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Should Child Pain Anxiety Be Modeled as a Multidimensional Latent Construct or as a Network of Interrelated Symptoms? A Psychometric Comparison in Spanish Clinical and Community Populations

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Abstract

Background: Pain anxiety—an anxiety response specifically focused on pain and its anticipation—is a clinically significant psychological process in children and adolescents, predicting functional disability and poorer adjustment over and above pain intensity itself. How this construct is conceptualised and assessed therefore has direct implications for clinical evaluation and intervention. A long-standing question is whether the symptoms captured by pain anxiety scales reflect a single underlying latent trait or a network of directly interacting, mutually reinforcing symptoms—a distinction with both theoretical and clinical consequences that has never been examined in a paediatric pain instrument. Using the Spanish version of the Child Pain Anxiety Symptoms Scale (CPASS), we directly compared latent variable and psychometric network models to clarify how pain anxiety in children is best understood and measured.

Methods: In 415 children and adolescents (8-18 years) from clinical (n=195) and community (n=220) settings, we applied a fully cross-validated pipeline: exploratory factor and exploratory graph analysis on a first random split, and confirmatory factor and confirmatory network estimation on the held-out split. Three competing latent models (two-factor, four-factor and second-order) and a confirmatory network model were compared on identical data using non-overlapping RMSEA confidence intervals and AIC. Measurement invariance and network-structure invariance were evaluated in parallel across sex, age and clinical status, and two estimation packages (lavaan and psychonetrics) were contrasted for ordinal data.

Results: The methodological choice proved consequential. The confirmatory network model fitted better than every latent specification (highest CFI and TLI, lowest RMSEA with non-overlapping confidence intervals, and lowest AIC). Items that a four-factor solution would discard behaved as clinically meaningful bridge symptoms within the network, and both measurement and network invariance broke down between clinical and community samples—conclusions a conventional CFA-only evaluation would have missed. Within the latent framework, a parsimonious two-factor structure (ω=.90) showed the strongest cross-sample congruence.

Conclusions: Pediatric pain anxiety is better characterised as a network of mutually reinforcing symptoms than as the passive reflection of a single latent trait, with highly central and bridge symptoms representing promising targets for clinical assessment and intervention. The Spanish CPASS is supported as a psychometrically sound measure of pain anxiety, best summarised by a parsimonious two-factor structure (Fear and Catastrophizing about Pain; Anxiety and Avoidance Response to Pain), although the breakdown of measurement and network invariance between clinical and community samples means that scores require contextualised interpretation across these populations. More broadly, directly comparing latent and network models—rather than defaulting to confirmatory factor analysis—can reshape the substantive and clinical conclusions drawn from a psychological assessment instrument.

Background

Pain is one of the most universal yet most challenging experiences for humans to assess. In children, the painful experience is particularly subjective because their cognition is still developing and their communication skills are more limited and dependent on the caregiver's interpretation [1]. This developmental dependency introduces unique measurement challenges, as children's ability to identify, label, and communicate their pain experiences changes substantially across developmental stages. Chronic pain affects approximately 20.8% of children and adolescents, constituting a significant health problem with far-reaching consequences for physical functioning, school attendance, social participation, and psychological well-being [2]. Contemporary models conceptualise pain as a multidimensional experience integrating sensory, affective, cognitive and behavioural components within a biopsychosocial framework that evolves throughout development. This biopsychosocial perspective recognizes that biological, psychological, and social-environmental influences interact dynamically to shape the child's pain experience. Within this framework, psychological variables play a crucial role in the study of paediatric pain. Fear of pain, catastrophising and anxiety are strong predictors of long-term functional disability and adjustment; often explaining more variability in outcomes than pain intensity itself [3]. These findings highlight the importance of assessing psychological processes related to pain when evaluating children and adolescents living with it. The concept of pain anxiety has emerged as particularly relevant, both theoretically and clinically. It refers to an anxiety response specifically focused on pain or pain-related stimuli, characterised by catastrophic thoughts, emotional distress, physiological arousal, and avoidance behaviours. Pain anxiety differs conceptually from generalised anxiety disorders (GADs) due to its specific stimulus and fear relating to acute pain, as well as its prospective orientation towards anticipated pain [4–6]. This distinction is clinically important because, while generalised anxiety is characterised by diffuse worry across multiple life domains, pain anxiety is specifically triggered by pain-related cues and oriented towards the anticipation of future pain episodes. According to the fear

avoidance model of chronic pain [7], pain anxiety and fear initiate a vicious cycle of avoidance behaviours, hypervigilance and emotional distress, which contributes to pain persistence and functional disability. Importantly, this model emphasises that fear and anxiety, rather than pain intensity per se, are the primary drivers of long-term disability, positioning pain anxiety as a key therapeutic target. High levels of pain anxiety have been linked to an increased risk of chronic pain, greater disability, higher analgesic consumption and greater use of healthcare services [8, 9].

The Children's Pain Anxiety Symptom Scale (CPASS) was developed by Pagé et al. [10] as the first instrument specifically designed to assess pain anxiety in children and adolescents, adapting the Adult Pain Anxiety Symptom Scale (PASS [6, 11]). The scale originally comprised four interrelated dimensions, which were assessed using 20 items: cognitive anxiety, fear, avoidance and physiological anxiety. These four dimensions were theoretically grounded in the multidimensional conceptualization of pain anxiety proposed by McCracken and colleagues, who posited that pain anxiety manifests through distinct but interrelated cognitive, emotional, behavioural, and physiological channels. Initial validations in community and clinical samples in Canada showed satisfactory reliability and validity, supporting the four-factor theoretical structure [10, 12]. In Spanish-speaking contexts, two validation studies have been conducted in Spain: Sánchez-Rodríguez et al. [13] validated the Catalan version in a community sample of adolescents, while Ceniza-Bordallo et al. [14] validated the Peninsular Spanish version in hospitalised children, replicating the four-factor model after removing two items. Although valuable, these studies were limited by homogeneous samples, relatively small sample sizes for advanced psychometric modeling and the absence of systematic evaluation of measurement invariance across clinically relevant groups. The lack of invariance testing is a notable gap, given that measurement equivalence is a prerequisite for meaningful score comparisons across populations and for ensuring that observed group differences reflect true differences in the construct rather than differential item functioning. Furthermore, no study has examined whether a network structure better accounts for the relationships among symptoms compared to a latent variable model.

Psychological phenomena studied using psychometric methods have traditionally been examined within the latent variable framework, which assumes that unobserved common causes—latent variables or factors—account for the covariation among observed indicators. Under this framework, items on a questionnaire are considered interchangeable reflections of a common underlying construct, and their correlations are explained by the shared influence of that construct. Over the past decade, however, psychometric network models have emerged as a viable alternative framework, attributing covariation to direct interactions among observed variables rather than to shared latent causes [15]. For instance, in intelligence research, network models have challenged traditional g-factor explanations by showing that networks of cognitive indicators can provide a better fit to the data than hierarchical g models, thereby supporting alternative theories like mutualism theory [16]. These ideas have also been extended to the field of personality, where network-based frameworks have been proposed to study the validity of personality questionnaires [17]. However, one of the fields in which the debate between latent and network frameworks has been most prominent is psychopathology, particularly in the theoretical conceptualization of symptoms. Comorbidity has increasingly been conceptualized as arising from direct relations among symptoms across disorders—through symptom bridges, overlapping symptoms, and fuzzy diagnostic boundaries—rather than from relations between latent disorders [18]. Network approaches have been used in large samples of depression and anxiety to identify bridge symptoms and symptom communities as mechanisms underlying comorbidity [19, 20]. It therefore seems that modeling the symptomatology of a disorder in one way or another may lend support to different theoretical frameworks for understanding the phenomenon, highlighting the importance of directly comparing these models.

In this context, Kan et al. [21] recently proposed a method for comparing psychometric network models with latent variable models using the R package psychonetrics [22]. This method has been applied, for example, to compare factor and network models of cognitive abilities [23]. However, to date, no study has applied network models, nor conducted comparisons with factor models, in child pain anxiety questionnaires such as the CPASS.

The present study addresses these methodological gaps through a comprehensive analysis of the psychometric properties of the Spanish version of the CPASS in a large and diverse sample of Spanish children and adolescents (8–18 years) that includes both clinical and community populations. Specifically, our study examines: (1) alternative exploratory factor solutions to those proposed in the previous literature, (2) comparisons of fit between confirmatory factor and network models; (3) measurement and network invariance across age, gender, and clinical status; and (4) additional psychometric properties, including essential unidimensionality and internal consistency.

Method

Participants

A total of 415 children and adolescents took part in the study. The sample size exceeds the minimum recommended for advanced psychometric modeling, including confirmatory factor analysis, network analysis, and multigroup invariance testing, which typically require at least 200 participants per group for stable parameter estimation [24]. The community sample comprised 220 participants recruited from public, private and state-funded schools in the city of Toledo, Spain. The clinical sample included 195 participants recruited from inpatient units of the University Hospital and the National Hospital for Paraplegics in Toledo (Spain). Clinical settings included general pediatrics (27.9%), pediatric surgery (27.4%), oncology (8.1%), traumatology (6.1%), intensive care (6.1%), neurosurgery (3.0%), day hospital and inpatient units at the National Hospital for Paraplegics (21.3%). This diversity of clinical settings was intentionally sought to enhance the ecological validity of the findings and to capture the heterogeneous nature of pediatric pain presentations encountered in routine clinical practice.

Inclusion criteria were: (a) age between 8 and 18 years, (b) ability to read and understand Spanish, and (c) informed consent provided by legal guardians and assent by the children or adolescent. Exclusion criteria were refusal to participate and presence of intellectual disability that impaired comprehension or fulfilment of the questionnaires.

No statistically significant differences were found between clinical and community samples in age ($p = .30$) or sex ($p = .051$). The clinical sample had a mean age of 12.58 years ($SD = 2.61$; 45.18% girls) while the community sample had a mean age of 12.89 years ($SD = 2.61$; 54.71% girls). As expected, the clinical sample reported a higher prevalence of pain in the past 24 hours (63.78% vs. 48.88%; $p = .002$) and higher pain intensity scores ($M = 4.70$, $SD = 3.12$) compared to the community sample ($M = 3.77$, $SD = 2.89$; $p = .002$) (Table 1 Appendix in the online repository).

Table 1
Descriptive item analysis and exploratory factor analysis models

Item								2F EFA		Bifactor EFA		
	N	Mean	*SD*	Skew	Kurtosis	pBis	α*	F1	F2	GF	F1	F2
1	415	1.157	1.420	1.162	.506	.477	.895	0.563	0.121	0.47	0.29	-
2	415	1.836	1.669	.508	− .982	.593	.891	0.855	-0.02	0.60	0.43	-
4	410	1.505	1.692	.771	− .762	.447	.896	0.557	0.072	0.44	0.30	-
7	412	1.495	1.646	.798	− .605	.472	.895	0.525	0.086	0.44	0.26	-
9	410	1.063	1.338	1.216	.619	.575	.893	0.547	0.278*	0.56	0.31	-
13	413	1.337	1.658	1.033	− .247	.579	.892	0.95	-0.091	0.60	0.42	-
16	412	0.495	1.126	2.650	6.566	.377	.897	0.481	0.073	0.33	0.22	-
18	413	1.896	1.778	.495	-1.114	.538	.893	0.374	0.276*	0.51	0.26	-
19	413	2.530	1.738	.031	-1.330	.660	.889	0.559	0.29*	0.63	0.26	-
3	414	3.444	1.608	− .720	− .683	.444	.896	-0.04	0.552	0.40	-	0.26
5	415	2.325	1.712	.097	-1.245	.583	.892	0.052	0.7	0.54	-	0.38
6	412	2.585	1.773	− .072	-1.295	.558	.892	-0.11	0.778	0.53	-	0.39
8	411	2.219	1.924	.244	-1.474	.412	.897	0.077	0.48	0.39	-	0.27
10	410	2.039	1.729	.296	-1.257	.645	.890	0.225*	0.618	0.59	-	0.38
11	413	2.169	1.782	.258	-1.285	.537	.893	-0.013	0.721	0.50	-	0.36
12	413	1.637	1.702	.693	− .842	.451	.895	0.079	0.449	0.41	-	0.27
14	413	2.090	1.794	.344	-1.257	.634	.890	0.407*	0.499	0.61	-	0.28
15	405	1.185	1.560	1.222	.384	.374	.897	0.079	0.475	0.34	-	0.25
17	414	2.529	1.745	.038	-1.294	.681	.889	0.254*	0.593	0.63	-	0.37
20	415	3.263	1.757	− .658	− .924	.441	.896	-0.143	0.682	0.41	-	0.29
								CFI = 0.964; TLI = 0.954 SRMR = 0.06; RMSEA = 0.07 rF1-F2 = 0.673		ECV = 0.695; ω T = .90; ω F1 = .84; ω F2= .83; RMSEA = 0.068		

Note: SD: standard deviation. α* = alpha if item is deleted (α Total = .893); (*)=crossloading > 0.20; (-) = loadings magnitude < 0.20; GF=General Factor; F1 = Factor 1; F2 = Factor 2

Instruments

Sociodemographic and Clinical Questionnaire

Participants reported demographic information (age, sex, school grade, number of siblings) and clinical variables including pain presence across different time frames (past 24 hours, past month, past six months, and duration > 3 months), pain location, medical conditions, and analgesic use.

Child Pain Anxiety Symptoms Scale (CPASS)

The CPASS is a 20-item scale that measures symptoms of pain anxiety in children and adolescents aged 8 to 18 years. Items are rated on a six-point Likert-type scale from 0 (never) to 5 (always), with total scores ranging from 0 to 100. Higher scores indicate greater pain anxiety. Each item describes a specific cognitive, emotional, behavioural, or physiological reaction to pain or the

anticipation of pain. The scale comprises four original subscales: cognition, anxiety, fear and avoidance. The psychometric properties of the scale have been previously evaluated in adults [6], and in children in community [10] and clinical [12] samples. Adequate psychometric properties were demonstrated by the studies of Sánchez-Rodríguez et al. [13] in Catalan and Ceniza-Bordallo et al. [14] in Spanish.

Procedure

The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and received approval from the Ethics and Clinical Research with Medicines Committee of the Toledo University Hospital (CEIC 8/03/2023: 976). Written informed consent was obtained from legal guardians and assent or consent was obtained from participants when appropriate. Data collection in educational settings was supervised by school staff, whereas in healthcare settings the principal investigator explained the study objectives and administered the questionnaires in a standardised order. The administration of the CPASS was identical across settings to ensure consistency and reduce potential sources of measurement error. All data were treated confidentially in accordance with Spanish data protection legislation (Organic Law 3/2018 on Personal Data Protection and Guarantee of Digital Rights).

Data Analysis

Missing data, floor and ceiling effects, and comprehension of the questionnaire were assessed descriptively. Floor or ceiling effects were considered present when ≥ 15% of respondents obtained the lowest or highest possible scores [25]. Descriptive statistics for each item were calculated, assuming that asymmetry and kurtosis values did not exceed absolute values of 2 [26]. The Anderson–Darling test [27] and the Mardia test [28] were used to examine univariate and multivariate normality, respectively. Dimensionality was explored using parallel analysis with principal axis extraction, as well as Exploratory Graph Analysis based on the Louvain algorithm with 500 bootstrap samples [29–31]. The Kaiser–Meyer–Olkin (KMO) measure was used to assess sampling adequacy for factor analysis, with values above 0.80 considered acceptable [32]. All analyses were conducted in R version 4.4.1 [33] using the following packages: MVN version 5.9 [34]; CTT version 2.3.3 [35]; EGAnet version 2.0.7 [36].

To enable cross-validation between exploratory and confirmatory approaches, and to subsequently assess invariance across clinical status samples, each sample was randomly divided into two subsamples: the clinical (n1 = 110, n2 = 110) and the community (n3 = 98, n4 = 97) sample. The first subsamples (n1 + n3=208) were combined for exploratory analyses, both latent and network, whereas the second subsamples (n2 + n4=207) were reserved for confirmatory analyses, again including both latent and network approaches. This split-sample design ensures that model parameters estimated in the exploratory phase are genuinely cross-validated on independent data, thereby reducing the risk of capitalisation on chance and enhancing the generalisability of findings. Importantly, this approach also allowed for the assessment of measurement invariance between clinical and community subsamples within each split.

The estimation of the Exploratory Factor Analysis (EFA) was conducted following the recommendations set out in the literature [37, 38]. Based on our dimensionality results, the internal structure of the CPASS scale was subsequently assessed using EFA with four, three and two correlated factors, applying Oblimin rotation and Weighted Least Squares estimation (WLSMV) [39]. For each model, we focused on three aspects: (a) goodness of fit, (b) the magnitude of factor loadings and cross-loadings, and (c) the congruence between EFA solutions in the clinical and community samples, assessed using the Tucker Congruence Index (coefficients of .85–.94 indicate moderate similarity; above .95, factor equality) [40].

Confirmatory factor analysis (CFA) was conducted on the second subsample to cross-validate the factor structure identified in the exploratory analyses. The model derived from the current study (two-factor solution) was compared with models recommended in the previous literature: the four-factor model proposed by Pagé et al. [12] and the second-order model with four first-order factors suggested by Ceniza-Bordallo et al. [14]. CFA was performed using the unweighted least squares (ULS) estimator, treating items as ordered and handling missing data pairwise. Other estimators commonly used for ordinal variables, such as diagonally weighted least squares (DWLS), were not selected because, in our analyses, they produced overestimated fit indices (e.g., CFI > 1), which are theoretically implausible and potentially misleading. Since the authors of the psychonetrics package currently note on its website that "ordinal data support is experimental and has not yet been fully validated" for its CFA function, these analyses were complemented using both psychonetrics (version 0.13.2) [22] and lavaan (version 0.6–19) [41] R packages.

For the estimation of the exploratory network model and the comparison between confirmatory factor and network models, we followed the procedure outlined by Kan et al. [21]. From the first combined subsamples, a psychometric network was extracted. Specifically, the full partial correlation matrix was first computed, and then this matrix was pruned at α = 0.05. The skeleton (adjacency matrix) of the pruned network is referred to as "the network model." This model was then fitted in a truly confirmatory approach to the second combined subsamples. This procedure is comparable to the cross-validation approach applied to the exploratory-confirmatory factor models, ensuring that the comparison between latent and network frameworks is conducted on the same confirmatory data for a fair and methodologically rigorous evaluation.

The fit of the three confirmatory factor models and the confirmatory network model was evaluated using a comprehensive set of fit indices. These included the Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Standardized Root Mean Square Residual (SRMR), and Root Mean Square Error of Approximation (RMSEA). The use of multiple fit indices from different families—incremental (CFI, TLI), absolute (SRMR), and parsimony-adjusted (RMSEA)—ensures a balanced evaluation of model adequacy. The following recommended thresholds were used as indicators of good and acceptable fit, respectively: CFI ≥ .95 and .90; TLI ≥ .95 and .90; RMSEA ≤ .06 and .08; and SRMR ≤ .08 and .10 [42, 43]. The Akaike Information Criterion (AIC) was also estimated, with lower values indicating a better balance between model fit and parsimony. The model with the lowest AIC was considered to provide the best relative fit and, therefore, the best summary of the data. Bayesian Information Criterion (BIC) could not be computed using the psychonetrics package with ordinal estimators.

To examine potential differences in network structure across groups, we first estimated separate networks for each group: males versus females, children under 12 versus those 12 and older, and clinical versus community samples. In the unconstrained model, the network structure (Ω matrix) was allowed to vary freely across groups. We then estimated a constrained model in which the network structure (Ω) was held equal across groups. The fit of the unconstrained and constrained models was compared using a chi-square difference test to determine whether imposing equality of the network structure significantly reduced model fit. Visualization of each group network was performed using the qgraph package (version 1.9.8) [44].

Measurement invariance was studied using the lavaan R package according to gender, age (under 12 years old versus those over or equal to 12 years old) and population type, evaluating configural invariance (equal structure), metric invariance (equal factor loadings) and scalar invariance (equal intercepts) by inspecting the loss of fit with each new degree of restriction by estimating the second-order model to the responses obtained in the 20 items. Specifically, changes in the CFI, TLI and RMSEA indices were used to evaluate each level of measurement invariance, considering that values of ΔCFI and ΔTLI ≤ −.010 and ΔRMSEA ≥ .015 indicate a relevant loss of fit and therefore, a lack of invariance [45]. In cases where scalar invariance was observed, independent two-sample Student's t-tests were conducted to compare the CPASS mean scores between the respective groups. Effect sizes were estimated with Cohen's d and interpreted following prior guidelines, with values of approximately 0.10, 0.20, and 0.30 representing small, medium, and large effects [46].

The essential unidimensionality of the CPASS was examined in line with the recommendations of Reise et al. [47]. Proportional reduction of mean squared errors (PRMSEs) compared true score estimates using domain-specific versus total scores via the Haberman method [48]. An exploratory bifactor model was also estimated using the Schmid-Leiman transformation, Oblimin rotation, and ULS estimator. Internal consistency was assessed using Cronbach's alpha (α), McDonald's omega (ω) and hierarchical omega (ωh), following Doval et al. [49] recommendations. Values above .70 were considered satisfactory. The following R packages were used for previous analysis: subscore (version 3.3) [50] and psych (version 2.4.12) [51].

With the intention of being as transparent as possible the R syntax, the anonymized database and the appendix tables were provided at an Open Science Framework (OSF) online repository: https://osf.io/qk3sv/overview?view_only=767aa6879e664b35a8f0fd1e40550e1c

Results

Item Analysis

Analysis of missing data revealed a minimal pattern of missingness for the CPASS. The overall percentage of missing values was 0.63%, with 9.37% of participants presenting at least one missing response and 90.60% providing complete data. Only six participants (1.6%) reported not fully understanding the CPASS items. These participants were significantly younger (M = 9.83, SD = 1.94) than

those who reported full comprehension (M = 12.75, SD = 2.72; p = 0.014), suggesting that younger children may benefit from additional guidance when completing the scale. No participant achieved the maximum possible score (100), and only 1% obtained the minimum score (0). Therefore, no floor or ceiling effects were observed, indicating that the response scale adequately captures the range of individual differences in pain anxiety.

Table 1 presents a descriptive analysis of the items on the CPASS scale. Item level skewness and kurtosis values were within acceptable limits (absolute values < 2) for all items except Item 16 ("When I am in a lot of pain, I think I will never be able to move again"), which showed marked skewness (3.15) and kurtosis (6.57), as well as the lowest mean score (M = .50, SD = 1.13). This suggests that catastrophic immobility beliefs were rarely endorsed by participants, possibly reflecting the extreme nature of this cognitive distortion which may be less accessible to children with limited pain experiences. Corrected item-total correlations ranged from .37 (Item 15) to .68 (Item 17), indicating that all items contributed meaningfully to the total score. Deletion of individual items produced only minimal increases in internal consistency, with the largest changes observed for Items 16 and 15 (α = .897), suggesting that no single item substantially compromised scale reliability.

Exploratory Factor Analysis

Sampling adequacy for factor analysis was excellent (Kaiser–Meyer–Olkin index = .91). Parallel analysis based on principal components suggested a two-factor solution, whereas Exploratory Graph Analysis using the Louvain algorithm identified a four-factor structure in 67.6% of bootstrap samples and a five-factor structure in 15.6%. However, the replication stability of the bootEGA solution was below 0.50 for a few items, meaning that these items were classified into the final suggested community in less than 50% of the bootstrap samples. Based on these results, EFAs with two, three, and four correlated factors were estimated. The four-factor model showed the best absolute fit indices (CFI = .982, TLI = .971, RMSEA = .056, SRMR = .043), followed by the three-factor model (CFI = .972, TLI = .959, RMSEA = .066, SRMR = .051) and the two-factor model (CFI = .964, TLI = .954, RMSEA = .07, SRMR = .06). However, factorial congruence analyses between clinical and community samples revealed that the two-factor solution showed the highest stability and replicability. Tucker's congruence coefficients for the two-factor model were .80 and .72 for Factors 1 and 2, respectively, indicating factorial equivalence across samples. In contrast, congruence coefficients for the four-factor model and three-factor model ranged from .55 to .77 and from 0.38 to 0.78, respectively, suggesting poor structural replicability. This discrepancy between absolute fit and cross-sample stability underscores the importance of evaluating factorial congruence alongside model fit when selecting an optimal factor solution in heterogeneous samples.

Given the criteria of parsimony, interpretability, and factorial stability, the two-factor solution was retained as the optimal model (Table 1). Factor 1 was defined by items 1, 2, 4, 7, 9, 13, 16, 18, and 19, with standardized factor loadings ranging from .374 to .950. This factor, labeled "Fear and Catastrophizing about Pain," comprises items reflecting worry, fear, and catastrophic thoughts related to pain. Factor 2 included items 3, 5, 6, 8, 10, 11, 12, 14, 15, 17, and 20, with factor loadings between .449 and .778. This factor, labeled "Anxiety and Avoidance Response to Pain," encompasses items related to cognitive responses, avoidance behaviors, and somatic reactions. The correlation between factors was .673, indicating a strong yet discriminable association. Five items showed cross-loadings above .20: Item 9 ("When I feel pain I think I might be really sick"), 10 ("When I have pain, it is hard for me to think about anything else"), 14 ("When I have pain, I think about it all the time"), 18 ("I find it hard to relax after pain") and 19 ("I worry when I feel pain"). Alternative solutions were not retained because multiple items exhibited substantial cross-loadings across factors, reducing the clarity and stability of the factor structure. Specifically, the three and four-factor models showed 9 and 10 items with cross-loadings (λ > 0.20), respectively (see Table 2 Appendix in the online repository).

Table 2
Confirmatory Network and Factor Model comparisons

Model	*Software package psychonetrics*						*Software package lavaan*					
	χ² (df)	**p**	**CFI**	**TLI**	**RMSEA [CI 95]**	**AIC**	**χ² (df)**	**p**	**CFI**	**TLI**	**RMSEA [CI 95]**	**SRMR**
Network model	**532.12 (152)**	**< 0.001**	**0.990**	**0.988**	**0.116 [0.105; 0.127]**	**688.12**	—	—	—	—	—	—
Latent Model 2F	1204.59 (169)	< 0.001	0.975	0.972	0.172 [0.163; 0.181]	1326.59	305.269 (169)	< 0.001	0.978	0.975	0.052 [0.039; 0.064]	0.078
Latent model 4F	1047.97 (164)	< 0.001	0.979	0.976	0.161 [0.152; 0.171]	1179.97	240.706 (164)	< 0.001	0.983	0.980	0.046 [0.033; 0.059]	0.074
Second Order latent Model (4F)	1092.40 (166)	< 0.001	0.978	0.975	0.164 [0.155; 0.174]	1220.40	267.476 (166)	< 0.001	0.979	0.975	0.051 [0.038; 0.063]	0.078

Note: preferred model in bold;

Confirmatory Factor and Network Analysis

The range of factor loadings was very similar across latent models: 0.449–0.769 for the two-factor model, 0.467–0.725 for the second-order model, and 0.467–0.757 for the four-factor model. The CFA fit results obtained using the lavaan and psychonetrics R packages were almost identical between factor models for the CFI and TLI indices (ΔCFI = .003, ΔTLI = .003) but differed notably for RMSEA, with psychonetrics producing a higher RMSEA value. However, this pattern of RMSEA differences between package estimations was consistent across all three factor models (ΔRMSEA = 0.120; ΔRMSEA = 0.115; ΔRMSEA = 0.113), suggesting that relative comparisons across models can still be carefully conducted. This systematic discrepancy is likely attributable to differences in the handling of ordinal data and the experimental nature of the ordinal support in the psychonetrics package. Overall, the CFI and TLI values indicated satisfactory fit for all models, and the RMSEA and SRMR values provided by lavaan were also within acceptable ranges. Notably, the network model yielded the highest CFI and TLI values, the lowest RMSEA value (with non-overlapping 95% confidence intervals), and the lowest AIC value, reflecting a better fit compared to the factor models (see Table 2).

Using the visualization of the estimated network, Fig. 1 illustrates that, if one aims to examine the dimensionality of this questionnaire within a latent variable framework, the two-factor structure appears more clearly differentiated than the four-factor structure. Some items exhibit strong correlations with each other, such as items 19 and 13, yet they are assigned to different factors in previous literature. Given that model fit was nearly identical across the factor models (Table 2), a two-factor solution—being more parsimonious and previously validated in another independent sample through EFA—may provide a better factorial representation of the questionnaire's dimensionality in a large, heterogeneous sample of clinical and community participants spanning a wide age range. Certain items, such as 19, 14 and 9, exhibit high centrality within the network, which is consistent with the occurrence of cross-loadings in the EFA. This convergence between network centrality and cross-loadings suggests that these items occupy meaningful positions at the intersection of different symptom domains.

Network Structure Invariance

The constrained models (imposing equality of the network structure) significantly reduced model fit between clinical and community samples ($\Delta\chi^2 = 1335.79$; $\Delta df = 38$; $p < .001$; $\Delta RMSEA = 0.05$), male and female groups ($\Delta\chi^2 = 731.75$; $\Delta df = 38$; $p < .001$; $\Delta RMSEA = 0.02$), and children and adolescents ($\Delta\chi^2 = 577.11$; $\Delta df = 38$; $p < .001$; $\Delta RMSEA = 0.01$). As shown in Fig. 2, the positioning of nodes in the network appears to differ across groups, revealing some differences in the connectivity of the estimated networks. For instance, item 19 shows a stronger association with items 13 and 14 in the community sample, among males, and in children under 12 years of age. These differential connectivity patterns suggest that the bridge function of specific symptoms may be moderated by demographic and clinical variables, with implications for context-sensitive assessment and intervention.

Measurement Invariance

Measurement invariance across sample type (clinical vs. community) showed good configural fit (see Table 3). Although metric and scalar models also demonstrated acceptable overall fit, changes in fit indices (metric: ΔCFI = − .006, ΔTLI = − .007, ΔRMSEA = .010; scalar: ΔCFI = − .014, ΔTLI = − .015, ΔRMSEA = .020) indicated only partial support for invariance. By gender, configural invariance was adequate, and both metric and scalar invariance were supported despite significant χ^2 differences, given the minimal changes in fit indices (metric: ΔCFI = − .003, ΔTLI = − .002, ΔRMSEA = .004; scalar: ΔCFI = − .010, ΔTLI = − .005, ΔRMSEA = .007), supporting meaningful comparisons of latent means. Similarly, invariance across age groups (< 12 vs. ≥12 years) was supported at configural, metric, and scalar levels, with negligible changes in fit indices (metric: ΔCFI = − .003, ΔTLI = − .001, ΔRMSEA = .002; scalar: ΔCFI = − .007, ΔTLI = − .004, ΔRMSEA = .003), allowing valid latent mean comparisons.

Finally, females (M = 2.04, SD = 0.94) scored significantly higher than males (M = 1.81, SD = 0.98; p = .005, d = − .279) on the CPASS mean total score, a pattern that was consistent across both factors. No significant differences were found between participants younger than 12 years (M = 1.91, SD = 0.97) and those aged 12 years or older (M = 1.96, SD = 0.97; p = .60, d = 0.058). This absence of age-related differences in mean scores is consistent with the measurement invariance findings and suggests that the overall level of pain anxiety remains relatively stable across the developmental range assessed in this study.

Essential Unidimensionality

Essential unidimensionality was evaluated using PRMSE indices and an exploratory bifactor model. When the original four-factor structure was considered, PRMSE values favored the use of the total score only for Physiological Anxiety (PRMSE total score = 0.74; PRMSE subscale = 0.68). However, when applying the two-factor structure identified in the EFA, PRMSE values were higher for the subscale scores (PRMSE = .83 for Factor 1 - Fear and Catastrophizing about Pain - and .84 for Factor 2 - Anxiety and Avoidance Response to Pain) than for the total score (PRMSE = .79 and .83, respectively), suggesting greater precision for the subscales. This pattern indicates that the two-factor structure captures specific variance that would be lost when only the total score is computed, reinforcing the clinical value of reporting both subscale scores. The bifactor model yielded an Explained Common Variance (ECV) of .695, indicating a strong but non-dominant general factor. According to established criteria, this pattern reflects multidimensionality with a meaningful general factor. Omega total for the CPASS was .90, with specific omega coefficients of .84 for Factor 1 and .83 for Factor 2. Model fit for the bifactor solution was acceptable (RMSEA = .068).

Internal Consistency

Internal consistency for the CPASS total score was excellent (Cronbach's α = .90; McDonald's ω = .90). The two-factor solution showed satisfactory reliability for both Fear and Pain Catastrophizing (α = .84; ω = .84) and Anxiety and Avoidance Response (α = .83; ω = .83), supporting its robustness. In contrast, although the original four-factor structure yielded reliability coefficients comparable to those reported in previous studies, these were consistently lower than those observed for the two-factor solution. Notably, the Physiological Anxiety subscale demonstrated only marginal reliability (α = .67), reinforcing concerns about its internal consistency and suggesting limited utility as a distinct dimension. Overall, these findings provide additional support for the superiority and parsimony of the two-factor model over the original four-factor structure (Table 3 Appendix in the online repository).

Discussion

The present study provides a comprehensive psychometric evaluation of the Spanish version of the Child Pain Anxiety Symptoms Scale (CPASS) in a large and heterogeneous sample of clinical and community children and adolescents. The findings offer novel evidence with important theoretical and clinical implications for the assessment of pain anxiety in pediatric populations.

A central and novel contribution of this study is the direct comparison between latent variable and network models applied to the CPASS. The network model yielded the highest CFI and TLI values, the lowest RMSEA and AIC value, reflecting a superior fit compared to all confirmatory factor models. This pattern suggests that modeling pediatric pain anxiety symptoms as a network of directly interrelated indicators, rather than solely as manifestations of an underlying latent construct, provides a more adequate representation of the observed data. To our knowledge, this is the first study to apply network models and conduct formal comparisons with factor models in a child pain anxiety questionnaire. This result extends to the pediatric pain anxiety domain what has been previously documented in adjacent fields. In intelligence research, network models have outperformed hierarchical g-factor models, lending support to mutualism theory [16, 23]. In psychopathology, network approaches have increasingly been adopted to

model comorbidity between depression and anxiety as arising from direct symptom-to-symptom interactions rather than from covariation among latent disorders [19, 20].

From a theoretical standpoint, the superiority of the network model aligns with contemporary conceptualizations of psychopathology and pain-related constructs that challenge the assumption of latent common causes. According to the network theory of mental disorders [15, 52], symptoms are not passive indicators of an underlying entity but rather causally interconnected elements whose mutual activation sustains and propagates psychological disturbance. Applied to pain anxiety, this perspective implies that catastrophic cognitions, fear responses, avoidance behaviors, and physiological arousal do not merely reflect a single latent pain anxiety construct; instead, they directly influence one another in a dynamic system. For instance, catastrophic thoughts about pain (e.g., item 2: "When I feel pain I am afraid that something terrible will happen") may directly activate worry (item 19: "I worry when I feel pain"), which in turn fuels avoidance behavior and somatic hyperarousal, creating self-reinforcing cycles consistent with the fear-avoidance model of chronic pain [7]. This theoretical integration between the network perspective and the fear-avoidance model offers a more mechanistic understanding of how pain anxiety maintains itself in pediatric populations.

The network visualization further revealed that certain items exhibited high centrality, notably items 19, 14, and 9. These are the same items that showed substantial cross-loadings in the exploratory factor analysis, suggesting that they function as bridge symptoms connecting different domains of pain anxiety. The concept of bridge symptoms has been central to network approaches to comorbidity [18, 19], and their identification in the CPASS has important clinical implications. Bridge symptoms represent potential leverage points for intervention: targeting a symptom that connects different symptom domains—such as worry (item 19), which bridges fear/catastrophizing with anxiety/avoidance responses—could disrupt the reinforcing dynamics across domains and thus yield broader therapeutic effects.

Notably, these bridge items include items 18 ("I find it hard to relax my body after I feel pain") and 19 ("I worry when I feel pain"), which Ceniza-Bordallo et al. [14] proposed eliminating from the scale on the basis of poor fit within the four-factor structure. From a network perspective, however, the removal of these items would be inadvisable. Their cross-domain connectivity is not a psychometric weakness but rather substantive evidence that they capture clinically meaningful interrelations between symptom domains. Bridge symptoms, by definition, do not belong neatly to a single factor; they span the boundaries between symptom clusters. Eliminating them would impoverish the measure's ability to capture the interconnected nature of pain anxiety and would discard potentially critical targets for clinical intervention. This finding supports the broader idea, advanced by network theorists, that strict boundaries between symptom domains or diagnostic categories are artificial [15, 18], and that psychometric instruments should preserve items that reflect the interconnectedness of psychological phenomena.

The clinical implications of these findings are noteworthy. If pain anxiety symptoms are mutually reinforcing rather than arising from a common latent cause, therapeutic interventions might benefit from targeting highly central and bridge symptoms rather than attempting to modify the putative underlying construct as a whole. Cognitive-behavioral interventions for pediatric pain could prioritize symptoms with high network centrality—such as worry, fear of being seriously ill, and somatic shaking—as disrupting these nodes may cascade through the symptom network and attenuate the broader constellation of pain anxiety. This approach aligns with recent proposals in clinical psychology for network-informed intervention strategies that identify the most influential symptoms as primary therapeutic targets [15].

When examined within the latent variable framework, the two-factor structure—Fear and Catastrophizing about Pain and Anxiety and Avoidance Response to Pain—emerged as the most parsimonious solution. Although the four-factor model proposed by Pagé et al. [10] yielded marginally better absolute fit indices in the exploratory analyses, the two-factor model demonstrated substantially superior factorial congruence between clinical and community samples, stronger internal consistency for its subscales, and a more coherent theoretical interpretation.

These two dimensions—catastrophizing fear and pain on the one hand, and anxiety and avoidance response on the other—align closely with the distinction between cognitive-emotional appraisals of threat and behavioral-physiological responses that has been endorsed in previous research. López-Martínez et al. [53] similarly identified a two-factor structure in the adult Spanish PASS differentiating anxiety (an emotional response to fear) from fear (a cognitive response to threat), and Sharif-Nia et al. [54] reported a two-dimensional solution in an Iranian post-surgical adult population. The discrepancy with the four-factor structures reported by Pagé et al. [10, 12], Sánchez-Rodríguez et al. [13], and Ceniza-Bordallo et al. [14] likely reflects methodological differences: the present

study applied stricter factorial congruence criteria, systematically evaluated replicability across samples, and included both clinical and community populations. Both methodological features led to the identification of a more generalizable structure.

The essential unidimensionality analysis provided further evidence in favor of the two-factor solution. The bifactor model yielded an Explained Common Variance (ECV) of .695, indicating a strong but non-dominant general factor that, according to established criteria [47], reflects multidimensionality with a meaningful general component. Critically, the PRMSE analysis revealed that, under the two-factor structure, subscale scores provided more reliable estimates than the total score. This contrasts with the four-factor model, in which the total score provided more reliable estimates than most subscale scores. This finding means that, when applying the two-factor structure, reporting the two subscale scores yields greater precision than reporting a single total score—a pattern that did not hold for the original four-factor solution and that further supports the clinical utility and psychometric superiority of the two-dimensional model.

Regarding internal consistency, the CPASS demonstrated excellent overall reliability, comparable to or better than previous studies. The two-factor solution produced satisfactory reliability for both subscales, whereas the four-factor model yielded consistently lower coefficients, with the Physiological Anxiety subscale showing only marginal reliability, replicating the concerns reported by Pagé et al. [10], Sánchez-Rodríguez et al. [13], and Ceniza-Bordallo et al. [14]. These convergent findings across multiple independent studies conducted in different languages and cultural contexts further reinforce the adoption of the more parsimonious two-factor structure as the preferred dimensional model for the CPASS.

The question of whether to use total or subscale scores has been debated in the CPASS literature. Pagé et al. [10] found moderate to high factorial correlations suggesting related yet distinguishable factors, and subsequently observed that different subscales differentially predicted postoperative outcomes [12]. Sánchez-Rodríguez et al. [13] reported that subscales had greater predictive validity for functional interference than the total score. Our results suggest that both scoring approaches are useful but serve different purposes: the total score is appropriate for initial screening and general group comparisons, whereas subscale scores are preferable for detailed individual assessments, planning of targeted interventions, and research examining specific pain anxiety mechanisms.

A distinctive feature of this study is the separate examination of both measurement invariance (within the latent variable framework) and network structure invariance across age, gender, and clinical status groups. Regarding measurement invariance, configural invariance was confirmed across all grouping variables, and both metric and scalar invariance were supported across gender and age groups. These results support the validity of comparing latent means between boys and girls and between children and adolescents, confirming that the CPASS items function equivalently across these demographic groups. Consistent with this, females scored significantly higher than males on the CPASS, a pattern that aligns with the broader literature on sex differences in pain-related anxiety and fear in pediatric populations. A key finding of our study was the absence of strict metric invariance between clinical and community samples. While practical fit indices pointed to acceptable invariance, a significant chi-square test revealed differences in factor loadings between populations. This suggests that certain items may be potentially less relevant depending on the context. As this is the first study to assess CPASS invariance between clinical and community populations, our findings suggest that direct comparisons of scores between these groups should be approached with caution and may require population-specific norms.

Similarly, regarding network structure invariance, constraining the network structure (Ω matrix) to equality across groups produced significant chi-square difference tests for all three grouping variables. However, the practical loss of fit across gender was modest. The multigroup network visualizations provide a more nuanced understanding of these differences. Regarding gender, the overall network topology was broadly similar between males and females, although some differences in the strength of specific edges were apparent. In particular, item 19 ("I worry when I feel pain") showed a stronger association with items 13 ("Feeling pain is very scary") and 14 ("When I feel pain, I think about it all the time") in males compared to females, suggesting that the bridge function of worry between fear and cognitive preoccupation may be more pronounced in boys. By age, children under 12 years also exhibited stronger connectivity between item 19 and items 13 and 14 compared to adolescents aged 12 and older. This developmental difference may reflect changes in the cognitive elaboration of pain anxiety across childhood and adolescence: younger children may experience a more tightly interconnected symptom cluster in which worry, fear, and rumination about pain reinforce each other more directly, whereas in adolescents, the differentiation of cognitive and emotional processes may lead to a more modular network structure. These age-related differences in network connectivity are consistent with developmental models of pain processing that emphasize increasing cognitive sophistication and emotional regulation capacity throughout adolescence [55]. Despite these group-specific variations in network connectivity by gender and age, the overall pattern of symptom interrelations was sufficiently preserved to

suggest that the CPASS network captures a broadly similar architecture of pain anxiety symptoms across these demographic groups—a conclusion that converges with the acceptable measurement invariance observed in the latent variable framework.

However, both measurement and network invariance were markedly problematic between clinical and community samples. In the measurement invariance analysis, changes in fit indices at the metric and scalar levels exceeded recommended thresholds, indicating only partial support for invariance. Network structure invariance showed an even more pronounced deterioration, the largest across all group comparisons. The multigroup network visualizations revealed notable differences in the positioning and connectivity of nodes between clinical and community samples. Compared to the community sample, the clinical network displayed a different pattern of symptom clustering, with altered edge strengths between several symptom pairs. For instance, the association between item 19 and items 13 and 14 was stronger in the community sample, whereas the clinical sample appeared to show a more diffuse pattern of connectivity—possibly reflecting the greater heterogeneity of pain experiences in a clinical population encompassing diverse pathologies (general pediatrics, surgery, oncology, traumatology, intensive care, and neurorehabilitation). These structural differences in the symptom networks between populations suggest that the way pain anxiety symptoms interact with one another may fundamentally differ depending on whether children are experiencing acute clinical pain versus the more common pain experiences reported in community settings. From a network theory perspective, this implies that the causal dynamics sustaining pain anxiety may operate differently across populations, potentially requiring distinct intervention targets.

These converging results from both psychometric frameworks—latent and network—indicate that certain items may function differently depending on clinical context, a finding consistent with the heterogeneous nature of clinical pain populations where the specific manifestation and relative salience of anxiety symptoms may vary with the type, chronicity, and intensity of the pain condition. Consequently, direct comparisons of CPASS scores between clinical and community populations should be approached with caution and may require population-specific norms or interpretation guidelines. Indeed, the most significant methodological limitation we encountered when evaluating the conclusions of previous studies was the absence of invariance analysis. Only Sharif-Nia et al. [54] verified factorial invariance before comparing gender differences, and no previous study has examined network invariance in child pain anxiety instruments.

Despite these contributions, several limitations should be acknowledged that contextualize the interpretation of our findings. The cross-sectional design precluded the assessment of temporal stability (test-retest reliability) and longitudinal predictive validity for acute-to-chronic pain transitions. Responsiveness to change was not evaluated, limiting the applicability of the CPASS for intervention assessment. Incremental validity over established measures was not examined. Although the sample was large and diverse, the clinical subsample was heterogeneous in terms of underlying pathology, which may limit the generalizability of findings to specific pediatric pain conditions. Furthermore, the network model comparison relied on confirmatory cross-validation within the same dataset; replication in independent samples from different cultural and clinical contexts would strengthen the conclusions regarding the superiority of the network model and increase the generalisability of these findings.

Future research should address several priorities to build upon the present findings and advance the field of pediatric pain anxiety assessment: (1) longitudinal studies examining developmental trajectories of pain-related anxiety and its role in pain chronification, ideally incorporating temporal network models to examine how symptom interactions unfold over time; (2) the establishment of clinically significant cutoff scores through criterion validity studies; (3) cross-cultural comparisons across Spanish-speaking countries; (4) the examination of CPASS psychometric properties in specific pediatric conditions, such as headaches, recurrent abdominal pain, and musculoskeletal pain; and (5) intervention studies that directly test whether targeting high-centrality and bridge symptoms in the network produces greater therapeutic effects than conventional approaches, thereby empirically evaluating the clinical utility of the network perspective.

Conclusions

In conclusion, the Spanish version of the CPASS is a psychometrically sound instrument for assessing pain anxiety in children and adolescents. The proposed bidimensional structure—Fear and Catastrophizing about Pain and Anxiety and Avoidance Response to Pain—provides a theoretically coherent and empirically supported representation of the construct, improving both interpretability and reliability relative to the original four-factor model. Network analyses further indicate that pain anxiety symptoms are better characterized as a system of mutually reinforcing indicators than as mere reflections of a single latent dimension, highlighting the clinical relevance of highly central and bridge symptoms. The integration of both latent variable and network perspectives offers a comprehensive framework for understanding pain anxiety that transcends the limitations of either approach alone and provides

actionable insights for clinical intervention. Overall, these findings support the use of the CPASS in both research and clinical practice, while underscoring the need for contextualized interpretation and cautious score comparison across clinical and community populations in light of only partial evidence for measurement and network invariance.

Abbreviations

CPASS
Child Pain Anxiety Symptoms Scale
PASS
Pain Anxiety Symptoms Scale
GAD
generalised anxiety disorder
EFA
exploratory factor analysis
CFA
confirmatory factor analysis
EGA
exploratory graph analysis
KMO
Kaiser–Meyer–Olkin
WLSMV
weighted least squares mean- and variance-adjusted estimator
ULS
unweighted least squares
DWLS
diagonally weighted least squares
CFI
comparative fit index
TLI
Tucker–Lewis index
RMSEA
root mean square error of approximation
SRMR
standardized root mean square residual
AIC
Akaike information criterion
BIC
Bayesian information criterion
PRMSE
proportional reduction of mean squared error
ECV
explained common variance
SD
standard deviation
OSF
Open Science Framework.

Declarations

Ethics approval and consent to participate

The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and was approved by the Ethics and Clinical Research with Medicines Committee of the Toledo University Hospital (reference CEIC 976; 8/03/2023). Written informed consent was obtained from the legal guardians, and assent or consent was obtained from the participating children and adolescents.

Consent for publication

Not applicable.

Availability of data and materials

The datasets generated and analysed during the current study, together with the R syntax and the appendix tables, are available in the Open Science Framework (OSF) repository: https://osf.io/qk3sv/

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

CRediT role	Author(s)	Specific contribution
Conceptualization	B. Huidobro Labarga, E. López Dolado, R Castañeda Vozmediano	Defined research question; framed the latent-vs-network comparison; selected target population (clinical + community).
Methodology	B. Huidobro Labarga, R Castañeda Vozmediano	Designed analytic pipeline (EFA + EGA + CFA + network + invariance); selected estimators; specified split-sample cross-validation.
Software	R Castañeda Vozmediano	R scripts in lavaan, psychonetrics, EGAnet, qgraph, MVN, CTT, psych, subscore. All code deposited at OSF.
Validation	B. Huidobro Labarga, R Castañeda Vozmediano	Cross-validated models on independent subsamples; verified estimator behaviour by replicating analyses across lavaan and psychonetrics.
Formal analysis	B. Huidobro Labarga, R Castañeda Vozmediano	Conducted all statistical analyses: descriptives, EFA, EGA, CFA (three competing models), network estimation, invariance tests, bifactor, PRMSE, internal consistency.
Investigation	B. Huidobro Labarga, E. López Dolado, E Aguirre Sánchez	Recruitment and questionnaire administration in inpatient units (Toledo University Hospital, National Hospital for Paraplegics) and in collaborating schools (Colegio Mayol; Colegio Fábrica de Armas; Colegio Juan de Padilla; Colegio San Patricio; IES Sefarad; IES Universidad Laboral).
Resources	E. López Dolado,	Provision of clinical access, ethics committee gateway, hospital infrastructure, and school liaison.
Data curation	B. Huidobro Labarga,	Anonymisation, cleaning, missing-value coding, OSF deposition (https://osf.io/qk3sv/).
Writing — Original Draft	B. Huidobro Labarga, R Castañeda Vozmediano	Drafting of all manuscript sections.
Writing — Review & Editing	All authors	Critical revision for intellectual content; methodological refinement; English-language revision.
Visualization	R Castañeda Vozmediano	Network visualisations (Figures 1 and 2) using qgraph; tables.
Supervision	E. López Dolado, E Aguirre Sánchez, M Alvarez de Mon Soto	Senior oversight of clinical and methodological aspects; mentoring of first author.
Project administration	B. Huidobro Labarga, E. López Dolado	Coordination of recruitment in two hospital settings and six educational centres; ethics committee submission and follow-up.
Funding acquisition	B Huidobro Labraga.	Catedra de Cuidados Paliativos. Universidad Francisco de Vitoria.

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Table

Table 3 is available in the Supplementary Files section.

Figures

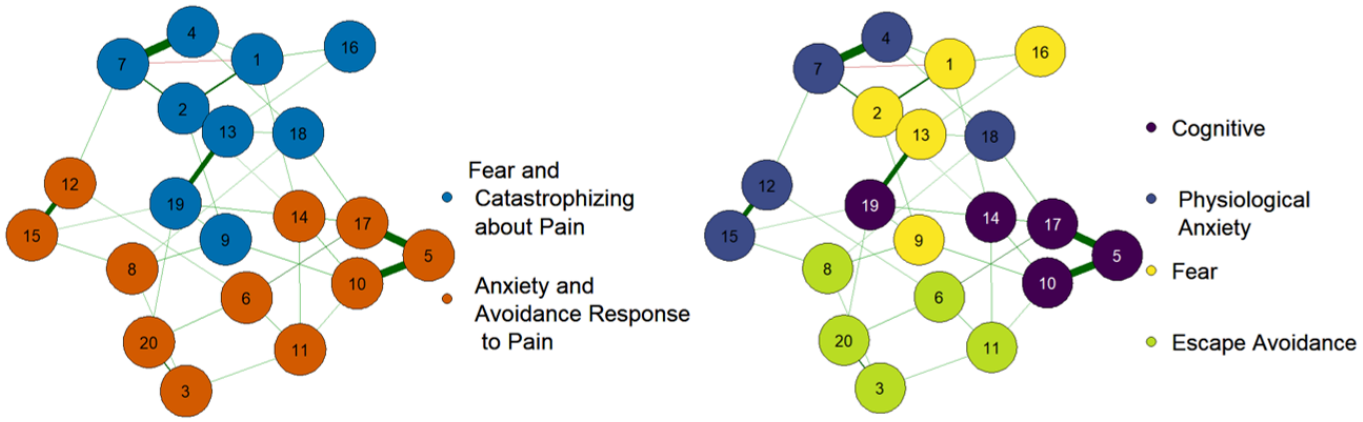


Figure 1

Graphical representation of the confirmatory CPASS network model (left: factors identified through exploratory factor analysis in this work; right: factors proposed in the previous literature by factor modelling).

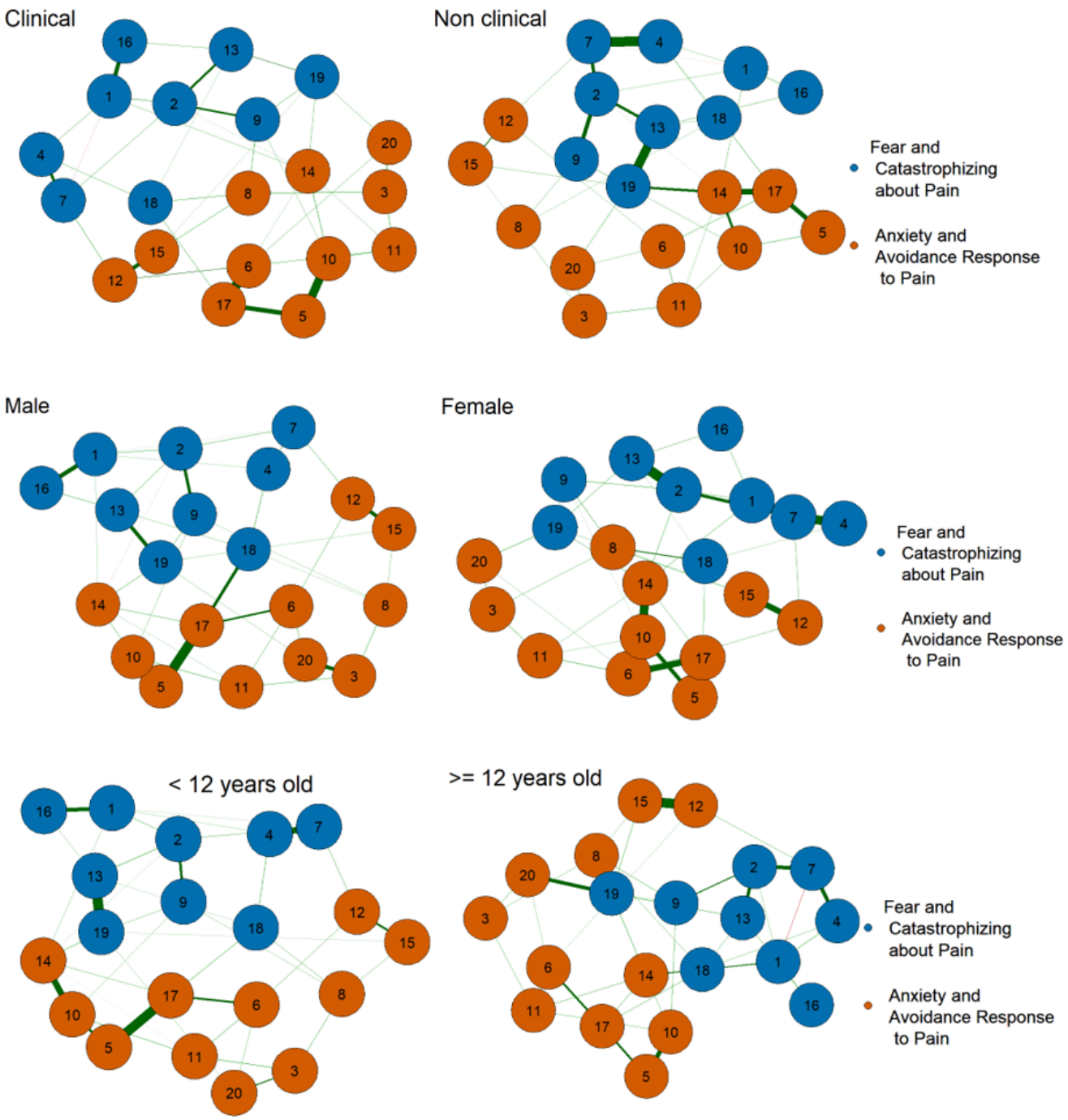


Figure 2

Multi-Group networks by age, gender, and clinical status

Supplementary Files

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- Table3.docx