEA = 0.093, CFI = .938): $\chi^2(64) = 302.59$, RMSEA = 0.089 90% CI [0.079, 0.099], CFI = 0.919, SRMR = 0.063. Nonetheless, this structure provided a better fit to our data than the original model with four factors: ΔAIC = -9,802.82, ΔBIC = -9,852.77, ΔRMSEA = -0.005, ΔCFI = 0.022, ΔSRMR = -0.012. Additionally, both dimensions demonstrated satisfactory internal consistency ($\omega_{F1} = 0.84$, $\omega_{F2} = 0.85$).

Finally, we analyzed the full sample to test for invariance across groups of good and bad sleepers in the EGA framework. First, we used EGA to confirm the two-dimensional structure and item assignments obtained from the derivation and confirmation sample. This structure was successfully replicated in 90.6% of 1000 bootstrap samples (Median[SE] = 2[.26]). We also found excellent stability values for Dimension 1 (89.7%) and Dimension 2 (99.7%), with item stability ranging from 0.911 to 1.

Next, we examined whether the same nodes formed the same communities in both groups (i.e., configural invariance). However, our initial results indicated non-equivalent community structures for good and bad sleepers, despite both samples conforming to a three-dimensional structure, as shown in Figure 3. These results were somewhat inconsistent when we ran the bootEGA, as the median number of dimensions generated was 2 (SE_{gs} = 0.66, SE_{bs} = 0.63), recovered across 65.9% of the bootstrap samples for the good sleepers' sample and 54.9% for the bad sleepers' sample. Additionally, at least one community of both typical structures had consistency levels below the acceptable cutoff of 0.75, with some items having poor stability.

Although configural invariance was not met, we investigated metric invariance as if it were. Considering the two-dimensional structure of the full sample, we found that only item 10 ("Sleep is unpredictable") showed a significant difference in network loading after controlling for false discovery rate with the Benjamini-Hochberg procedure. The loading was lower for bad sleepers, with a difference of 0.122 compared to good sleepers.

Table 5

Stability of the EGA dimensionality estimates across 1,000 bootstrap samples.

	Dimensions		
	1	2	3
Derivation sample (n = 693)			
Complete set of items	0.480	0.741	.
Item 15 removed	0.482	0.887	0.700
Items 15 and 3 removed	0.603	0.960	0.547
Items 15, 3, and 1 removed	0.678	0.846	.
Confirmation sample (n = 692)			
Items 15, 3, and 1 removed	0.802	0.956	.
Full sample (n = 1385)			
Items 15, 3, and 1 removed	0.897	0.997	.

Discussion

Dysfunctional beliefs and attitudes about sleep feature prominently in many popular models of insomnia and have been widely investigated using the DBAS-16 (Tang et al., 2023). With this study, we produced a Brazilian-Portuguese version of the questionnaire. We demonstrated its semantic and psychometric equivalence to the original version, making its use suitable for the Brazilian population. Additionally, to our knowledge, this is among the first studies to test the measurement invariance of the original four-factor DBAS-16 structure, which was noninvariant across good and bad sleepers (metric invariance was not supported) but stable over the 14-day interval (longitudinal invariance). Despite acceptable model fit indices in the confirmatory analysis, they were only obtained by correlating residuals. On top of that, modification indices also suggested that the model could be improved with the addition of cross-loadings. Using network psychometrics, we found that (1) items 1, 3, and 15 could be deleted without losing information, (2) two dimensionalities better represent the underlying structure of the DBAS scores, and (3) the item referring to the belief that sleep is unpredictable was noninvariant across good and bad sleepers.

Our confirmatory analysis of DBAS-16's structure aligns with much of the previous research (Boysan et al., 2010; Castillo et al., 2023; Morin et al., 2007). The four-factor structure had acceptable indices by traditional and dynamic fit indices. The "Worry about sleep" and "Consequences" subscales had strong internal consistency, while the "Expectations" and "Medication" subscales had modest values. These results suggest that the idea that these 16 items assessing dysfunctional beliefs and attitudes about sleep conform to a four-factor structure is questionable. The reliability of the "Expectations" and "Medication" subscales could be affected by the small number of items composing them and their low factor loadings (ranging from 0.58 to 0.68).

Adopting suggestions of modification indices can be risky, as the model might not generalize to other samples (MacCallum et al., 1992). However, we obtained a better model fit by correlating residuals of items 3 and 4, in line with previous research (Boysan et al., 2010; Castillo et al., 2023; Morin et al., 2007). We can at least infer that these items share something in common that is not accounted for by the latent factor, such as similar wording or content overlap. Our results, in part, are consistent with prior confirmatory analyses of DBAS-16's four-factor structure and were obtained in a large sample (more than 1,000 participants) that included both individuals seeking treatment for insomnia and self-identified good sleepers.

Our study found that model structure and factor loadings remained consistent over 14 days. However, we did not find conclusive evidence of item intercept equivalence during this period. There were no significant differences in model fit between good and bad sleepers.

Nevertheless, the items' loadings on the factors varied across groups. These findings have critical implications for studies assessing dysfunctional beliefs before and after an intervention. Although the DBAS-16 remained stable over time, participants did not change in their insomnia severity status. Improvement in insomnia symptoms can likely change how DBAS-16 items are interpreted. Hence, researchers should not assume measurement invariance but test it, as a possible decrease in dysfunctional beliefs about sleep cannot be interpreted straightforwardly.

Regarding convergent validity, except for "Expectations," DBAS-16 factors had positive moderate-to-strong correlations with insomnia severity, anxiety, and depression. These findings are not unexpected, as Morin et al. (2007) observed a similar pattern but retained the "Expectations" items for their clinical relevance. A partial correlation network revealed the centrality of the "Worry" node and a negative partial correlation between sleep expectations and insomnia severity. The first development suggests the importance of worrying about sleep, given its strong overall connectivity within the network. It also agrees with Clemente et al.'s (2023) IRT analysis showing that the "Worry about sleep" subscale provided the most information and the highest level of precision. They also found that items measuring expectations provided more information about individuals with lower unhelpful beliefs about sleep. Their results help us understand the negative partial correlation between expectations about sleep and insomnia severity, since these beliefs may also be common among good sleepers and are not good indicators of sleep problems. Our study also answers their call to evaluate their findings with a clinical sample.

The second objective of this research was to explore the structure of DBAS-16. Unique Variable Analysis identified three pairs of redundant items with a wTO score greater than 0.25. These pairs were item 1 ("Need 8 hours of sleep") and item 2 ("Need to catch up on sleep loss"), item 3 ("Consequences of insomnia on health") and item 4 ("Worried about losing control of sleep"), and item 6 ("Better taking sleeping pills") and item 15 ("Medication as a solution"). Interestingly, Cha et al. (2024) found strong edge weights between these same pairs of items when modeling DBAS-16 items as a network. They also found that items 7 and 8 were highly associated, which were not identified as redundant in our analysis.

We removed items 1, 3, and 15 based on quantitative and qualitative criteria. Some may question why we considered items 1 and 2 redundant, as their wTO score slightly exceeded the cutoff and originally formed a latent factor. We believe that the emergence of a minor factor comprising only these two items was due to the failure to consider local dependence. Our decision to drop item 15 differs from Clemente et al.'s (2023) recommendation to keep it, given its highest discriminatory value among the items in the "Medication" subscale, and to delete item 6 due to its flat item characteristic curve. This illustrates that our study is not advocating a shorter "DBAS-13", as there may be additional factors to consider when deciding on a specific item-removal criterion. Nonetheless, we achieved a two-dimensional structure with excellent item and structure stability levels by removing those items. The redundancy of items 1, 3, and 15 has both methodological and substantive implications. Methodologically, each item formed a redundant pair with a retained item (item 1 with item 2, item 3 with item 4, and item 15 with item 6), indicating local dependence, or content overlap not explained by the dimensional structure, rather than representing three additional, distinct facets of dysfunctional beliefs. Because the redundant items closely duplicate their retained counterparts and the broader dimensions to which they belong, their removal does not substantially reduce the content coverage of the scale. Beliefs about sleep needs, the perceived consequences of and control over poor sleep, and reliance on medication remain represented by the retained items. Therefore, removing these items results in a more parsimonious and locally independent measure. It is important to emphasize, however, that redundancy is a psychometric property and does not indicate clinical unimportance; specific beliefs such as needing eight hours of sleep or viewing medication as the only solution may still serve as valuable clinical targets. Their exclusion should be interpreted as reducing measurement redundancy rather than eliminating clinically relevant content.

Our EGA research revealed that two dimensions reflect the underlying structure of dysfunctional beliefs and attitudes toward sleep in our sample. Dimension 1 is composed of items from the original “Consequences of insomnia” factor (items 5, 7, 9, 12, and 16), along with item 2 (“When I don’t get a proper amount of sleep on a given night, I need to catch up on the next day by napping or sleeping longer”) from “Expectations” and item 8 (“When I sleep poorly on one night, I know it will disturb my sleep schedule for the whole week”) from “Worry about sleep.” Since items 2 and 8 share a semantic value related to the consequences of poor sleep, we may keep the original terminology and label Dimension 1 as “Consequences of insomnia.” Dimension 2 is composed of the remaining items from the “Worry about sleep” subscale (items 4, 10, 11, and 14) and item 6 (“In order to be alert and function well during the day, I believe I would be better off taking a sleeping pill rather than having a poor night’s sleep”) and 13 (“I believe insomnia is essentially the result of a chemical imbalance”) from “Medication.” Assuming that worry about sleep leads to medication use, we label Dimension 2 as “Worry about sleep.”

Using a new technique in the EGA framework to test measurement invariance, we found that the network structure was noninvariant for both good and bad sleepers, as predicted by the theoretical model. However, we couldn’t determine the best structure for either group due to low structure stability. We found that item 10 (“I can’t ever predict whether I’ll have a good or poor night’s sleep”) was the only noninvariant regarding network loadings. This result supports Clemente et al.’s (2023) discovery that item 10 effectively distinguishes between good and bad sleepers. Regardless, we must be cautious when interpreting this finding, as we cannot assume the network structure is identical across groups.

Limitations

Our research is among the few to explore the potential insights that network psychometrics can provide on the DBAS-16 (see also Cha et al., 2024). However, it is important to acknowledge certain limitations in our findings. The EGA methods we used were selected based on simulation studies, which may not entirely reflect the nature of our data. EGA is a relatively new technique, and more research is needed to address still unanswered questions (Golino et al., 2022). For example, selecting Louvain over Leading Eigenvalue to test for unidimensionality led to a unidimensional structure for poor sleepers. While we based our choices on the best available evidence, these results are preliminary and suggest a direction for further investigation.

In both our confirmatory and exploratory analyses, we found that certain biases could have influenced our data. First, the participants who had sleep problems were seeking treatment for insomnia, which meant that they were likely to be more severely affected by the disorder. Additionally, our data were unbalanced toward bad sleepers, which could have contributed to the heavy skew and low statistical power to test measurement invariance across groups. Secondly, we administered the questionnaires online, and participants were required to complete all fields. This may have introduced bias, as participants may have provided an answer even if it did not apply to their situation. Third, we did not include elderly people; therefore, the outcomes cannot be generalized to all adults with insomnia. Fourth, most of our sample comprised white women with a university degree. Future studies should focus on collecting more representative samples, including those with lower levels of education. Fifth, it is important to note that our study used the Brazilian-Portuguese adaptation of the DBAS-16. Although we ensured that it was equivalent to the English version, specific terms or cultural characteristics may have influenced the results. These findings should be replicated in samples from different countries. Finally, we used the same total sample for derivation and confirmation. We tried to mitigate this issue by splitting the sample into two halves, but we recognize that it cannot eliminate sampling bias. Therefore, it is highly recommended that our findings be replicated with a larger, more diverse, and older sample, ensuring a more balanced representation of good and poor sleepers. Additionally, further research should test longitudinal invariance over at least eight weeks to reflect typical cognitive-behavioral treatment protocols for insomnia (Harvey et al., 2014).

Conclusion

Our research shows that the DBAS-16 is suitable for a Brazilian-Portuguese-speaking population. It also provides initial insights into the network structure of dysfunctional beliefs and attitudes about sleep. Our CFA results show weak evidence for the original four-factor structure. The borderline model fit values caution against adopting this structure. After accounting for redundant items, our exploratory analysis favored a two-factor structure, which was ultimately found to be more stable.

As noted previously in this manuscript, network psychometrics and latent variable modeling adopt different premises regarding how a phenomenon is constituted. Latent variable modeling generally operates under the common cause hypothesis, in which the covariation between observable indicators is entirely attributable to a single common cause. In the network perspective, factors are systems of causally connected symptoms or mutually interacting elements (Borsboom & Cramer, 2013). Whether any of these frameworks is more appropriate for interpreting the construct under study, nor our results, nor any statistical approach can settle this; modeling the 13 items across two dimensions using CFA did not yield completely satisfactory results either. The general conclusion may be that, although useful, the DBAS-16's underlying structure is not settled, and further qualitative and quantitative refinements are needed.

While not definitive, our findings can have immediate impacts: Clinicians may benefit from a more streamlined way to conceptualize a patient's dysfunctional beliefs. Also, the "Worry" factor, for example, could be a key target given its central role in the network model. Researchers, especially those adopting psychometric network modeling, now have a starting point for further inquiry into the interactions between dysfunctional beliefs and related symptoms.

Author contributions

Marwin Carmo: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. **Charles Morin**: Conceptualization, Writing – review & editing. **Rosa Hasan**: Investigation, Funding acquisition, Methodology, Resources, Writing – review & editing. **Andrea Toscanini**: Investigation, Methodology, Writing – review & editing. **Renatha Rafihi-Ferreira**: Conceptualization, Data curation, Funding acquisition, Investigation, Project administration, Resources, Supervision, Writing - review & editing.

Conflict of Interest

The authors declare no potential conflict of interest.

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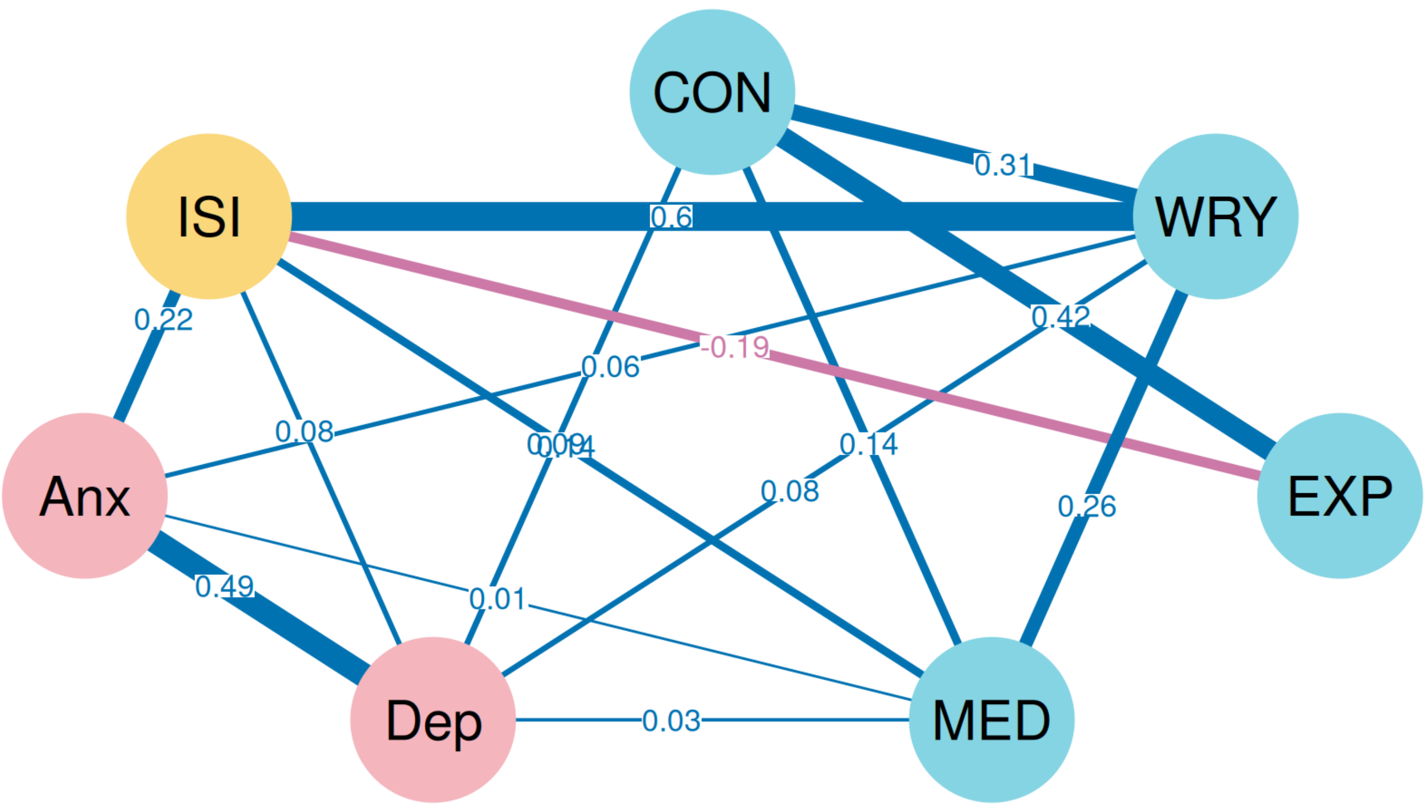
Data availability statement

Data and code used in the analyses reported in this paper are available at https://osf.io/qcbwn/?view_only=115971d9519c46f4b74c8e288d80dbc3.

Figure 1

Partial correlation network of DBAS-16 factors, Insomnia severity, Anxiety, and Depression. The nodes represent the sum scores of each variable, and the edges represent the partial correlations between them. The strength of the partial correlations is represented by the edge thickness, and the numbers superimposed on them indicate the estimated values. Blue edges represent positive associations and red edges represent negative ones.



Note. The network was estimated on the full analytic sample (N = 1,385). MED=Medication, WRY=Worry, CON=Consequences, EXP=Expectations, ISI=Insomnia severity index, Dep=Depression, Anx=Anxiety.

Figure 2

Weighted graph structure of the DBAS-16's items obtained with EGA. Panel A is the graph obtained with all items included, Panel B is the graph estimated without item 15, Panel C shows the graph obtained without items 15 and 3, and Panel D is the graph estimated without items 15, 3, and 1. In all graphs, nodes represent items, and the thickness of edges indicates the strength of the partial correlations. Blue edges represent positive associations and red edges represent negative ones. The different node colors indicate the communities identified by the Walktrap algorithm, meaning that nodes with the same color belong to the same community.

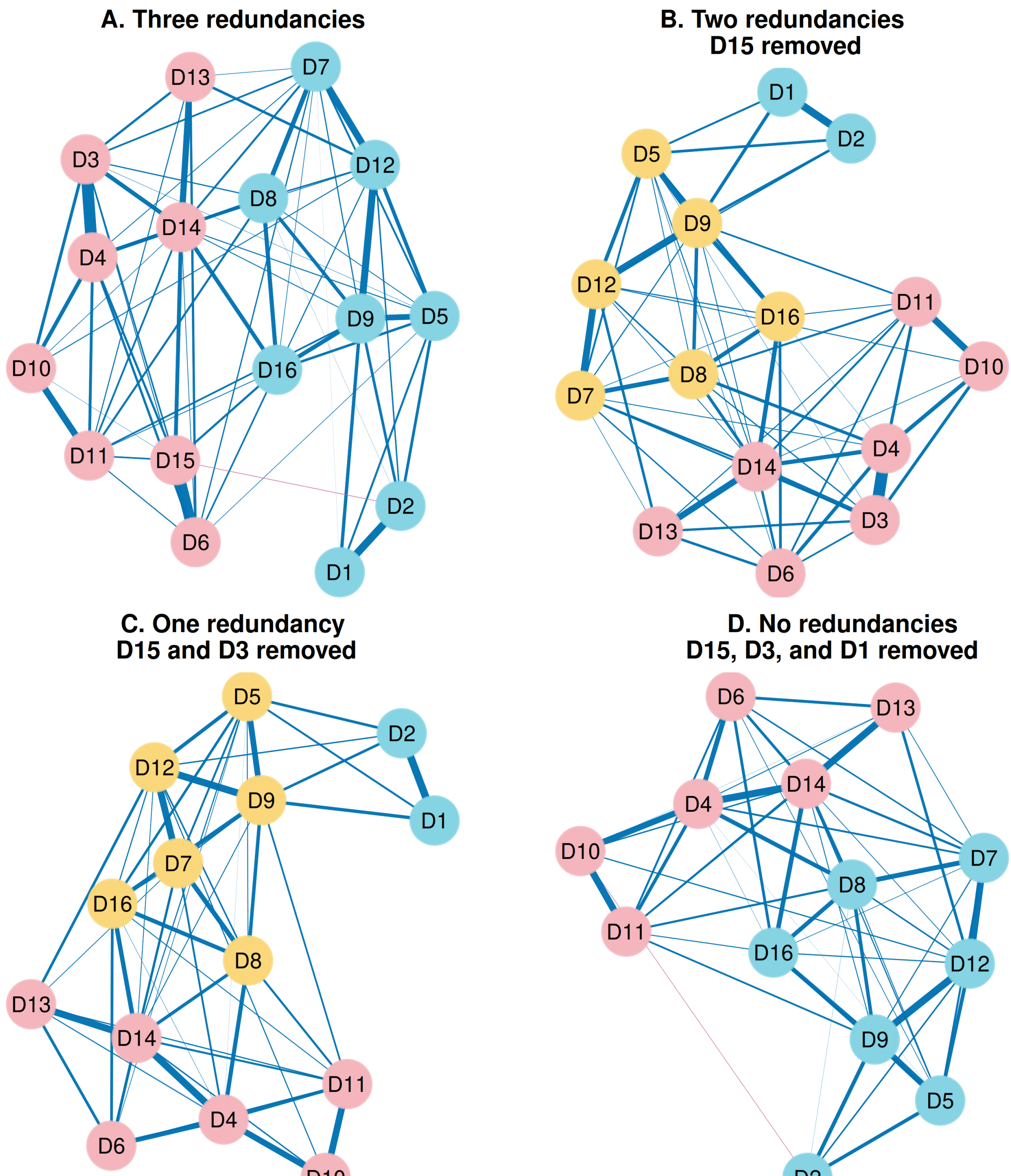
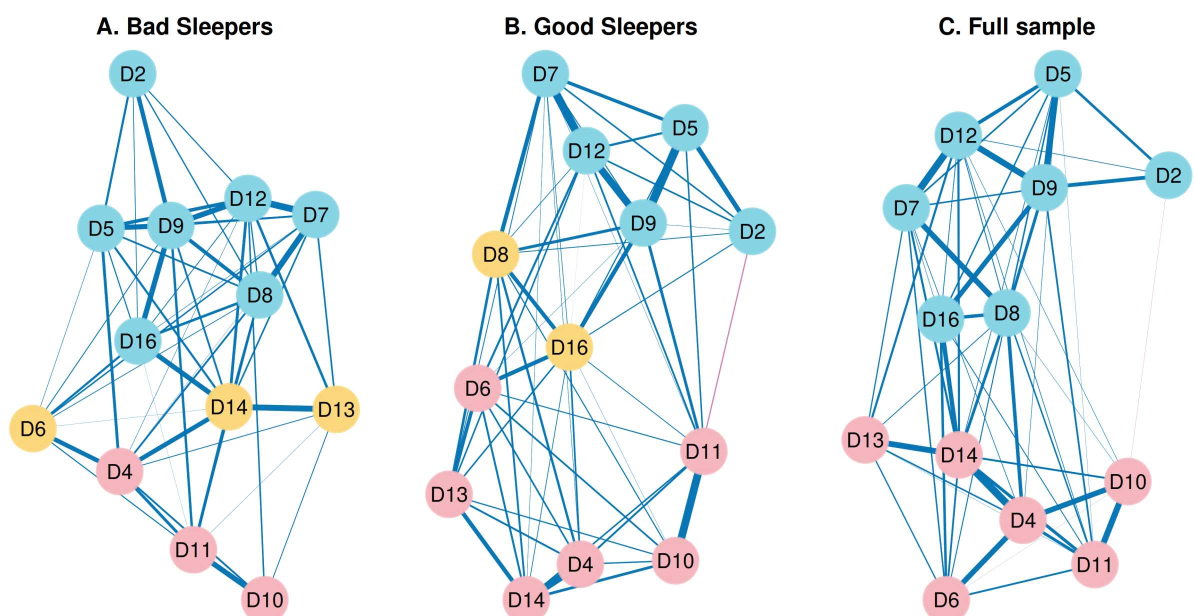


Figure 3

EGA plots for the subgroups of bad sleepers (Panel A), good sleepers (Panel B), and for the full sample (Panel C). Colors identify different item clustering. Blue edges represent positive associations and red edges represent negative ones.



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