Primenjena psihologija
Vol. 17, No. 3, pp. 331–359, 2024

Research Article

What Can Network Analysis Tell Us About the Intolerance of Uncertainty?

Marija Volarov [1] ✉, Mina Velimirović [1], Bojan Janičić [1], and Ljiljana Mihić [1]

[1] *Department of Psychology, Faculty of Philosophy, University of Novi Sad, Serbia*

ABSTRACT

In this study, we explored the network structure of intolerance of uncertainty (IU) using a community sample. We tested the interplay of emotions, behaviors, and beliefs about uncertainty (as measured by the Serbian Intolerance of Uncertainty-11 Scale) and evaluated whether our results would align with those obtained by the Italian researchers, considering the use of somewhat different versions of the scale in somewhat different cultural settings. The walktrap community detection algorithm yielded two communities referring to 1) Inhibitory anxiety and 2) Prospective anxiety. Thus, our findings suggest that IU can be decomposed into these two aspects regardless of which approach is used – network approach or factor analysis. The three most central nodes referred to perceiving uncertainty as upsetting and intolerable and believing one must avoid all the uncertainty. Two central nodes belonged to the Prospective anxiety community, and the third one belonged to the Inhibitory anxiety community and indicated reduced overall quality of life due to uncertainty. The roles of these three constituents in understanding the nature of IU are discussed further in the paper.

Keywords: intolerance of uncertainty, intolerance of uncertainty scale, network analysis, community detection, vulnerability, anxiety

UDK: 159.923.072
DOI: 10.19090/pp.v17i3.2519
Received: 19.12.2023.
Revised: 11.04.2024.
Accepted: 07.05.2024.

✉ Corresponding author email: marija.volarov@ff.uns.ac.rs

Introduction

Intolerance of uncertainty (IU) is a trait-like risk factor for mood and anxiety disorders (Carleton, 2016). With a growing number of studies focused on understanding the nature of IU, the definition of the construct has evolved. According to the most recent definition, IU represents "an individual's dispositional incapacity to endure the aversive response triggered by the perceived absence of the salient key, or sufficient information, and sustained by the associated perception of uncertainty" (Carleton, 2016, p. 31). The origin of IU can be traced back to the time when a Canadian research group proposed that IU is an important concept for understanding uncontrollable worry and generalized anxiety disorder (GAD; Dugas et al., 1998; Freeston et al., 1994). This idea led to the development of the 27-item Intolerance of Uncertainty Scale (IUS) which was supposed to measure „cognitive, emotional and behavioral reactions to uncertainty in everyday life situations" (Freeston et al., 1994, p. 792). However, later studies implicated that IU is not only related to GAD but instead, that it is a transdiagnostic factor in nature. Although the definition of IU has been elusive, researchers have kept the IUS as a measure of IU, and all definitions/conceptual understanding of the construct rely on study findings that included the IUS and its consecutive, shorter version, the IUS-12.

Even though the IUS has been in use for quite a long time, factor analytical studies revealed its unstable latent structure. According to Birrell et al.'s review (2011), the latent structure of the IUS varied between two factors (i.e., Bottesi et al., 2015; Sexton & Dugas, 2009), four factors (Berenbaum et al., 2008; Buhr & Dugas, 2002; Norton, 2005), and five factors (Freeston et al., 1994). However, Birrell and colleagues (2011) concluded that two factors overlapped across these studies. In other words, regardless of the total number of extracted factors, the two factors seemed to replicate – one that can be described as a desire for predictability and the other capturing an inability to act when faced with uncertainty. Carleton and colleagues (Carleton et al., 2007) also recognized psychometric flaws of the IUS, which led to a refinement of the scale and development of the IUS-12. The IUS-12 still stands as a gold standard for measuring IU (McEvoy et al., 2019), has two factors named prospective IU and inhibitory IU (Bottesi et al., 2015; Carleton et al., 2007; Helsen et al., 2013; Kretzman & Gauer, 2020), and has been translated into several languages (e.g., Serbian, Italian, Brazilian Portuguese, Greek, Dutch). Prospective IU reflects a tendency towards proactive information-seeking with the aim of reducing uncertainty. However, this can easily turn into seeking excessive amounts of information before being able to make a decision in an ambiguous situation. At the same time, the prospective IU is also likely to manifest itself in impulsive decision-making (Sankar et al., 2017). Inhibitory IU manifests as "uncertainty paralysis" (Berenbaum et al., 2008) or the inability to act in uncertain situations. Given that some people perceive the uncertainty as threatening, the inhibitory IU seems to reflect a physiological "freeze" response (Birrell et al., 2011; Mihić et al., 2015). Based on the definitions of the two factors, one can also understand prospective IU as a dysfunctional approach coping strategy and inhibitory IU as an avoidance coping strategy in uncertain situations (Birrell et al., 2011). A recent meta-analysis supported this idea by showing that the IU was related to different aspects of emotion dysregulation (Sahib et al., 2023).

McEvoy and Mahoney's study findings (2011) supported the two factors by showing that prospective IU partially mediated the relationship between neuroticism and symptoms of GAD and obsessive-compulsive disorder, while inhibitory IU significantly mediated the relationship between neuroticism and symptoms of social anxiety, panic disorder, and depression. In addition, Carleton and colleagues (2010) have also found that inhibitory IU is uniquely related to the symptoms of social anxiety. However, creating the IUS-12 has not solved all conceptual problems of IU. Several recent studies gave support for a bifactor model of the IUS-12, with a general IU factor explaining most of the shared item variance and indicating that perhaps we should consider using the total IUS-12 score only (Hale et al., 2016; Hernández-Posadas et al., 2023; Lauriola et al., 2016; Saulnier et al., 2019; Shihata et al., 2018). Yet, one should be aware that bifactor models tend to overfit (or better fit) data compared with models with correlated factors even when the bifactor model does not reflect the true latent structure (Eid et al., 2018; Watts et al., 2019). In conclusion, one should bear in mind the shortcomings of different models when making conclusions about the nature of the IU and consider different approaches in addition to the factor analytical perspective to further validate the structure of IU.

Another way to address the nature of IU is by using the network approach. In the latent variable framework, a shared variance of observed variables is assumed to reflect a latent construct, whereas in the network framework, it is assumed to reflect a causal network. In other words, according to the network approach, items do not cluster together because they are all indicators of the same latent factor (i.e., IU). Instead, the construct (i.e., IU) is assumed to emerge from a dynamic interplay of beliefs, emotions, and behaviors that these items are describing (Borsboom & Cramer, 2013). For example, in an ambiguous situation, a person can believe that the uncertainty is unbearable, which can trigger an aversive emotional response that can further cause a behavioral tendency to collect information to reduce the uncertainty. This interconnectedness of cognition, emotion, and behavior forms a network representing the IU itself. Thus, the latent variables and network framework propose contrasting data-generating mechanisms, which lead to different substantive interpretations of the statistical models. However, it is worth noting that these divergent hypothesized causal processes do not necessarily translate into different statistical data structures (van Bork et al., 2021). Network analysis can be used to test the overall network structure, providing information on how the items are related to one another. Additionally, it can provide insights into the importance of different items (i.e., *nodes*) within the network, a feature often referred to as node centrality (Boccaletti et al., 2006). The most central item (i.e., *node*), when estimated using the strength centrality index, is the one that is most connected to all other items in the network. In a practical sense, a belief, emotion, or behavior that is central to the network may represent a reasonable treatment target (e.g., Borsboom & Cramer, 2013; Fried et al., 2016). It is assumed that by focusing on what is central in the network we can destabilize the network and substantially reduce the IU.

Thus, the network approach not only offers an opportunity to understand the nature of a construct, but also might have very important practical implications. In addition to centrality, network analysis enables us to detect groups of nodes (i.e., *communities*) that are more densely connected to each other than to the rest of the elements within the network (Fortunato, 2010). By telling us which nodes tend to cluster together, the community detection algorithms within network analysis provide additional insights into the structure of the construct of interest, and can even serve as a psychometric tool for determining the number of dimensions of a psychological instrument (Golino & Epskamp, 2017).

An Italian group of researchers was the first to rely on the network approach while trying to provide new insights into the nature of IU by exploring the internal structure of the Intolerance of Uncertainty Scale-Revised (IUS-R; Bottesi et al., 2020). The IUS-R is an Italian translation of the IUS-12 but with slightly modified language to make the items more understandable for the adolescent population. They used a sample of undergraduates and a sample of older participants from the community to test two networks. Bottesi and colleagues (2020) found that there were no differences in network structures in these two samples. Also, they found that the irrational belief that one cannot stand unpredictable outcomes and the belief that things should be organized in advance were the most central nodes in both samples, leading them to assume that those are the two essential components for the development of dysfunctional levels of IU (Bottesi et al., 2020). They also detected three communities (in both samples) labeled: negative beliefs about uncertainty, behavioral reactions to uncertainty, and emotional reactions to uncertainty (Bottesi et al., 2020). The detected communities seem to reflect one of the first definitions of IU, such as the one proposed by Freeston and colleagues (1994).

In the current study, we aimed to replicate study findings presented by Bottesi and colleagues (2020) using a general community sample. Specifically, we aimed to explore the structure of IU from the network perspective, using the Serbian IUS-11 (Mihić et al., 2014) and following, to a certain extent, the procedure applied by Bottesi and colleagues (2020). This seems to be important especially because the Serbian IUS-11 differs in three items from the IUS-12 (Carleton et al., 2007) and IUS-R (Bottesi et al., 2019, 2023). Precisely, item #11 (*A small unforeseen event can spoil everything, even with the best of planning.*), item #18 (*I always want to know what the future has in store for me.*), and item #21 (*I should be able to organize everything in advance.*) are not part of IUS-11 but can be found in IUS-12. Also, IUS-11 contains items #3 (*Uncertainty makes my life intolerable.*) and #5 (*My mind can't be relaxed if I don't know what will happen tomorrow.*) from IUS-27 that are not part of IUS-12. Despite the differences, IUS-11 consists of two factors, prospective IU and inhibitory IU, and seems to be an equivalent measure of the IUS-12 in the Serbian language context (Mihić et al., 2014; Volarov et al., 2021). Thus, it is reasonable to expect that the network structure of the IUS-11 will resemble the network structure of the IUS-R (Bottesi et al., 2020). The current study could advance the existing knowledge about the nature of IU by replicating a network structure of the construct in a different cultural setting using a slightly different measure from the original study. Finally, it is important to mention that we explored network structure using the entire sample, while the Italian group of authors split their sample into a subsample of undergraduates and a subsample of people from the community (Bottesi et al., 2020). Our decision was based on the results from the Italian study in which the authors did not find any differences between the two tested networks (Bottesi et al., 2020).

Method

Sample and Procedure

The sample consisted of 3096 participants from the general population (M_{age}= 26.81, *SD* = 7.87, 66.2% women). Data were collected in January 2021 within the project that examined mental health during the COVID-19 pandemic. Sixty percent of participants had higher education, 39.5% had a high school degree, and 0.5% had elementary education. In terms of employment, 35.8% of study participants had fixed-term employment, 15.8% had permanent contracts, 13.2% were unemployed, 34.9% were students, and 0.2% were retired. Eighty-two percent of participants reported they did not seek help in the past (before the pandemic) from a mental health professional. The survey link was shared via social network sites (i.e., Facebook and Instagram). The only inclusion criterion was that participants are +18 years old. All participants answered survey questions voluntarily without receiving any compensation for their participation. The study was approved by the institutional review board at the Faculty of Philosophy, University of Novi Sad, Serbia.

Instruments

Intolerance of Uncertainty Scale – 11 (IUS-11)

Intolerance of Uncertainty Scale – 11 (IUS-11; Mihić et al., 2014) is a Serbian version of the instrument used for measuring IU. The IUS-11 consists of eleven items with a 5-point response choice and has excellent reliability (α = .93).

Data Analytic Plan

Network estimation

For network estimation, *bootnet* (Epskamp et al., 2018, version 1.5) and *qgraph* (Epskamp et al., 2012, version 1.9.2) R-packages were used. The network structure was estimated using the *ggmModselect* algorithm. The *ggmModSelect* is an iterative method that selects an optimal unregularized Gaussian graphical model (GGM; Lauritzen, 1996) by minimizing the Bayesian Information Criterion (for more details on ggmModSelect, see: http://psychosystems.org/qgraph_1.5). We opted for an unregularized estimator as regularization was deemed unnecessary and may even lead to increased estimation errors when the sample size is large compared to the number of nodes (for details, see Isvoranu & Epskamp, 2021; Williams & Rast, 2020). Spearman correlations were specified as a correlation method when estimating the network structure because the data did not meet the assumption of multivariate normality (a table with descriptive statistics of the IUS-11 items, such as *M, SD,* skewness, and kurtosis is in Supplement A). Thus, the nodes in the resulting network represent the items of IUS-11, while the edges represent partial (Spearman) correlations between pairs of nodes (Epskamp et al., 2018). The network was visualized using the Fruchterman–Reingold algorithm (Fruchterman & Reingold, 1991), which places nodes with the strongest (or most) connections into the center of the graph.

Centrality and predictability indices

To assess the importance of each node for the network, strength centrality indices were computed. Strength indices show how well each node is directly connected to all other nodes within the network (Epskamp et al., 2018) and were shown to be highly replicable (e.g., Isvoranu & Epskamp, 2021). In addition to centrality, predictability indices were computed. Predictability in the form of R^2 quantifies how well each node is predicted by all its neighboring nodes (Haslbeck & Waldorp, 2018), and is computed using the R-package *qgraph*.

Accuracy and stability

Accuracy and stability were assessed in order to assess the replicability and robustness of the estimated network, as recommended by Borsboom (2018; 2021). For this purpose, the R-package *bootnet* (Epskamp et al., 2018, version 1.5) was used (for more details on methods for assessing accuracy and stability, see Epskamp & Fried, 2018).

Community detection

To detect communities within the network, meaning groups of nodes with strong internal links and weaker links with other communities (Fortunato, 2010), *spinglass* and *walktrap*, from the *igraph* package (Cs´ardi & Nepusz, 2006, version 1.2.6) in R were used. We also used a bootstrapped version of the method (Exploratory Graph Analysis – EGA from the *EGAnet package*, version 2.0.5; Golino & Christensen, 2024) to assess the stability of solutions obtained by spinglass and walktrap. Namely, we calculated community (dimension) stability (i.e., a proportion of bootstrapped samples in which communities exactly replicate) and node (item) stability statistics (i.e., a proportion of bootstrapped samples in which item replicates as a part of specific communities; Golino et al., 2022). Finally, we compared different communities-related solutions by calculating the total entropy fit index (TEFI; Golino et al., 2021). Community detection provided us with the opportunity to gain insight into how the IUS network is structured.

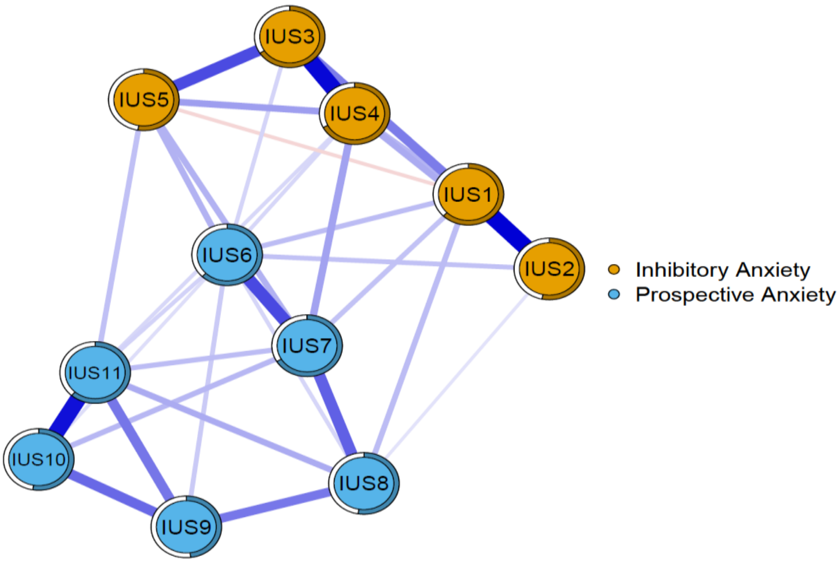
Results

Network estimation and local network properties

In the first step, unregularized partial correlation networks were constructed (Figure 1). The network had a density of .618 (34/55 edges), with a mean weight of 0.092. As shown by the network visualization, most edges were positive (indicated by blue lines), and only one was negative (indicated by a red line). The connections between the nodes were of variable strength, as shown by the variability in lines' thickness and saturation (the greater the magnitude of strength, the thicker and more saturated the line).

Figure 1

Network of unregularized partial correlations between nodes (items) of the IUS-11



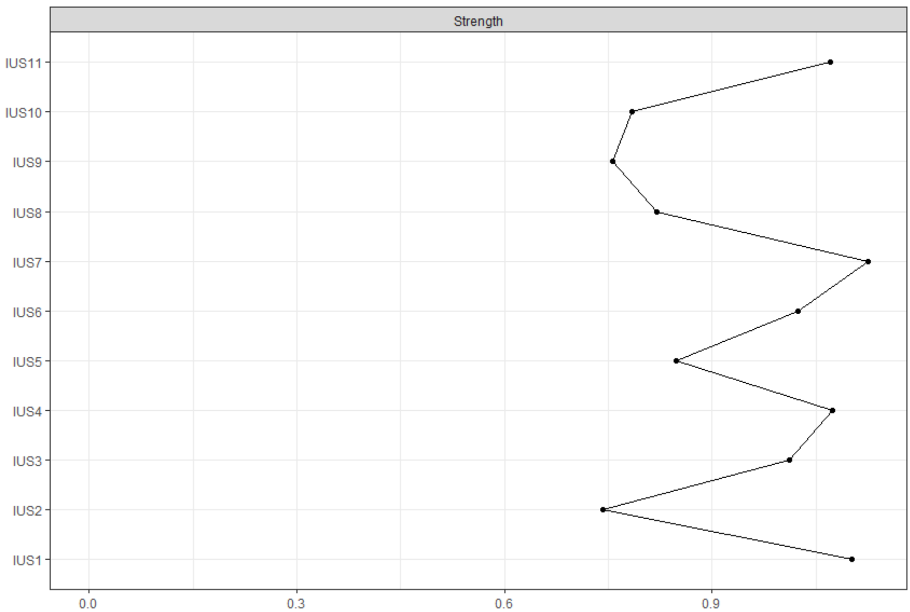
Inhibitory Anxiety	Prospective Anxiety
• IUS1: Uncertainty makes life intolerable	• IUS6: My mind can't be relaxed if I don't know what will happen tomorrow.
• IUS2: Uncertainty keeps me from living a full life.	• IUS7: Unforeseen events upset me greatly.
• IUS3: When it's time to act, uncertainty paralyzes me.	• IUS8: It frustrates me not having all the information I need.
• IUS4: When I am uncertain, I can't function very well.	• IUS9: One should always look ahead so as to avoid surprises.
• IUS5: The smallest doubt can stop me from acting.	• IUS10: I can't stand being taken by surprise.
	• IUS11: I must get away from all uncertain situations.

Centrality and predictability

Figure 2 shows the centrality indices for the IUS network. Items *#7* (*Unforeseen events upset me greatly*), *#1* (*Uncertainty makes life intolerable*), and *#11* (*I must get away from all uncertain situations*) seemingly showed the greatest strength, meaning the strongest direct links with all other nodes. Items *#2* (*Uncertainty keeps me from living a full life*), *#9* (*One should always look ahead to avoid surprises*), #10 (*I can't stand being taken by surprise*), and *#8* (*It frustrates me not having all the information I need*), on the other hand, seemed to be the least strong, respectively.

Figure 2

Strength Indices (Standardized z-scores)



The predictability indices ranged from .480 to .676 (for details, see Supplement B), with average network predictability being estimated at .588 (*SD* = .070). In other words, on average, 58.8% of a node's variance is explained by its direct neighbors in the network.

Accuracy and stability

The correlation stability coefficient, used for quantifying the stability of strength indices, was judged as excellent (CSstrength = 0.75). In other words, the order of nodes would remain similar even if we dropped 75% of our sample (for details about the CS coefficient, see Epskamp et al., 2018). Thus, the strength ranking values can be interpreted with confidence.

Bootstrapped confidence intervals (Figure 1, Supplement C), computed to assess the edge-weight accuracy, were relatively wide, suggesting that many edges do not differ from one another. However, the difference test showed that even though most edges did not differ from one another, some edges were still statistically stronger than others. Specifically, edges *#1-#2* (*Uncertainty makes life intolerable* - *Uncertainty keeps me from living a full life*), *#3-#4* (*When it's time to act, uncertainty paralyzes me - When I am uncertain, I can't function very well*), and *#10-#11*(*I can't stand being taken by surprise - I must get away from all uncertain situations*) were identified as statistically stronger than all other edges (for details, see Figure 2, Supplement C).

The nonparametric bootstrapped difference-test in the R package bootnet, using the differenceTest function, revealed that items *#7*, *#1*, and *#11* (previously mentioned as seemingly having the greatest strength) do not significantly differ from one another in terms of strength. These three items are not different from items *#3* and *#4* either. On the other hand, nodes *#2*, *#8*, *#9*, and *#10* were significantly less strong than all other nodes (for node difference test, see Figure 3, Supplement C).

Community detection

To test whether separate communities could be identified within the network, we first used the spinglass algorithm. As the spinglass algorithm does not necessarily produce identical solutions every time it is run, we run it 1001 times (for details, see Fried, 2016). We then computed the proportion of different solutions and the median number of communities. Our initial idea was to set a seed (using a set.seed() function) that reproduces the median number of communities before running spinglass and to report the obtained final solution.

Out of 1001 spinglass re-runs, two communities were identified 21 times (2.09%), three communities 500 times (49.95%), and four communities 480 times (47.95%). Of note, not all three-community solutions and four-community solutions were identical. Namely, the most frequent three-community solution emerged 475/500 times, while the most frequent four-community solution emerged 313/480 times. Bootstrap EGA with a spinglass algorithm for community detection provided the same results: two communities emerged in 7.9% of re-runs, three communities in 45.82%, and four communities 46.28% with three communities being a median solution. The first community comprised items #1 and #2, which both seem to capture decreased quality of life due to uncertainty. The second community consisted of items #3, #4, and #5, which all seem to capture acute behavioral inhibition due to uncertainty. The third community comprised items #6, #7, #8, #9, #10, #11, capturing prospective anxiety. The stabilities of these three communities was as follows: .84, .99, and .42. The average stabilities of nodes was .84, .99, and 78, respectively.

As the solutions obtained using the spinglass algorithm were not entirely consistent, communities were also assessed via walktrap, a more deterministic algorithm (Fried, 2016). Walktrap yielded a two-community solution, thus conflicting with the spinglass results. Walktrap, with and without bootstrapping, suggested two communities. The first community contained nodes (items) #1 to #5, and the second community included nodes (items) #6 to #11 and as such, these communities reflected the two-factor solution of the IUS-11. Both communities had satisfactory stability (.94 and .68, respectively). Additionally, the average stability of nodes was also satisfactory with stability values of .99 and .87. Considering that detected communities were stable and consistent with what we know so far about the structure of the IUS-11, as well as that this solution with two communities was not substantially different from three communities found by spinglass, we decided to accept the solution with two communities as the best one. This decision was also supported by TEFI, which was lower for the walktrap two-community solution (TEFI = -6.28) than for the spinglass three-community solution (TEFI = -4.68).

Discussion

The present study aimed to explore the structure of IU from the network approach, relying to a fair extent on the study conducted by Bottesi and colleagues (2020). As opposed to the study conducted by the Italian researchers, we used the Serbian IUS-11 as a measure of IU, and we used the sample as a whole to test the network structure of IU. Our decision not to divide our sample into subsamples of undergraduates and participants from the community was based on the findings from the original study. Namely, the Italian authors did not find differences in the network structure of IU when they compared undergraduate students with other community members (Bottesi et al., 2020).

According to the strength indices, nodes (items) #1, #7, and #11 appeared as the most central in the network. The first one was related to reduced quality of life due to experiencing uncertainty, the second resembled emotional reactions to uncertainty (*feeling upset*), and the third resembled avoidance as a strategy for dealing with the unpleasantness that uncertainty brings. However, the difference test for node strength revealed that these three nodes did not differ in strength from nodes #3 and #4 which capture inhibition under uncertain circumstances. This potentially tells us that the four aspects of the construct (behavior, emotion, and beliefs related to uncertainty as well as overgeneralized implications of experienced uncertainty) are interconnected and possibly equally relevant. The lack of one node that is unequivocally central implies that the activation of the entire network could start from any of these. These findings suggest that different aspects of IU might be important for understanding the development of IU in a non-clinical sample. They also imply that maladaptive responses to uncertainty may have different forms and may appear in different aspects of human functioning, which could be of particular importance if we are interested in those with heightened levels of this trait (i.e., the vulnerable ones). This can also be understood from the Cognitive-behavioral theoretical perspective (i.e., Beck, 1976; Ellis, 2004). According to this theory, holding negative (irrational) beliefs about uncertainty (such as *"I must get away from all uncertain situations"*) may trigger both negative emotions (i.e., unpleasantness, frustration) and behavioral responses (i.e., inhibition) when faced with uncertainty. Alternatively, those who associate aversive emotional reactions to uncertainty might use different behavioral strategies, such as avoidance, to cope with these emotions.

Items that we detected as the most central were different from those found to be central in Bottesi et al.'s study (2020). While the item *"I can't stand being taken by surprise"* was one of the two most central items in both of their samples, this item appeared as one of the least strong in our sample. In addition, another central item that the Italians found (*I should be able to organize everything in advance*) is not included in the Serbian IUS-11 scale. While it seems that the most central items from Bottesi et al.'s study reflect the desire for predictability, the content of central items in our study describes the essential parts of IU – that the uncertainty is upsetting, intolerable, inhibiting, and thus should be avoided, which corresponds to a description of IU provided by Freeston et al. (1994).

Community analysis, performed by using a spinglass, walktrap, and bootstrapping version of the community detection algorithms suggested that the network was best described via two communities. These two communities were comparable with the two-factor structure of the IUS-11 (Mihić et al., 2014), and were thus labeled as Inhibitory anxiety and Prospective anxiety. Central items from our study and results of the community detection can be linked to the conclusion from Birrell and colleagues' study (2011). Precisely, after comparing different factor analytical studies that explored the structure of the IUS, they noticed that two factors that were related to "unacceptability and avoidance of uncertainty, and uncertainty leading to the inability to act" (Birrell et al., 2011, p. 1204) were stable and consistent across the studies even when the total number of extracted factors differed. To conclude, it seems that no matter whether we are using the factor analytical approach or the network approach to investigate the structure of IU, mostly the same defining characteristics emerge. Our findings are somehow comparable to those detected by Bottesi et al.'s study (2020) given that the community they labeled as Behavioral reactions to uncertainty contained all items from the Inhibitory anxiety factor of the IUS-R. It is interesting that, on the one hand, item #11 (*I must get away from all uncertain situations*) is a part of Prospective anxiety community in this study, as well as part of the factor with the same name in the factor analytical studies of IUS-11 (Mihić et al., 2014) and IUS-12 (Carleton et al., 2007), and on the other hand, part of the Inhibitory anxiety factor of the IUS-R (Bottesi et al., 2019) and part of the community that replicates this factor (Bottesi et al., 2020).

At the same time, items from the Prospective anxiety subscale formed two communities in an Italian study, and one community in our study. This difficulty in replicating the Prospective anxiety community (or dimension, if we think of factor analytic studies) is not new. Commenting on the differences between factor solutions of the IU scales, Bottesi and colleagues (2019) suggested that perhaps the problem with the Prospective anxiety subscale comes from the fact that it contains items that tap two different components of IU (emotional reactions to uncertainty and desire for predictability) that should be treated independently. This is reflected in their communities labeled as Emotional reactions to uncertainty and Negative beliefs about uncertainty. Overall, the detected differences between the studies do not seem to be substantial and do not impede the understanding of the internal structure of IU but possibly are a consequence of cultural and language specifics of translated instruments. Some differences between the structure of communities detected in our study versus an Italian study might be a consequence of differences in versions of IUS that were used (e.g., three items from the Prospective anxiety of the IUS-R are not part of the IUS-11).[1]

[1] We noticed that the algorithm for estimating communities has changed and it produces different results than its previous versions (the latest version of the algorithm gave us a different number of communities compared to the results that we initially obtained with an older version of the algorithm). We believe it is important to emphasize this because changes in the algorithm limit the direct comparison of our findings with the findings of the Italian authors.

We should also comment on the solution with three communities that emerged when spinglass was used. This solution was not substantially different from the two community solution given that the Prospective anxiety community was entirely replicated, while two items (#1 and #2) from the Inhibitory anxiety community formed a separate community representing reduced quality of life due to uncertainty. Identifying the decreased quality of life due to uncertainty as a separate community implies that cognitive, emotional, and behavioral reactions to uncertainty are somewhat distinct from the general impression that uncertainty negatively impacts one's quality of life. Knowing that uncertainty is an inevitable part of our everyday functioning and cannot ever be fully avoided, it does not surprise that holding irrational beliefs about uncertainty and attempting to reduce it or avoid it entirely could negatively impact one’s perception of the overall quality of life. Also, it could be that these two items formed a separate community because this particular aspect of IU potentially differentiates those whose overall psychosocial functioning is affected by IU, from those who manage to adapt to uncertainty better. It is possible that it was difficult to replicate this community because only two items are related to an overall functionality within the IUS-11. If we take into account the importance of the functionality of an individual in the context of clinical assessment, adding more items related to the impact of uncertainty on people’s lives in a broader sense is worth considering. At the same time, a lack of a separate reduced quality of life community in the Italian study is unsurprising as the Italian IUS-R contains only one item related to the perceived effect of uncertainty on the quality of life. Specifically, IUS-R includes only item #2 but not item #1 of IUS-11, and a single item cannot form a community.

Limitations and Recommendations for Future Research

Based on our findings, it seems that all aspects of IU should be considered if we truly want to understand the conceptual nature of this construct and the risk that IU imposes on those highly intolerant to uncertainty. Moreover, it would be of great importance to investigate whether focusing interventions on one of the central nodes from one community would trigger the cascade of changes across the entire network (Bottesi et al., 2020; van Bork et al., 2021) or it would be necessary to target simultaneously all processes (emotions, beliefs, and behavior; which is more in line with Hayes at al.'s [2015] notion). It should be noted that, although a network such as the one estimated for this paper can provide insights into the possible causal relations between different elements of IU (i.e., every edge suggests a possible causal link), the limitation of the present study is that it relied on cross-sectional data, thus limiting our ability to draw conclusions about the direction of causal relations. To obtain such information, thereby obtaining insight into possible developmental pathways of IU, directed networks are needed (Borsboom & Cramer, 2013). Moreover, some authors disagree that centrality measures can be used as a proxy for treatment targets (Dablander & Hinne, 2019), especially when it is debatable whether there is causal influence among different indicators in real life. Thus, interventions tailored to the results of network analysis should be empirically evaluated further.

The predictability analysis revealed that over 40% of the variance of the IUS-11 network could not be explained by the interrelationships between the items. Therefore, future studies should aim to include other trait constructs with a status of vulnerability factors and contextual factors that could possibly explain additional variance of IU. In addition, it would be interesting to test whether different exogenous factors explain different components (i.e., communities) of IU. Next, future studies should aim to use a longitudinal design to test directed networks of IU (in both vulnerable and non-vulnerable individuals) in the presence of stressful events and/or in situations when people are facing uncertainty related to important life events. Finally, this research field could benefit from a comparison of the network structure of IU and its dynamic between men and women, as well as between individuals from the community sample who are low on trait IU to those who are high on IU but currently without any diagnosis, and those with ongoing psychopathology.

Other limitations of our study are related to the sampling procedure and sample structure and should be kept in mind when extrapolating findings to the general population. First, considering that the data were collected online via social media networks (e.g., Facebook and Instagram), the pool of potential study participants was restricted to users of these networks. Next, more than half of the sample was composed of participants with higher education and such sample structure does not adequately represent the general population in Serbia, and neither does the predominance of women in the sample. Also, participants in our study were on average younger than the general population in Serbia. The fact that the data were collected in the context of the COVID-19 pandemic should not be ignored. Although IUS-11 measures IU as a general tendency, it is likely that the pandemic-related uncertainties altered scale scores for some participants. However, despite these limitations, our results are consistent with research findings from earlier studies that offered us insights into the structure of the IU from the factor analytic perspective, thus they seem to be credible.

Conflict of Interest

The authors do not have any interests that would potentially influence the research.

Data availability statement

The data and R code used in this study are available in an OSF repository on the following link: https://osf.io/6xwrj/?view_only=b8b75a814a314dfd9e3a8a0f01fbb735

References

Berenbaum, H., Bredemeier, K., & Thompson, R. J. (2008). Intolerance of uncertainty: Exploring its dimensionality and associations with need for cognitive closure, psychopathology, and personality. *Journal of Anxiety Disorders, 22*(1), 117–125. https://doi.org/10.1016/j.janxdis.2007.01.004

Birrell, J., Meares, K., Wilkinson, A., & Freeston, M. (2011). Toward a definition of intolerance of uncertainty: A review of factor analytical studies of the Intolerance of Uncertainty Scale. *Clinical Psychology Review*, *31*(7), 1198-1208. https://doi.org/10.1016/j.cpr.2011.07.009

Borsboom, D., & Cramer, A. O. (2013). Network analysis: an integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology*, *9*, 91-121. https://doi.org/10.1146/annurev-clinpsy-050212-185608

Borsboom, D., Deserno, M. K., Rhemtulla, M., Epskamp, S., Fried, E. I., McNally, R. J., Robinaugh, D. J., Perugini, M., Dalege, J., Costantini, G., Isvoranu, A-M., Wysocki, A. C., van Borkulo, C. D., van Bork, R., & Waldorp, L. J. (2021). Network analysis of multivariate data in psychological science. *Nature Reviews Methods Primers*, *1*(1), 1-18. https://doi.org/10.1038/s43586-021-00055-w

Bottesi, G., Ghisi, M., Novara, C., Bertocchi, J., Boido, M., De Dominicis, I., & Freeston, M. H. (2015). Intolerance of Uncertainty Scale (IUS-27 e IUS-12): Due studi preliminari [Intolerance of Uncertainty Scale (IUS-27 and IUS-12): Two preliminary studies]. *Psicoterapia Cognitiva e Comportamentale, 21*(3), 345–365.

Bottesi, G., Iannattone, S., Carraro, E., & Lauriola, M. (2023). The assessment of Intolerance of uncertainty in youth: An examination of the Intolerance of Uncertainty Scale-Revised in Italian nonclinical boys and girls. *Research on Child and Adolescent Psychopathology, 51*(2), 209–222. https://doi.org/10.1007/s10802-022-00944-y

Bottesi, G., Marchetti, I., Sica, C., & Ghisi, M. (2020). What is the internal structure of intolerance of uncertainty? A network analysis approach. *Journal of Anxiety Disorders*, *75*, 102293. https://doi.org/10.1016/j.janxdis.2020.102293

Bottesi, G., Noventa, S., Freeston, M. H., & Ghisi, M. (2019). Seeking certainty about Intolerance of Uncertainty: Addressing old and new issues through the Intolerance of Uncertainty Scale-Revised. *PloS One, 14*(2), e0211929. https://doi.org/10.1371/journal.pone.0211929

Bringmann, L. F., Elmer, T., Epskamp, S., Krause, R. W., Schoch, D., Wichers, M., Wigman, J. T. W., & Snippe, E. (2019). What do centrality measures measure in psychological networks? *Journal of Abnormal Psychology, 128*(8), 892-903. https://doi.org/10.1037/abn0000446

Buhr, K., & Dugas, M. J. (2002). The intolerance of uncertainty scale: psychometric properties of the English version. *Behaviour Research and Therapy, 40*(8), 931–945. https://doi.org/10.1016/s0005-7967(01)00092-4

Carleton, R. N., Collimore, K. C., & Asmundson, G. J. G. (2010). "It's not just the judgements—It's that I don't know": Intolerance of uncertainty as a predictor of social anxiety. *Journal of Anxiety Disorders, 24*(2), 189–195. https://doi.org/10.1016/j.janxdis.2009.10.007

Carleton, R. N., Norton, M. P. J., & Asmundson, G. J. (2007). Fearing the unknown: A short version of the Intolerance of Uncertainty Scale. *Journal of Anxiety Disorders*, *21*(1), 105-117. https://doi.org/10.1016/j.janxdis.2006.03.014

Carleton, R. N. (2016). Into the unknown: A review and synthesis of contemporary models involving uncertainty. *Journal of Anxiety Disorders, 39,* 30-43. https://doi.org/10.1016/j.janxdis.2016.02.007

Chen, J., & Chen, Z. (2008). Extended Bayesian information criteria for model selection with large model spaces. *Biometrika*, *95*(3), 759-771. https://doi.org/10.1093/biomet/asn034

Cramer, A. O., Van Borkulo, C. D., Giltay, E. J., Van Der Maas, H. L., Kendler, K. S., Scheffer, M., & Borsboom, D. (2016). Major depression as a complex dynamic system. *PloS One*, *11*(12), e0167490. https://doi.org/10.1371/journal.pone.0167490

Cs´ardi, G., & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal*, Complex Systems, 1695(5), 1-9. https://igraph.org.

Dablandor, F., & Hinne, M. (2019). Node centrality measures are poor substitute for causal inference. *Scientific Reports, 9*, 6846. https://doi.org/10.1038/s41598-019-43033-9

Dugas, M. J., Gagnon, F., Ladouceur, R., & Freeston, M. H. (1998). Generalized anxiety disorder: A preliminary test of a conceptual model. *Behaviour Research and Therapy, 36*(2), 215–226. https://doi.org/10.1016/s0005-7967(97)00070-3

Eid, M., Krumm, S., Koch, T., & Schulze, J. (2018). Bifactor Models for Predicting Criteria by General and Specific Factors: Problems of Nonidentifiability and Alternative Solutions. *Journal of Intelligence, 6*(3), 42. https://doi.org/10.3390/jintelligence6030042

Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, *50*(1), 195-212. https://doi.org/10.3758/s13428-017-0862-1

Epskamp, S., Cramer, A. O., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software, 48*(1), 1-18. http://dx.doi.org/10.18637/jss.v048.i04

Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods*, *23*(4), 617- 634. https://psycnet.apa.org/doi/10.1037/met0000167

Freeston, M. H., Rhéaume, J., Letarte, H., Dugas, M. J., & Ladouceur, R. (1994). Why do people worry?. *Personality and Individual Differences*, *17*(6), 791-802. https://doi.org/10.1016/0191-8869(94)90048-5

Hale, W., Richmond, M., Bennett, J., Berzins, T., Fields, A., Weber, D., Beck, M., & Osman, A. (2016). Resolving uncertainty about the Intolerance of Uncertainty Scale–12: Application of modern psychometric strategies. *Journal of Personality Assessment*, *98*(2), 200-208. https://doi.org/10.1080/00223891.2015.1070355

Fried, E. (2016, October 19). R tutorial: how to identify communities of items in networks. Psych Networks. Retrieved December 20, 2021, from https://psych-networks.com/r-tutorial-identify-communities-items-networks/

Fried, E. I., Epskamp, S., Nesse, R. M., Tuerlinckx, F., & Borsboom, D. (2016). What are 'good' depression symptoms? Comparing the centrality of DSM and non-DSM symptoms of depression in a network analysis. *Journal of Affective Disorders*, *189*, 314-320. https://doi.org/10.1016/j.jad.2015.09.005

Friedman, J., Hastie, T., & Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics, 9*(3), 432-441. https://doi.org/10.1093/biostatistics/kxm045

Fruchterman, T. M., & Reingold, E. M. (1991). Graph drawing by force-directed placement. *Software: Practice and Experience*, *21*(11), 1129-1164. https://doi.org/10.1002/spe.4380211102

Fortunato, S. (2010). Community detection in graphs. *Physics Reports*, *486*(3-5), 75-174. https://doi.org/10.1016/j.physrep.2009.11.002

Foygel, R., & Drton, M. (2010). Extended Bayesian information criteria for Gaussian graphical models. *arXiv preprint arXiv:1011.6640*.

Golino, H., & Christensen, A. P. (2024). *EGAnet: Exploratory Graph Analysis – A framework for estimating the number of dimensions in multivariate data using network psychometrics*. R package version 2.0.5, https://r-ega.net.

Golino, H., Christensen, A. P., & Garrido, L. E. (2022). Invited commentary: Exploratory graph analysis in context. *Psicologia: Teoria e Prática, 24*(3), 1-10. https://doi.org/10.5935/1980-6906/ePTPIC15531.en

Golino, H. F., & Epskamp, S. (2017). Exploratory graph analysis: A new approach for estimating the number of dimensions in psychological research. *PLoS ONE, 12*(6), Article e0174035. https://doi.org/10.1371/journal.pone.0174035

Golino, H., Moulder, R., Shi, D., Christensen, A. P., Garrido, L. E., Nieto, M. D., Nesselroade, J., Sadana, R., Thiyagarajan, J. A., & Boker, S. M. (2021). Entropy fit indices: new fit measures for assessing the structure and dimensionality of multiple latent variables. *Multivariate Behavioral Research, 56*(6), 874–902. https://doi.org/10.1080/00273171.2020.1779642

Haslbeck, J. M., & Waldorp, L. J. (2018). How well do network models predict observations? On the importance of predictability in network models. *Behavior Research Methods*, *50*, 853-861. https://doi.org/10.3758/s13428-017-0910-x

Hayes, A. M., Yasinski, C., Barnes, J. B., & Bockting, C. L. (2015). Network destabilization and transition in depression: New methods for studying the dynamics of therapeutic change. *Clinical Psychology Review, 41*, 27-39. https://doi.org/10.1016%2Fj.cpr.2015.06.007

Helsen, K., Van den Bussche, E., Vlaeyen, J. W., & Goubert, L. (2013). Confirmatory factor analysis of the Dutch Intolerance of Uncertainty Scale: Comparison of the full and short version. *Journal of Behavior Therapy and Experimental Psychiatry*, *44*(1), 21-29. https://doi.org/10.1016/j.jbtep.2012.07.004

Hernández-Posadas, A., De la Rosa-Gómez, A., Lommen, M., Bouman, T., Mancilla-Díaz, J., & Valdés, D. (2023). Psychometric properties of the Mexican version of the Intolerance of Uncertainty Scale: The IUS-12M. *Interacciones, 9*, e358. https://doi.org/10.24016/2023.v9.358

Isvoranu, A. M., & Epskamp, S. (2021). Which estimation method to choose in network psychometrics? Deriving guidelines for applied researchers. *Psychological Methods*. Advance online publication. https://doi.org/10.1037/met0000439

Kretzmann, R. P., & Gauer, G. (2020). Psychometric properties of the Brazilian Intolerance of Uncertainty Scale - Short Version (IUS-12). *Trends in Psychiatry and Psychotherapy, 42*(2), 129–137. https://doi.org/10.1590/2237-6089-2018-0087

Lauriola, M., Mosca, O., Trentini, C., Foschi, R., Tambelli, R., & Carleton, R. N. (2018). The intolerance of uncertainty inventory: validity and comparison of scoring methods to assess individuals screening positive for anxiety and depression. *Frontiers in Psychology, 9*, 388. https://doi.org/10.3389/fpsyg.2018.00388

Lauritzen, S. L. (1996). *Graphical models*. Clarendon Press.

McEvoy, P. M., & Mahoney, A. E. (2011). Achieving certainty about the structure of intolerance of uncertainty in a treatment-seeking sample with anxiety and depression. *Journal of Anxiety Disorders, 25*(1), 112-122. https://doi.org/10.1016/j.janxdis.2010.08.010

Mihić, L., Sokić, J., Samac, N., & Ignjatović, I. (2014). Srpska adaptacija i validacija upitnika netolerancije na neizvesnost. [Serbian adaptation and validation of the intolerance of uncertainty scale]. *Primenjena Psihologija, 7*(3-1), 347-370. https://doi.org/10.19090/pp.2014.3-1.347-370

Norton P. J. (2005). A psychometric analysis of the Intolerance of Uncertainty Scale among four racial groups. *Journal of Anxiety Disorders, 19*(6), 699–707. https://doi.org/10.1016/j.janxdis.2004.08.002

Sahib, A., Chen, J., Cárdenas, D., & Calear, A. L. (2023). Intolerance of uncertainty and emotion regulation: A meta-analytic and systematic review. *Clinical Psychology Review, 101*, 102270. https://doi.org/10.1016/j.cpr.2023.102270

Sankar, R., Robinson, L., Honey, E., & Freeston, M. (2017). 'We know intolerance of uncertainty is a transdiagnostic factor but we don't know what it looks like in everyday life': A systematic review of intolerance of uncertainty behaviours. *Clinical Psychology Forum, 296*, 10-15.

Saulnier, K. G., Allan, N. P., Raines, A. M., & Schmidt, N. B. (2019). Depression and intolerance of uncertainty: Relations between uncertainty subfactors and depression dimensions. *Psychiatry, 82*(1), 72-79. https://doi.org/10.1080/00332747.2018.1560583

Sexton, K. A., & Dugas, M. J. (2009). Defining distinct negative beliefs about uncertainty: validating the factor structure of the Intolerance of Uncertainty Scale. *Psychological Assessment, 21*(2), 176–186. https://doi.org/10.1037/a0015827

Shihata, S., McEvoy, P. M., & Mullan, B. A. (2018). A bifactor model of intolerance of uncertainty in undergraduate and clinical samples: Do we need to reconsider the two-factor model? *Psychological Assessment, 30*(7), 893–903. https://doi.org/10.1037/pas0000540

van Bork, R., Rhemtulla, M., Waldorp, L. J., Kruis, J., Rezvanifar, S., & Borsboom, D. (2021). Latent Variable Models and Networks: Statistical Equivalence and Testability.

Multivariate Behavioral Research, 56(2), 175–198. https://doi.org/10.1080/00273171.2019.1672515

van Borkulo, C. D., van Bork, R., Boschloo, L., Kossakowski, J. J., Tio, P., Schoevers, R. A., Borsboom, D., & Waldorp, L. J. (2022). Comparing network structures on three aspects: A permutation test. *Psychological Methods*, 10.1037/met0000476. Advance online publication. https://doi.org/10.1037/met0000476

Volarov, M., Saulnier, K. G., Allan, N. P., Shapiro, M. O., & Mihić, L. (2021). Are we still uncertain about the latent structure of intolerance of uncertainty: Results from factor mixture modeling in a Serbian sample. *Journal of Affective Disorders*, *294*, 505-512. https://doi.org/10.1016/j.jad.2021.07.081

Watts, A. L., Poore, H. E., & Waldman, I. D. (2019). Riskier Tests of the Validity of the Bifactor Model of Psychopathology. *Clinical Psychological Science, 7*(6), 1285–1303. https://doi.org/10.1177/2167702619855035

Williams, D. R., & Rast, P. (2020). Back to the basics: Rethinking partial correlation network methodology. *The British Journal of Mathematical and Statistical Psychology*, *73*(2), 187–212. https://doi.org/10.1111/bmsp.12173

Supplementary materials

Supplement A

Table 1

Means, standard deviations, skewness and kurtosis values of the IUS-11 items

	M	*SD*	Skewness	Kurtosis
Item 1	2.77	1.28	.211	-1.019
Item 2	3.04	1.40	.029	-1.281
Item 3	2.14	1.23	.847	-.344
Item 4	2.57	1.36	.556	-.877
Item 5	2.12	1.16	.880	-.083
Item 6	2.33	1.29	.673	-.670
Item 7	2.66	1.27	.402	-.902
Item 8	3.03	1.31	.024	-1.166
Item 9	2.97	1.28	.070	-1.076
Item 10	2.34	1.25	.661	-.562
Item 11	2.31	1.23	.669	-.534

Supplement B

Table 1

Predictability Indices (R^2)

	R^2
IUS1	.626
IUS2	.534
IUS3	.661
IUS4	.676
IUS5	.527
IUS6	.625
IUS7	.665
IUS8	.527
IUS9	.480
IUS10	.527
IUS11	.617

Supplement C

Figure 1

Nonparametric 95% Bootstrapped Confidence Intervals of the Estimated Edges