

Original Research

From the Intolerance of Uncertainty Scale–5 to the Intolerance of Uncertainty Scale–4: Psychometric Evaluation and Refinement of an Ultra-Brief Intolerance of Uncertainty Scale in a Sample of Spanish Adults

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Abstract

Background: Intolerance of uncertainty (IU) is a central transdiagnostic vulnerability factor across emotional disorders. However, currently available scales present important limitations, particularly excessive length and factorial instability. **Methods:** This study evaluated the psychometric properties of the Intolerance of Uncertainty Scale–5 (IUS-5) in a sample of Spanish adults ($n = 998$) using a cross-sectional online study design with a cross-validation approach that included exploratory graph analyses, redundancy testing, confirmatory factor analyses, and assessments of reliability and convergent validity. **Results:** Network analyses supported a unidimensional structure but identified item redundancy. Confirmatory analyses indicated that a four-item model (IUS-4) provided the best fit to the data. The IUS-4 demonstrated adequate internal consistency ($\omega = 0.79$), satisfactory convergent validity at the construct level (average variance extracted [AVE] = 0.53), moderate to large correlations with anxiety sensitivity ($r = 0.53$), and moderate correlations with anxiety, depressive, and obsessive–compulsive symptoms ($r = 0.41$ – 0.42). **Conclusions:** These findings support the IUS-4 as a brief, psychometrically robust, unidimensional measure of IU in the Spanish population. Further research is warranted to examine its applicability in clinical samples and its potential utility as a screening tool.

Keywords: intolerance of uncertainty; IUS; psychometric validation; Spanish population

1. Introduction

The transdiagnostic model of psychopathology seeks to identify the shared mechanisms driving different mental disorders (Dalglish et al., 2020). Within this compelling framework, intolerance of uncertainty (IU) stands out as a key vulnerability and maintaining factor across a wide spectrum of psychopathology (Antuña-Cambor et al., 2024; McEvoy et al., 2019; Shihata et al., 2018). IU has been defined as “an individual’s dispositional incapacity to endure the aversive response triggered by the perceived absence of salient, key, or sufficient information, and sustained by the associated perception of uncertainty” (Carleton, 2016, p. 31). People with a high level of IU regularly experience distress (McEvoy et al., 2019), particularly in ambiguous situations (Costello et al., 2025; Kusec et al., 2024; McEvoy et al., 2019) and tend to anticipate the worst possible outcome.

This construct was originally conceptualized as a cognitive vulnerability specific to worry and generalized anxiety disorder (GAD) (Dugas et al., 1998; Freeston et al., 1994). However, previous studies have shown that ele-

vated IU is also associated with depressive and obsessive–compulsive symptoms, eating pathology, and other emotional difficulties, thus supporting IU as a broad transdiagnostic vulnerability factor rather than a disorder-specific construct (Correa et al., 2019; Nelson et al., 2014; Yao et al., 2022). Longitudinal studies and meta-analyses (McEvoy et al., 2019; McEvoy and Erceg-Hurn, 2016) have found robust, moderate associations between IU and a range of emotional symptoms. Those studies have also reported potential associations between IU and the severity and maintenance of emotional psychopathology, particularly anxiety-related disorders.

Given the importance of this construct in different mental disorders, several scales have been developed to measure IU. Of these, the most commonly used scale is, without question, the Intolerance of Uncertainty Scale (IUS-27; Freeston et al., 1994). The IUS-27 is widely regarded as the gold standard tool. This scale has demonstrated excellent psychometric properties and it has been extensively and successfully used in cross-cultural settings. However, the factorial structure varies widely across sam-



ples and contexts (de Bruin et al., 2006; Sexton and Dugas, 2009). Concerns about length and structural inconsistency of this scale have prompted the development of more efficient measures, most notably the 12-item scale (IUS-12; Carleton et al., 2007), which is widely used and has been validated in multiple languages and populations (McEvoy et al., 2019; Shapiro et al., 2020). Although the IUS-12 has shown good reliability and convergent validity, questions remain regarding its dimensionality, with some studies supporting a two-factor model, which distinguishes between prospective and inhibitory IU, and others supporting a largely unidimensional structure dominated by a strong general IU factor.

While studies such as Carleton et al. (2007) have shown that the IUS-12 has a bifactorial structure formed by prospective and inhibitory IU, other studies have found that the prospective dimension of this scale is unreliable, leading them to propose a more parsimonious model, with a single general factor of intolerance to uncertainty (Bottesi et al., 2019; Shihata et al., 2018). In this context, recent research efforts have sought to develop a scale to capture the core construct using the fewest number of items possible. Bottesi et al. (2020) developed a five-item version (IUS-5) as a unidimensional instrument to measure IU, with promising results. More recently, Khamis et al. (2025) adapted this tool for use in a sample of nurses in Saudi ArabiaOman. However, they found a unidimensional structure with four items (item 5 did not correlate with all the other items). Ultra-short scales have certain advantages in both clinical and research settings. For researchers, a 4-item scale is valuable because it minimizes participant burden and survey fatigue, thus allowing the IU to be included in larger batteries of tests, where the use of longer instruments such as the IUS-27 would be impractical. For clinicians, an abbreviated tool serves as an efficient screening instrument in high volume settings such as primary care, thus allowing for the rapid identification of individuals who may require more intensive diagnostic evaluation. Although brief scales can undoubtedly make routine monitoring more feasible, the present study primarily focuses on the psychometric validation of the instrument in a general population.

This study aimed to validate the IUS-5 in a general population sample in Spain. This study also sought to examine the factor structure, estimate its reliability through internal consistency, and to examine the relationship between emotional symptoms (depressive, anxious, and obsessive-compulsive symptoms) and anxiety sensitivity. We hypothesized that the scale would show adequate fit and correlate with emotional symptoms and anxiety sensitivity as a transdiagnostic variable, and that the Omega index would demonstrate good internal consistency.

2. Materials and Methods

2.1 Participants and Procedure

A cross-sectional study was conducted using a self-administered, online survey (SurveyMonkey). Data were collected between August 2022 and September 2023. The study followed a snowball sampling approach in which a group of clinicians publicized the study by distributing promotional materials (infographics, social media, collaboration with professionals, and contact with associations). Participation was not incentivized monetarily or by any other means.

The mean time to complete the battery of test was approximately 30 minutes. Due to the observational nature of the study, the only inclusion criterion was being of legal age (age ≥ 18). At the end of the data collection period (approximately 13 months), a total of 1763 individuals had started the survey. However, only 998 (56.61%) of participants who met the inclusion criterion completed it correctly. Only questionnaires with complete responses on the variables included in the analyses were retained. Participants who failed to complete one or more items from the IUS or other measures included in this study were excluded. Missing data primarily reflected partially completed questionnaires rather than sporadic item omissions. To perform a cross-validation design, the total sample was randomly divided into two independent subsamples, one for exploratory graph analysis (EGA) ($n = 499$) and another for confirmatory factor analysis (CFA) ($n = 499$). Table 1 provides detailed information on the sociodemographic profile of the total sample and the subsamples.

In addition, given that some of the tested models differed in their item composition, model comparisons were conducted using information criteria (akaike information criterion [AIC], bayesian information criterion [BIC], and sample-size adjusted BIC), which are appropriate for non-nested models. To enable this comparison, all models were re-estimated using the robust maximum likelihood estimator (MLR). Lower values were interpreted as indicating better model fit and greater parsimony.

2.2 Instruments

Intolerance Uncertainty Scale-5 (IUS-5): This is an abbreviated version of the original 12-item IUS (Carleton et al., 2007). The IUS-5 assesses the tendency to react negatively to uncertain and unforeseen situations. This questionnaire consists of five items rated on a 5-point Likert scale, where 1 corresponds to “not at all characteristic of me” and 5 to “completely characteristic of me”. The total score is obtained by summing the item scores. Thus, total scores range from 5 to 25 points, with higher scores indicating greater intolerance of uncertainty. The internal consistency of the IUS-5 in the original study ranged from 0.76 to 0.87 (Bottesi et al., 2020).

Brief Symptom Checklist (LSB-50): This instrument assesses a set of psychological and somatic symptoms com-

Table 1. Characteristic of the sample.

Characteristics	Overall ($n = 998$)	Subsample 1 ($n = 499$)	Subsample 2 ($n = 499$)
Age	30.3 (15.3)	31.3 (15.3)	29.3. (15.3)
Gender			
Female	657 (65.8)	315 (63.1)	342 (68.5)
Male	341 (34.2)	184 (36.9)	157 (31.5)
Marital status			
Single	485 (48.6)	253 (50.7)	232 (46.5)
In a relationship	270 (27.1)	130 (26.1)	140 (28.1)
Married	195 (19.5)	91 (18.2)	104 (20.8)
Divorced	45 (4.5)	23 (4.6)	22 (4.4)
Widow	3 (0.3)	2 (0.4)	1 (0.2)
Education			
Primary education	23 (2.3)	12 (2.4)	11 (2.2)
Secondary education	99 (9.9)	50 (10.0)	49 (9.8)
High School	609 (61.0)	303 (60.7)	306 (61.3)
Bachelor	267 (26.8)	134 (26.9)	133 (26.7)
Level of income			
Low	30 (3.0)	13 (2.6)	17 (3.4)
Medium-Low	472 (47.3)	229 (45.9)	243 (48.7)
Medium-High	485 (48.6)	251 (50.3)	234 (46.9)
High	11 (1.1)	6 (1.2)	5 (1.0)

Note: Age is given in mean years (standard deviation [*SD*]); for all other characteristics n (%).

mon to various psychological disorders (de Rivera et al., 2012). Participants rate items on a five-point Likert scale, with higher scores indicating greater symptom severity. For this study, three of the subscales (depression, anxiety, and obsessive sensitivity) were used as a measure of convergent validity with the IUS-5 scale. The internal consistency of those three subscales was good: depression: $\alpha = 0.91$; $\omega = 0.91$; anxiety: $\alpha = 0.89$; $\omega = 0.90$; and obsessive sensitivity: $\alpha = 0.87$; $\omega = 0.88$.

Anxiety Sensitivity Index-3 (ASI-3): This is a self-report measure containing 18 questions that assess the degree to which individuals fear the negative consequences of anxiety-related symptoms and feelings (Taylor et al., 2007). The ASI-3 consists of one general factor with three subscales (physical, cognitive, and social concerns). All items are scored on a 5-point Likert scale ranging from 0 (very low) to 4 (very high). A higher score indicates a greater degree of sensitivity or fear of anxiety. For the present study, the general factor was used as a measure of convergent validity with the IUS-5. The internal consistency was good ($\alpha = 0.92$; $\omega = 0.92$).

2.3 Statistical Analyses

We assessed the structural validity, internal consistency, and convergent validity of the IUS-5 scale. The statistical programmes R (version 4.3.3; R Foundation for Statistical Computing, Vienna, Austria) and IBM SPSS (Version 29.0; IBM Corp., Armonk, NY, USA) were used for data management and analyses.

Structural validity was examined through a cross-validation design in which the total sample ($n = 998$) was randomly divided into two independent subsamples. In the first subsample ($n = 499$), an EGA was performed to identify the latent dimensional structure without prior theoretical restrictions (Golino and Epskamp, 2017). The EGA was estimated using the Graphical Least Absolute Shrinkage and Selection Operator (GLASSO) with the walktrap clustering algorithm (Christensen et al., 2024; Friedman et al., 2008). Item redundancy was evaluated with Unique Variable Analysis (UVA). The stability of the EGA solution was evaluated through a bootstrap with 5000 iterations (Christensen et al., 2023; Christensen and Golino, 2021). All EGA analyses were performed with the EGAnet package (v.2.3.0) in R.

In the second subsample ($n = 499$), a CFA was carried out using the lavaan package in R (0.6-19) to test the stability of the structure found (Rosseel, 2012). Given the ordinal nature of the items, the Weighted Least Squares Mean and Variance-adjusted (WLSMV) method was used, as this is the most appropriate estimator for non-normal categorical data (Li, 2016; Rhemtulla et al., 2012). For all models, the following were used to evaluate model fit: χ^2 index; comparative fit index (CFI); Tucker-Lewis index (TLI); root mean square error of approximation (RMSEA); and the standardised root mean square residual (SRMR) (Hu and Bentler, 1999; Kline, 2016). CFI/TLI values ≥ 0.90 and RMSEA/SRMR values < 0.08 are considered indicators of a good fit.

To ensure that the size of the subsamples ($n = 499$) provided sufficient statistical power for the EGA and CFA, a post-hoc verification was performed. For the CFA, the method proposed by MacCallum et al. (1996), based on the RMSEA, was used to assess the power of the overall fit test. For the EGA, the subsample was considered adequate based on Monte Carlo simulation studies, which have demonstrated that samples of ≈ 500 are highly accurate in identifying one-dimensional structures in psychometric networks (Golino et al., 2018).

Internal consistency was assessed with McDonald's omega (ω) coefficient, which is considered a more robust measure than Cronbach's alpha for scales containing ordinal data (McDonald, 1999). Convergent validity at the construct level was evaluated through the average variance extracted (AVE), which represents the average amount of variance explained by the latent factor relative to the variance due to measurement error (Fornell and Larcker, 1981). Cut-off levels to ensure adequate reliability and convergent validity, respectively, were as follows: $\omega > 0.70$ and AVE > 0.50 .

Convergent validity at the instrument level was examined using the entire sample ($n = 998$) by calculating Pearson's correlation coefficients (r) between the total IUS-4 score and other theoretically related constructs, as follows: the anxiety, depression, and obsessive-compulsive subscales of the LSB-50 and anxiety sensitivity (ASI-3). The magnitude of the associations was interpreted according to Cohen's (2013) criteria, where values of 0.10, 0.30, and 0.50 represent small, medium, and large effects, respectively.

3. Results

3.1 Attrition Analysis

To examine potential attrition bias, participants who completed the survey ($n = 998$) were compared with those who initiated but did not complete it ($n = 765$) on key sociodemographic variables. Independent samples t -tests and chi-square tests indicated no significant differences between completers and dropouts in age ($t = 1.21, p = 0.226$), gender ($\chi^2 = 1.84, p = 0.175$), marital status ($\chi^2 = 3.92, p = 0.416$), educational level ($\chi^2 = 4.11, p = 0.391$), or socioeconomic status ($\chi^2 = 2.76, p = 0.430$).

These findings suggest that attrition did not introduce systematic bias into the final sample.

3.2 Exploratory Graph Analyses

To examine the latent structure of the IUS-5, an EGA was performed on the first subsample. The analysis revealed the presence of a single global factor that grouped the five items of the scale, suggesting a clear unidimensional structure for the IU construct (Fig. 1). To assess the stability of this solution, a bootstrap EGA with 5000 iterations was performed. This analysis replicated the unidimensional structure in 99.96% of the 5000 iterations (95% CI: 0.96–

1.04), with no alternative solutions emerging. Furthermore, as shown in Table 2, all items showed 100% replicability. Network loadings ranged from 0.321 (item 2) to 0.621 (item 1).

UVA was used to study item redundancy based on weighted topological overlap (wTO). The results revealed significant redundancies between items 1–4 (wTO = 0.436), and 3–5 (wTO = 0.350).

3.3 Confirmatory Factor Analyses

CFAs were conducted on the second subsample. Four models were compared to determine the most parsimonious solution with the best psychometric fit (Fig. 2). The first model, the original five-item model (IUS-5^a), showed an inadequate fit, particularly in terms of approximation error (CFI = 0.973; TLI = 0.945; RMSEA = 0.124 [90% CI: 0.091–0.159]; SRMR = 0.047). Consistent with the EGA and UVA findings, the model modification indices suggested significant redundancy between items 3 and 5. Consequently, a second model (IUS-5^b) was evaluated, allowing for correlation between the error terms of these items. This respecification substantially improved the fit indices; however, the approximation error, although improved, remained close to the threshold of good fit (RMSEA = 0.068, 90% CI: 0.029–0.111) (Table 3). Considering the measurement noise and redundant variance associated with items 3 and 5, we decided to evaluate the fit of two more parsimonious models. First, we removed item 3 to create third model (IUS-4^a), which showed an excellent fit to the data that significantly outperformed the previous models (Table 3). Importantly, this superiority was further supported by information criteria comparisons, which confirmed that this model provided the best balance between fit and parsimony among all non-nested alternatives. Finally, a fourth model was specified in which item 5 was removed (IUS-4^b). However, this model showed a poor fit (Table 3). Moreover, removing item 3 resolved the most problematic overlap without compromising content validity, resulting in a model (IUS-4) where no new redundancies above the critical threshold (wTO > 0.20) were detected, thus achieving a balance between parsimony and representativeness.

The CFA results confirm that the IUS-4^a model is the most parsimonious and statistically robust solution. The post-hoc power check for this final model revealed a value of $1 - \beta > 0.99$ for the global fit test, confirming that the subsample size was sufficient to support the WLSMV estimator and ensure the stability of the parameters.

Because the evaluated models differed in their item composition, they constitute non-nested models. Therefore, model selection was additionally based on information criteria (AIC, BIC, and sample-size adjusted BIC [SABIC]) derived from models estimated using the MLR estimator. As shown in **Supplementary Material**, the IUS-4^a model consistently yielded the lowest values across all criteria (AIC = 5750.85; BIC = 5784.55; SABIC = 5759.16), out-

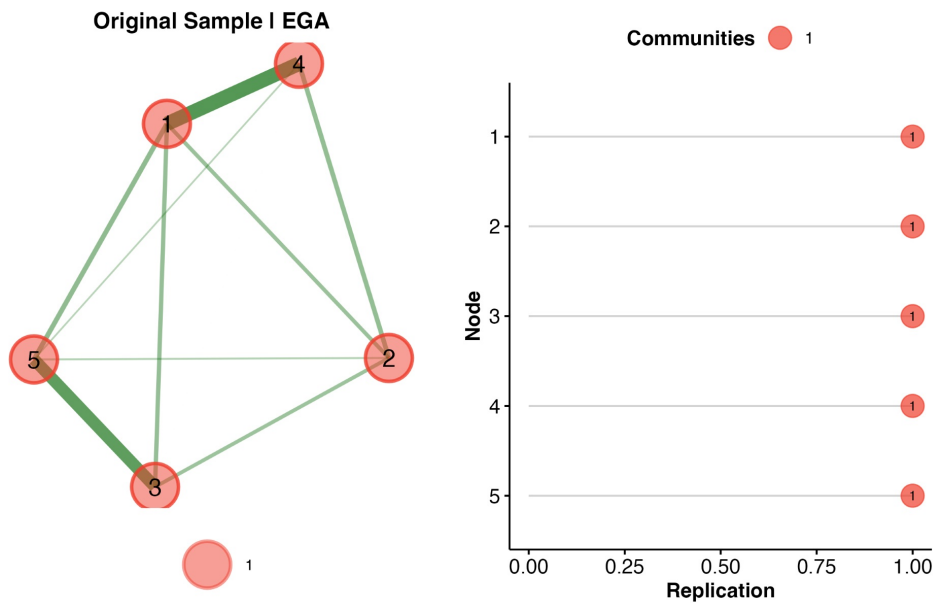


Fig. 1. Dimensionality assessment with exploratory graph analysis (EGA).

Table 2. Network loadings and percentage of replicability per item in dimensions on subsample 1.

Items		Network loadings	Percentage of replicability
Item 1	Los imprevistos me trastornan mucho	0.621	100%
Item 2	Cuando llega el momento de actuar, la incertidumbre me paraliza	0.321	100%
Item 3	Siempre quiero saber qué me depara el futuro	0.452	100%
Item 4	No soporto que me tomen por sorpresa	0.472	100%
Item 5	Debería poder organizar todo con anticipación	0.464	100%

Note: Replicability percentage obtained from bootstrapping with 5000 iterations.

Table 3. Summary of modelling adjustment.

Model	χ^2 (df)	p	CFI	TLI	RMSEA (90% CI)	SRMR
IUS-5 ^a	43.100 (5)	<0.001	0.973	0.945	0.124 (0.091–0.159)	0.047
IUS-5 ^b	13.281 (4)	0.010	0.993	0.983	0.068 (0.030–0.111)	0.026
IUS-4 ^a	0.648 (2)	0.723	1.000	1.003	0.000 (0.000–0.063)	0.007
IUS-4 ^b	10.871 (2)	0.004	0.992	0.975	0.094 (0.045–0.153)	0.030

Note: The IUS-5^a is the original 5-item model, the IUS-5^b allows the residuals of items 3 and 5 to correlate, the IUS-4^a removes item 3 from the model, and the IUS-4^b removes item 5 from the model. CFI, comparative fit index; RMSEA, root mean square error of approximation; TLI, Tucker-Lewis index; SRMR, standardized root mean square residual; χ^2 , chi-square; p , significance; df, degrees of freedom. In all cases, the indices were robust.

performing both the original five-item model and alternative four-item specifications. This result provides formal statistical support for the superiority of the IUS-4^a model in terms of parsimony and overall fit, reinforcing its selection as the final version of the scale.

3.4 Reliability and Convergence

The reliability of the models was assessed using the coefficient ω . Convergent validity at the construct level was analysed using AVE. Table 4 shows detailed results for the four proposed models. In terms of internal consistency, all

four models showed adequate values that were above the critical threshold level (0.70). The original IUS-5^a model was the most reliable ($\omega = 0.796$), followed by IUS-4^a ($\omega = 0.789$), IUS-4^b ($\omega = 0.762$), and IUS-5^b ($\omega = 0.761$). However, significant differences between the models in terms of AVE were observed, a finding that compromises the validity of all versions except model IUS-4^a. The IUS-5^a (AVE = 0.479), IUS-5^b (AVE = 0.465), and IUS-4^b (AVE = 0.498) models did not meet the minimum recommended cut-off of 0.50, suggesting that the measurement error in these models exceeds the variance explained by the latent factor. By con-

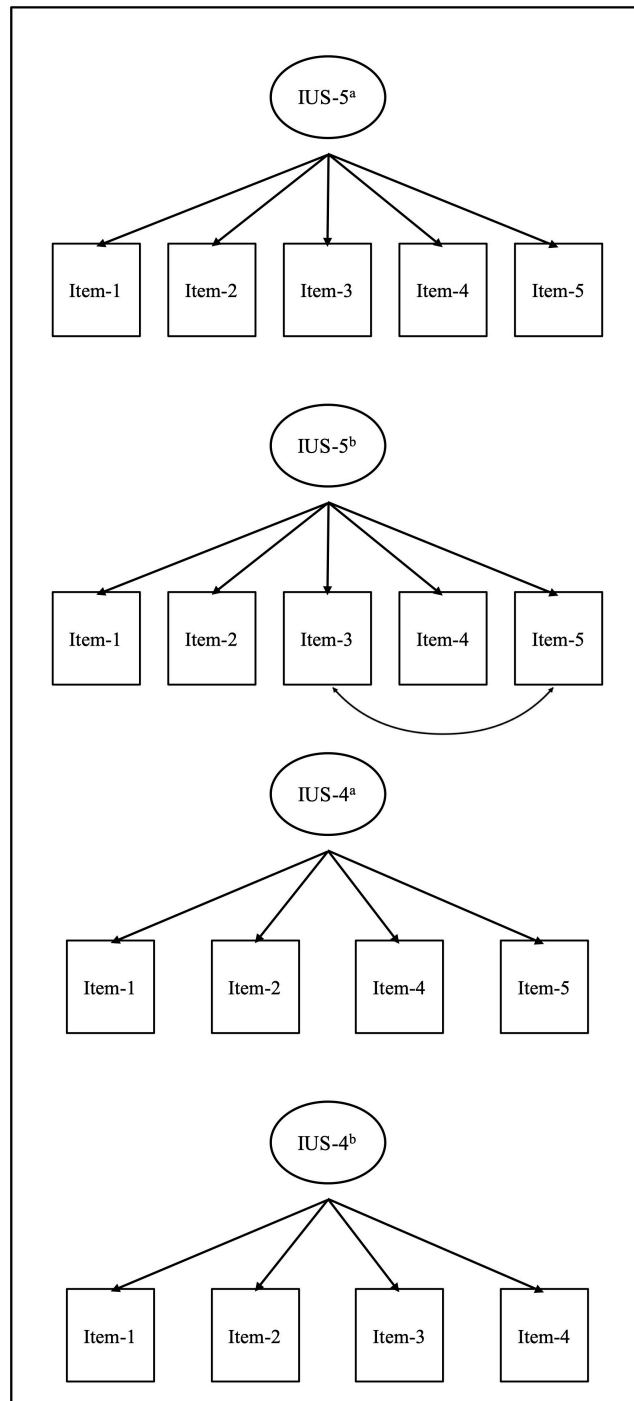


Fig. 2. Confirmatory factorial models proposed. The IUS-5^a is the original 5-item model, the IUS-5^b allows the residuals of items 3 and 5 to correlate, the IUS-4^a removes item 3 from the model, and the IUS-4^b removes item 5 from the model.

trast, the IUS-4^a model was the only one that demonstrated satisfactory convergence (AVE = 0.529).

Based on these findings, the IUS-4^a was selected as the definitive version of the scale. This decision was based on its parsimonious superiority and psychometric robustness, as it was the only model that simultaneously satisfied the criteria for structural fit, reliability, and convergent validity at the construct level. The exclusion of item 3, supported

by evidence of measurement noise and redundancy detected in the EGA and CFA phases, ensures a cleaner and more parsimonious structure to assess IU.

3.5 Convergent Validity With LSB-50 and ASI-3

The convergent validity of the IUS-4^a scale was examined with the LSB-50 and ASI-3 subscales. Pearson's correlation coefficients revealed positive and highly signif-

Table 4. Factor loadings, reliability and AVE.

Items	Standardised factor loadings			
	IUS-5 ^a	IUS-5 ^b	IUS-4 ^a	IUS-4 ^b
Item 1	0.864	0.884	0.879	0.883
Item 2	0.634	0.641	0.623	0.650
Item 3	0.515	0.455	-	0.455
Item 4	0.763	0.767	0.783	0.762
Item 5	0.629	0.583	0.584	-
ω	0.796	0.761	0.789	0.762
AVE	0.479	0.465	0.529	0.498

Note: The IUS-5^a is the original 5-item model, the IUS-5^b allows the residuals of items 3 and 5 to correlate, the IUS-4^a removes item 3 from the model, and the IUS-4^b removes item 5 from the model. AVE, Average Variance Extracted.

icant associations ($p < 0.001$) between the total IUS-4^a score and all dimensions assessed. The strongest correlation was observed with the ASI-3 ($r = 0.531$), underscoring the close theoretical link between IU and sensitivity to feelings of anxiety. The IUS-4^a showed moderate but consistent correlations with the LSB-50 symptom subscales, as follows: obsession-compulsion ($r = 0.424$), depression ($r = 0.418$), and anxiety ($r = 0.415$). These findings provide solid evidence of convergent validity, confirming that the 4-item brief version maintains the original instrument's capacity to capture a construct closely linked to emotional distress and anxiety sensitivity.

4. Discussion

The present study was performed to examine the psychometric properties of the Intolerance of Uncertainty Scale-5 (Bottesi et al., 2020) in a Spanish adult population. IU is a key transdiagnostic risk factor across multiple mental disorders (Antuña-Cambor et al., 2024; Dalgleish et al., 2020), which is why access to brief, psychometrically sound measures is crucial for both research and clinical applications. Overall, the findings presented in the present study support a unidimensional, four-item version of the IUS (IUS-4^a) as a psychometrically robust and parsimonious measure of this construct.

Consistent with contemporary transdiagnostic models of psychopathology, IU emerged in this study as a unified construct rather than a multidimensional one (Bottesi et al., 2019; Carleton et al., 2007; Yao et al., 2022), with the EGA revealing a clearly unidimensional structure. This result is consistent with prior research that supports a general factor model for IU rather than multidimensional solutions that distinguish between prospective and inhibitory components (Bottesi et al., 2020; Khamis et al., 2025; Shihata et al., 2018). From a theoretical standpoint, the unidimensional structure observed here supports the conceptualization of IU as a general dispositional tendency to perceive uncer-

tainty as aversive and threatening (Carleton, 2016), reinforcing its role as a core transdiagnostic vulnerability factor. Moreover, from a methodological point of view, unidimensionality is more appropriate for brief scales, such as the 4-item model proposed here (Stefana et al., 2025).

Although the original model was composed of five items, both network and confirmatory analyses identified redundancy and measurement noise, particularly involving item 3. The presence of significant weighted topological overlap between items 3 (“*I always want to know what the future has in store for me*”) and 5 (“*I should be able to organize everything in advance*”), as well as modification indices suggesting correlated residuals, indicated that these items shared variance not fully attributable to the latent IU factor. When item 3 was removed, the fit indexes of that model improved and, in fact, this was the only model to meet criteria for convergent validity ($AVE > 0.50$). Nonetheless, it is important to note that while an AVE of 0.53 is acceptable, it is close to the threshold, suggesting the presence of some unexplained variance that requires caution. Furthermore, although removing item 3 improved the statistical fit of the factorial model, removal of this item implies a potential loss of relevant content related to the construct. In this case, the explicit desire to know the future is represented only in the eliminated item. Consequently, the content of IUS-4^a must be interpreted in relation to the theoretical definition of IU, and it is essential to recognize that removing that item implies a trade-off: a slight narrowing in the conceptual breadth of the scale in exchange for increased psychometric precision. These findings suggest that parsimony is not merely a matter of brevity, but a prerequisite for cleaner measurement of the core IU construct. Similar difficulties with this item have been reported in other cultural contexts, including the recent Saudi Arabian adaptation by Khamis et al. (2025), where one of the items did not adequately correlate with the remaining indicators. In the cultural context of our study, it may have been possible to remove due to the specific sample, which primarily consisted of young adult Spaniards. In this regard, previous studies have shown that in Mediterranean setting and among speakers of Romance language (such as Spanish), the explicit, individualistic focus on the future is less central to people than it is in other cultural settings, and people in these cultures respond less readily to questions about future probability (Lee et al., 2017; Waid and Frazier, 2003). This is in line with validation studies in Spain for scales, in which some abstract or future-oriented items have poor loadings and such items must be discarded or reformulated in some cases due to cultural differences (Robles-Bello and Sánchez-Teruel, 2023). It is also important to note that the mean age of the participants in our sample was only 30 years, an age at which high objective uncertainty about life trajectories can make “always wanting to know the future” an atypical attitude, thus weakening the loading of that item (Zhang et al., 2024). Considered in this context, our results

raise the possibility that certain IU items may be more sensitive to cultural interpretation or contextual framing, underscoring the importance of empirical item-level evaluation in cross-cultural adaptations. In this regard, the present study extends the findings of the aforementioned studies by demonstrating that a four-item version not only preserves but in fact enhances the psychometric integrity of the scale in the Spanish population.

All of the models evaluated here demonstrated adequate internal consistency. Notably, the IUS-4^a maintained reliability levels comparable to the original five-item version, despite the reduction in item count. Evidence of convergent validity at the instrument level was strengthened by the pattern of associations observed between the IUS-4^a and theoretically-related constructs. The strongest correlation was found with anxiety sensitivity, underscoring the close conceptual link between IU and heightened reactivity to anxiety-related sensations (McEvoy et al., 2019). Moderate and consistent associations with anxiety, depression, and obsessive-compulsive symptoms replicate prior findings demonstrating the transdiagnostic relevance of IU across both internalizing and externalizing psychopathology (Correa et al., 2019; Nelson et al., 2014).

4.1 Limitations

This study has several limitations. First, the cross-sectional design does not allow us to make causal inferences or to evaluate the temporal stability, test-retest reliability, or predictive validity of the IUS-4. Consequently, the dynamic role of IU in the onset and maintenance of emotional symptoms remains unclear. Second, the exclusive use of self-report measures may have inflated associations due to shared method variance or response biases. Third, and most importantly, the study sample was recruited exclusively from a sample of non-clinical adults via an online platform. Because the sample did not include participants with formal diagnoses, the clinical applicability and validity of the IUS-4 remain insufficiently supported. The findings of this study thus represent the scale's performance within the general community and do not confirm its utility as a tool for clinical screening, diagnostic-assisted evaluation, or treatment outcome assessment. Another limitation related to the sample is that it consisted mainly of younger adults with internet access, which may further limit the generalizability of the results.

Future research studies should address these limitations through longitudinal interventional studies to assess temporal stability, sensitivity to change, and the predictive validity of the IUS-4. Critically, the psychometric properties of the IUS-4 need to be replicated in clinical samples. Future studies should incorporate group difference analyses between clinical and non-clinical populations to rigorously test the scale's discriminant validity and clinical sensitivity. In order to establish the IUS-4 as a robust tool for both research and clinical practice, it will be necessary to

utilize multimethod approaches such as clinician-rated assessments and/or ecological momentary assessment (EMA) and to test measurement invariance across diverse sociodemographic groups. Finally, the potential clinical utility of this tool (e.g., for screening), remains a subject for future research.

4.2 Clinical Implications

The findings of this study highlight the clinical utility of the IUS-4 as a brief, reliable, and psychometrically robust measure of IU. Its brevity makes it well-suited for time-limited clinical settings, large-scale screening, and routine outcome monitoring, while minimizing patient burden. Given the transdiagnostic relevance of IU, future studies should examine the potential value of the IUS-4 to identify individuals at elevated risk for anxiety, depressive, and obsessive-compulsive symptoms, particularly within transdiagnostic treatment frameworks. Finally, the strong correlation between the IUS-4 and anxiety sensitivity and emotional symptoms suggest that this tool may be useful for treatment planning and monitoring change in uncertainty-related processes over the course of psychological interventions.

5. Conclusions

The present study provides evidence showing that the IUS-4^a is a psychometrically robust, parsimonious, and theoretically coherent measure of intolerance of uncertainty in the Spanish adult population. These findings suggest that this scale may be a valuable tool to advance transdiagnostic research by improving assessment efficiency in both clinical and non-clinical contexts.

Abbreviations

ASI-3, anxiety sensitivity index-3; AVE, average variance extracted; CFA, confirmatory factor analyses; CFI, comparative fit index; CI, confidence interval; df, degrees of freedom; EGA, exploratory graph analyses; GAD, generalized anxiety disorder; GLASSO, graphical least absolute shrinkage and selection operator; IU, intolerance of uncertainty; IUS, intolerance of uncertainty scale; LSB-50, brief symptom checklist; M, mean; RMSEA, root mean square error of approximation; SD, standard deviation; SRMR, standardized root mean square residual; TLI, Tucker-Lewis index; UVA, unique variable analysis; WLSMV, weighted least squares mean and variance-adjusted; wTO, weighted topological overlap.

Availability of Data and Materials

All data reported in this paper are available from the corresponding author on reasonable request.

Author Contributions

CAC: conceptualization, investigation, writing—original draft, visualization, writing—review & editing. GEC: methodology, formal analysis, visualization, writing—original draft, writing—review & editing. RMN: conceptualization, visualization, writing—original draft, writing—review & editing. CEP: conceptualization, writing—original draft, writing—review & editing. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

The study was conducted in accordance with the Declaration of Helsinki. The research protocol was approved by the Research Ethics Committee of the Principality of Asturias (Ethic Approval Number: 2022.193), and all of the participants provided signed informed consent.

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Conflicts of Interest

The authors declare no conflicts of interest.

Supplementary Material

Supplementary material associated with this article can be found, in the online version, at <https://doi.org/10.31083/BP50981>.

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