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What is the internal structure of intolerance of uncertainty? A network analysis approach

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Abstract

Intolerance of uncertainty (IU) is a transdiagnostic vulnerability factor spanning psychological disorders. Although IU has been extensively studied, its internal structure is still not fully understood. In the current study, we applied network analysis to investigate IU – as measured by the Intolerance of Uncertainty Scale-Revised (IUS-R) - in two large non-clinical samples, consisting of undergraduates (N = 1172) and community individuals (N = 1759). Network analysis revealed that feeling a general internal uncertainty aversion and the belief that things have to be planned in advance are the most central nodes in both samples. Moreover, the community analysis revealed that, in both samples, the network of IU consists of three communities referring to negative beliefs about uncertainty, behavioral reactions to uncertainty, and emotional reactions to uncertainty. Lastly, the network was highly similar in undergraduates and community individuals in terms of network similarity, global connectivity, and structure and items mean levels; only minimal-to-negligible differences were found. The way current findings expand our knowledge of the internal structure of IU, along with theoretical and clinical implications, are discussed.

Key words: intolerance of uncertainty; Intolerance of Uncertainty Scale; network analysis; non-clinical samples.

1. Introduction

Intolerance of uncertainty (IU) is a trait-like disposition reflecting the tendency to fear unpredictable and uncertain future events and in the belief that feeling uncertain is undesirable (Buhr & Dugas, 2002). People with high IU negatively interpret uncertain situations, perceive themselves as unable to face uncertainty, and experience emotional distress (e.g., Carleton et al., 2012). IU as a construct was originally developed in the context of generalized anxiety disorder (GAD) (Dugas, Gagnon, Ladoceur, & Freeston, 1998; Freeston, Rhéaume, Letarte, Dugas, & Ladouceur, 1994). Within this framework, Freeston and colleagues (1994) defined it as “a relatively broad construct representing cognitive, emotional, and behavioral reactions to uncertainty in everyday life situations” (p. 792). Improvements in its understanding across the last two decades led to several refinements of its definition; the most recent one is by Carleton (2016), who described IU as the “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” (p. 31).

There is now vast evidence showing that IU is implicated in several psychological disorders beyond GAD, such as obsessive compulsive disorder, panic disorder and agoraphobia, social anxiety, depression, post-traumatic stress disorder, and eating disorders (e.g., McEvoy, Hyett, Shihata, Price, & Strachan, 2019; Shihata, McEvoy, Mullan, & Carleton, 2016). Consistently, recent literature supports the role of IU as a trans-therapeutic change process and the effectiveness of psychological treatments focusing on IU when targeting different psychopathologies has been demonstrated (e.g., McEvoy & Erceg-Hurn, 2016; Norton & Paulus, 2016).

Advances in the conceptual understanding of IU paralleled the development and refinement of its measurement, namely the Intolerance of Uncertainty Scale (IUS; Freeston et al., 1994). Originally, the IUS was intended as an atheoretical and clinically derived tool for the assessment of IU. Since 1994, this scale has been the most adopted measure of IU, but its internal validity was not unproblematic (Birrell, Meares, Wilkinson, & Freeston, 2011). Consequently, in 2007, Carleton, Norton, and Asmundson developed a 12-item version (IUS-12), which was intended to better capture the specific core aspects of IU, with all the IUS items that could map onto GAD symptoms being excluded. Several authors demonstrated that the IUS-12 was comparable to the original IUS in terms of internal consistency, convergent, and divergent validity (Carleton et al., 2007; Helsen, Van den Bussche, Vlaeyen, & Goubert, 2013; Khawaja & Yu, 2010). Moreover, high correlations between total scores of the IUS-12 and the original IUS were observed across studies (Pearson *r*s ranging between .92 and .96) (Carleton et al., 2007; Helsen et al., 2013; Khawaja & Yu, 2010). More recently, a minor refinement of the IUS-12 was carried out in order to streamline its phrasing and make the tool more suitable across the lifespan, namely the IUS-Revised (IUS-R; Bottesi, Noventa, Freeston, & Ghisi, 2019b; Walker, Birrell, Rogers, Leekam, & Freeston, 2010). The IUS-12 and its refinement are currently considered as the gold standard assessment of IU (McEvoy et al., 2019).

Despite the theoretical and methodological efforts for clarifying IU, critical aspects of this construct remain opaque. First, IU is a complex construct, consisting of beliefs, emotions, and behaviors (Freeston et al., 1994). However, the specific role played by these components in the context of IU is yet mostly unknown (Shihata et al., 2016). For instance, it is possible that beliefs play a major role in eliciting specific emotions and behaviors, while uncertainty-related emotions and behaviors are less influential (Borsboom & Cramer, 2013; Dalege et al., 2016). This is consequential as identifying the most influential elements of clinical constructs is of crucial importance in improving our understanding of psychopathology and its treatment (Borsboom & Cramer, 2013; Elliott, Jones, & Schmidt, 2019).

Second, there is not consensus with regard to how many dimensions the phenomenon of IU consists of. In their review of factor analytic studies of the original IUS, Birrell and colleagues (2011) found that the construct comprised two main factors, namely prospective IU (i.e., desire for predictability and active information seeking behavior) and inhibitory IU (i.e. behavioral paralysis in the face of uncertainty). Traditional factorial analysis identified that also the IUS-12 consists of these two dimensions (e.g. Carleton et al., 2007; Helsen et al., 2013). However, recent evidence questioned this factorial solution. In fact, a few recent studies suggested that the 12-item IUS is best represented by a bifactor model, wherein a general IU factor explains most of the reliable variance across the items (Bottesi et al., 2019b; Hale et al., 2016; Lauriola, Mosca, & Carleton, 2016; Shihata, McEvoy, & Mullan, 2018). Moreover, prospective IU emerged as an unreliable factor across all studies, with some items showing negative loadings. Interestingly, these items refer to emotional reactions to uncertainty (i.e. feeling upset/frustrated when dealing with uncertainty), thus suggesting that desire for predictability and uncertainty aversiveness may better represent distinct components of IU (Bottesi et al., 2019b). In sum, clarifying whether the phenomenon of IU comprises different processes could turn out to be relevant for both treatment and prognostic purposes.

Third, available evidence on the structure of IU derives from studies conducted on both clinical (e.g. Carleton et al., 2012; Jacoby, Fabricant, Leonard, Riemann, & Abramowitz, 2013; Khawaja & Yu, 2010; McEvoy & Mahoney, 2011; Shihata et al., 2018) and non-clinical samples. With specific respect to the latter, research has mainly relied on undergraduate students (e.g. Carleton et al., 2007; Helsen et al., 2013; Lauriola et al., 2016) and less frequently on individuals from the community (e.g. Bottesi et al., 2019b; Carleton et al., 2012). In our opinion, this is a consequential issue as well, since both the conceptualization and assessment of clinical constructs might vary according to age groups (e.g. Calling, Midlöv, Johansson, Sundquist, & Sundquist, 2017; Nolen-Hoeksema & Aldao, 2011). Importantly, it is claimed that college age is a period of the life course distinct from both adolescence and adulthood, characterized by frequent change and multiple possibilities of choice (Arnett, 2010). Specifically, college life requires students to adjust to separation from family, as well as to a new set of rules for living. Moreover, undergraduates have to deal with several uncertainties about their short- (e.g. academic requirements and financial concerns) and long- (e.g. post-graduation plans) term future (Ahern & Norris, 2011; Blanco et al., 2008; Hurst, Baranik, & Daniel, 2012). Although undergraduate students and adults may differ in the way they interpret and experience uncertainty, extant research has not explored this issue; rather, most of research about IU has been conducted on analogue student samples (Bottesi et al., 2016).

In order to address these important issues, we adopted a new and promising approach, namely network analysis (Borsboom & Cramer, 2013). According to this perspective, a certain phenomenon (i.e., IU) does necessarily not act as a latent factor that generates reflective indicators (i.e., items of the questionnaire), but it may emerge from the putatively causal interaction among specific beliefs, emotions, and behaviors. In other words, as compared to factor analysis that investigates *which* observable elements (i.e., items) are likely to cluster due to the presence of a latent factor, network analysis sheds light on *how* different elements are theoretically directed (i.e., inhibiting or reinforcing) to one another (Bansal, Goh, Lee, & Martel, 2020). It is worth mentioning that, although factor and network analysis are statistically equivalent, they propose contrasting data-generating mechanisms, which lead to substantially different interpretations of the statistical models (van Bork et al., 2019). From a latent factor standpoint, the presence of IU actively generates a variety of beliefs, emotions, and behaviors, which are independent from one another, in that they are epiphenomena of the same cause (i.e., latent IU). From a network analysis standpoint, a person might initially believe that unforeseen events are undesirable and, consequently, feel that he/she cannot stand being taken by surprise. These unhelpful beliefs and emotions could drive action planning in order to increase certainty and/or promote uncertainty paralysis, thus preventing effectively acting. As consequence, a person may start worrying about uncertain situations or avoiding them, which negatively reinforce all the negative thoughts and beliefs that make him/her feel incapable of tolerating uncertainty. In this case, beliefs, emotions, and behaviors related to IU strongly influence one another and eventually lead to IU.

Hence, network analysis could offer new ways to gain further knowledge about the internal structure of IU. By primarily focusing on single items of the IUS-R (i.e., *nodes*) and the link between them (i.e., *edges*), network analysis helps highlight: (i) the specific associations between the IUS-R items (i.e., *network structure*); (ii) which items are the most connected of the network (i.e., *node centrality*); (iii) whether specific groups of items function in a similar way (i.e., *communities*); and (iv) whether the internal structure of IU varies in undergraduate and community samples (i.e., *internetwork comparison*). Importantly, it is contentious whether cross-sectional data can be used to unveil causality over time in complex models, with different interpretations being proposed (Rodebaugh et al., 2018). In our study, we suggest that a network model of a specific construct can provide clues about its *causal skeleton* (Borsboom & Cramer, 2013; Dalege, Borsboom, van Harreveld, & van der Maas, 2017), in which the edges represent putative causal pathways that can be directed (A→B or B→A), bidirectional (A↔B), or causally influenced by an unmodeled variable (A←C→B) (Dalege et al., 2017). Consequently, cross-sectional data can be used to unveil possible causal links among nodes, which can later be tested in experimental and/or longitudinal studies. A similar interpretation of network analysis has been proposed for many phenomena in clinical psychology, such as rumination (Bernstein, Heeren, & McNally, 2019), hopelessness (Marchetti, 2019), and personality traits (Costantini et al., 2015).

In conclusion, in our study we first estimated a network model using the gold standard measure for this construct, namely the 12-item IUS (Bottesi et al., 2019b; Carleton et al., 2007). Then, specific features of the model were tested with the strength index, which identifies the most connected nodes, and the predictability index, which quantifies the amount of variance of each node explained by the neighboring nodes. We also investigated whether, within the network, it was possible to detect specific nodes that function in a similar way (i.e., communities). Finally, we investigated the presence of similarities and differences between the undergraduate and community populations. To do so, we used two large samples of undergraduate students and community individuals.

2. Material and Methods

2.1. Participants and Procedure

In this study, we used two data sets, including 1172 undergraduate students (323 males and

853 females) and one including 1759 community individuals (770 males and 993 females). Participants resided in several different midsized communities in northern, central, and southern Italy and they were engaged through advertisements requesting potential volunteers for psychological studies. None of them reported present or past psychiatric disorders and none of them reported using medications. All participants gave their written, informed consent before entering the research. Data presented in this study was partially published elsewhere in previous research aiming to test a revised conceptual model of GAD (Bottesi et al., 2016) and to provide evidence about the Italian validation of the IUS-R (Bottesi et al., 2019b). None of previous studies applied network analysis to explore the internal structure of IU. The research was conducted in accordance with the Declaration of Helsinki and it was approved by the Ethics Committee of Psychological Sciences of the University of Padova. Demographic data of the two groups are summarized in Table 1. *[Table 1 here]*

2.2. Measure

The *Intolerance of Uncertainty Scale-Revised* (IUS-R; Bottesi et al., 2019b). The IUS-R is a measure assessing IU across the lifespan developed as refinement of the IUS-12 (Carleton et al., 2007). Specifically, the language of the original IUS-12 was simplified so that it can be easily read by an average 11-year-old student (Walker et al., 2010). It contains 12 items to be rated on a 5-point Likert scale (1 = "Not at all like me"; 5 = "Entirely like me"). The IUS-R emerged as a reliable measure of IU across non-clinical (e.g., Bottesi et al., 2015; Wright, Lebell, & Carleton, 2016) and clinical (e.g., Boulter, Freeston, South, & Rodgers, 2014; Joyce, Honey, Leekam, Barrett, & Rodgers, 2017) samples and it is currently included among the recognized validated versions of the IUS-12 (McEvoy et al., 2019).

2.3. Statistical Analysis

In order to take a cautious approach, we preliminarily checked whether all the items across the two samples were suitable candidates for network analysis. First, we evaluated the level of informativeness of each item. Informativeness refers to an item's standard deviation and quantifies the amount of information that can be extracted from it (Mullarkey, Marchetti, Beevers, 2019). An item was deemed poorly informative if its standard deviation was 2.5 standard deviation below the mean of all the items standard deviations (i.e., $SD_{item} < 2.5SD_{all\_itemsSD}$; Mullarkey et al., 2019). Then, we evaluated whether each pair of items showed a substantially similar pattern of association with the other nodes of the network and could be considered as redundant. Two items were deemed redundant if they showed less than 25% of statistically different correlations with all the other items the network. Redundancy index below 0.25 indicated possible redundancy (Jones, 2018).

Before estimating the network models, a non-paranormal transformation was applied to relax the normality assumption (Zhao, Liu, Roeder, Lafferty & Wasserman, 2012). Then, we proceeded estimating a Gaussian graphical model (GGM; undirected network of partial correlations coefficients) and, more specifically, an Extended Bayesian Information criterion (EBIC) graphical least absolute shrinkage and selection operator (LASSO) network model (Epskamp & Fried, 2018). In detail, we computed the polychoric correlations between every pair of items, after controlling for all the other items of the network. The magnitude of each partial correlation was corrected for the LASSO regularization which limited the total sum of absolute parameter values and shrank small values to exactly zero. By doing so, every edge between two nodes was conditionally dependent and the network was more parsimonious and more interpretable (Costantini et al., 2015; Epskamp & Fried, 2018). In the context of network analysis, each variable is considered as a *node* of the network and the association between two nodes is defined as *edge*. Positive association between two nodes are usually represented as blue links, while negative association are depicted as red links. Thickness and saturation of the edges are proportional to the magnitude of the association.

The local properties of the network were investigated with the strength and predictability indices. Strength refers to the sum of the absolute values of the edges connecting a node to all the other nodes of the network, while predictability amounts to the explained variance of each item by all the other items of the network. The predictability index relies on the optimistic assumption that each node of the network is causally influenced by all its neighboring nodes and, as such, it should be considered as the statistical upper bound of accountability (Haslbeck & Waldorp, 2018).

Accuracy, stability, and intranetwork comparison analyses were performed in accordance with Epskamp and Fried (2018). In detail, the accuracy of the network edges and strength values was investigated by means of 1000-bootstrap 95% confidences intervals. Smaller confidence intervals indicated more precise estimates. Similarly, the stability of the network edges and strengths was formally tested, with the correlation stability coefficient (*CS-coefficient*) above 0.5 indicating optimally stable estimates. Finally, by relying on the bootstrap approach, we formally tested whether each edge was statically different from all the other edges of the same network. An identical comparison procedure was performed with the strength index (i.e., *intranetwork comparison*).

Moreover, in the context of network analysis, it is possible to detect nodes that share common properties and play a similar role within the network, namely communities (Fortunato, 2010). In our study, we mainly relied on the spinglass algorithm, which clusters the nodes that are highly connected within the same community and poorly connected with nodes belonging to other communities (Yang, Algesheimer, & Tessone, 2016). It has been argued that communities in networks are equivalent under certain conditions to latent variables (Golino & Epskamp, 2017), but, despite this similarity, the interpretations derived from the two approaches are markedly different. Within the latent factor model, all the indicators (i.e., items) are thought to stem from an underlying factor that causes them (i.e., IU), while the network community approach contends that it is the way the different beliefs, emotions, and behaviors causally reinforce one another that allows the emergence of the overall phenomenon (Dalege et al., 2016; Marchetti, 2019). We also complemented the *spinglass* analysis by relying on multiple community detection algorithms, such as *walktrap*, *leading eigenvector*, and *fast greedy* (details about the specific features of these algorithms can be found in Csárdi & Nepusz, 2010).

Finally, we investigated whether the networks estimated in the undergraduate and community samples were statistically different (i.e., *internetwork comparison*). First, we computed the degree of similarity in terms of network edges, strength, and predictability between the networks (Fried et al., 2017), by means of the Spearman's rank correlation coefficient. Second, we tested whether the networks showed different levels of global connectivity and a different network structure (van Borkulo et al., 2017). Global connectivity refers to the absolute sum of all the edges of the network, while network structure difference was tested by means of the maximum (absolute) elementwise difference among all the possible edges. Conditional upon this latter test, differences at level of each single edge were tested, after applying the Holm-Bonferroni correction. The internetwork comparison approach was based on a permutation test (i.e., 10000 permuted data sets) (for further details, see van Borkulo et al., 2017).

3. Results

3.1. Descriptive statistics and items check

Table 2 shows mean, standard deviation, and polychoric correlations of the IUS-R items in the undergraduate and the community samples. Preliminarily, we evaluated the level of informativeness and the redundancy of each item. Item #12 was found to be poorly informative (i.e., 2.5 SD below the mean) in the undergraduate sample (threshold = 0.75, item #12 = 0.72), but not in the community sample (threshold = 0.78, item #12 = 0.85). Moreover, items #1 and #2 were found to be potentially redundant in the community sample (redundancy index = 0.2), but not in the undergraduate sample. Given the inconsistency across samples, we preferred not excluding any item from the following analyses, in order to make our study more comparable with the vast literature on the IUS-R. *[Table 2 here]*

3.2. Network estimation and local network properties

Figure 1 shows the estimated EBIC graphical networks on the IUS-R across the undergraduate and community samples. Several features were similar in the two networks. First, all items were positively linked within the network, with some nodes being densely connected (i.e., #9, "*When it's time to act, uncertainty paralyses me*") and others being loosely connected (i.e., #4, "*A small, unforeseen event can spoil everything, even with the best of planning*"). *[Figure 1 here]*

Second, local proprieties analysis on the two samples revealed similar results as to what items were the strongest ones within the network (Figure 2). In detail, across the undergraduate and community samples, items #6 (“*I can’t stand being taken by surprise*”) and #7 (“*I should be able to organize everything in advance*”) showed the highest levels of strength (i.e., strength index ≥ 1.10). Similarly across the two data sets, items #3 (“*One should always look ahead so as to avoid surprises*”) and #4 (“*A small, unforeseen event can spoil everything, even with the best of planning*”) were those showing the lowest level of strength (i.e., strength index ≤ 0.58). *[Figure 2 here]*

Third, predictability analysis showed that the networks estimated on the undergraduate and the community samples reported similar level of predictability (M_{pred} = 0.46 ± 0.14, range: 0.17 - 0.60, and M_{pred} = 0.42 ± 0.12, range: 0.21 – 0.54, respectively). In other words, by considering the influence among the network nodes, on average only about 45% of variance could be explained, hence implying that more than half of variance is left unexplained.

3.3. Accuracy, stability and intranetwork comparisons

The accuracy analysis showed that the edges of two networks were precisely estimated, with each edge showing narrow confidence intervals (Figure S1). Moreover, it is worth stressing that the both models reported very high levels of stability for the edge values (*CS-coefficients* = 0.75 in both networks). In other words, very similar edge values would be obtained, even after removing up to 75% of the samples.

Moreover, consistently across the two samples, a few edges were statistically stronger than the rest of the network edges (Figure S2), namely #8-#9 (“*Uncertainty keeps me from living a full life*”, “*When it’s time to act, uncertainty paralyses me*”), #6-#7 (“*I can’t stand being taken by surprise*”, “*I should be able to organize everything in advance*”), #9-#10 (“*When it’s time to act, uncertainty paralyses me*”, “*When I am uncertain I can’t function very well*”), #1-#2 (“*Unforeseen events upset me greatly*”, “*It frustrates me not having all the information I need*”), #11-#12 (“*The smallest doubt can stop me from acting*”, “*I must get away from all uncertain situations*”), #5-#7 (“*I* *always want to know what the future has in store for me*”, “*I should be able to organize everything in advance*”), and #1-#6 (“*Unforeseen events upset me greatly*”, “*I can’t stand be taken by surprise*”).

Importantly, strength values were stable and reliable in the two networks (*CS-coefficient* = 0.75; Figure S3). In fact, after dropping up to 75% of the sample, similar strength values ranking would be obtained. Moreover, across the two data sets, the items #6 and #7 (“*I can’t stand being taken by surprise*”, “*I should be able to organize everything in advance*”) were statistically stronger than the rest of the items, while items #3 and #4 were statistically less strong than all the other nodes (Figure S4).

3.4. Community analysis

The network display showed that nodes differed in their interconnectedness. To formally test this impression, we initially used the spinglass algorithm, which detected three communities, identical similar across the two samples (Figure 1). The first community (i.e., items #8, #9, #10, #11, and #12; orange community) seemed to mostly consist of items that capture the *behavioral reactions to uncertainty*. The second community consisted of three items (i.e., #1, #2, and #6), with this second cluster of nodes mostly measuring the *emotional reactions to uncertainty*. Then, a third community capturing the *negative beliefs about uncertainty* was detected and it consisted of four items (i.e., #3, #4, #5, and #7). Importantly, very similar results were obtained when different community detection algorithms were used, with about 97% of the nodes being clustered consistently across the two samples (Table S1). These results confirmed the trustworthiness of the community analysis on in the IUS-R.

3.5. Internetwork comparison and mean levels comparison

We evaluated the degree of similarity, global connectivity difference, and structure difference of the IU network across the two samples. The analysis revealed the two models were highly similar in terms of edge values (r_s = 0.84 [0.79; 0.88]), strength values (r_s = 0.96 [0.85; 0.99]), and predictability values (r_s = 0.93 [0.76; 0.98]). Moreover, no difference in terms of global connectivity was found (global connectivity difference = 0.05; $p = 0.52$). Interestingly, the analysis revealed that the two networks showed a significantly different structure (maximum difference = 0.16; $p < 0.002$). In line with van Borkulo and colleagues (2017), we followed up this structure difference, by testing the difference between the two networks at the level of each single edge. After applying the Holm-Bonferroni correction, only about 9% of the edges were statistically different between the two networks. In detail, the edges between items #1 and #6, #4 and #11, and #3 and #10 were statistically stronger in the undergraduate sample than in the community sample, whereas the edge between #3 and #5, #4 and #7, and #4 and #9 were statistically stronger in the community samples than in the undergraduate sample. It is worth mentioning that the magnitude of these edge differences was small-to-negligible (edge difference < 0.1), with two exceptions, namely the edge between #1 and #6 ("*Unforeseen events upset me greatly*", "*I can't stand being taken by surprise*") (edge difference = 0.16) and the edge between #3 and #5 ("*One should always look ahead so as to avoid surprises*", "*I always want to know what the future has in store for me*") (edge difference = 0.13).

Mean levels comparison for each item of the IUS-R are reported in Table 2. Although six items were found to be statistically different, the magnitude of these differences were negligible (Cohen's s $d < 0.20$). Only item #3 ("*One should always look ahead so as to avoid surprises*") was statistically higher in the community sample than in the undergraduate sample with an effect size of small magnitude (Cohen's $d = 0.23$).

3.6. Further analysis

We performed some additional analyses to check for the robustness and trustworthiness of our results. Specifically, we re-estimated the networks, after controlling for gender, age, and marital status as covariates. Following the procedure proposed by Dalege and colleagues (2017), we obtained almost identical networks as those without covariates (edge similarity $r_s = 0.96$ [0.94; 0.97] and $r_s = 0.98$ [0.97; 0.98]; strength similarity $r_s = 0.99$ [0.95; 0.99] and $r_s = 0.99$ [0.97; 0.99]; predictability similarity $r_s = 0.99$ [0.97; 0.99] and $r_s = 0.98$ [0.95; 0.99] in the undergraduate and the community samples, respectively). Then, we investigated the possible role of gender, age, and marital status as moderators at level of each edge (i.e., moderated network analysis; Haslbeck, Borsboom, & Waldorp, 2018). Only one significant interaction was found. Specifically, the edge between item #9 and #12 was equal to zero in males and increased slightly (i.e., by .06 units) in females. Taken together, these results confirmed that the network of IU is substantially identical across gender, age, and marital status.

4. Discussion

In the current study, we adopted a network analysis approach in order to shed light on the internal structure of IU. To pursue this aim, we conducted our analyses on two large non-clinical samples, consisting of undergraduate students and adults from the local community. This also allowed us to look for similarities in the structure of IU across two populations potentially different in terms of interpretations and reactions to uncertainty (Arnett, 2010; Bottesi, Gürdere, Cerea, Sica, & Ghisi, 2020).

The analysis of the network structure showed that feeling uncomfortable when things happen unexpectedly (node #6) and beliefs about the importance of action planning (node #7) are the most central nodes in both samples. In other words, these two elements emerged as the most strongly connected of IU network. Although equating node centrality to causality is not always correct (Dablander & Hinne, 2019), this finding suggests that feeling uncomfortable with uncertainty and believing that something has to be done in advance may play a particularly important role in the development of IU. It is worth mentioning that this represents a hypothesis, which should be tested in an experimental and clinical manner (Fried et al., 2017).

Cognitive-behavioral models of psychopathology postulate that cognitions, emotions, and behaviors are causally related (Beck, 1976). In particular, beliefs – especially those about emotions – are assumed to play a pivotal role in triggering behaviors, which are usually implemented to modify an aversive emotional experience (Ouimet, Kane, & Tutino, 2016). Additionally, emotion regulation theories integrate this assumption positing that individuals - either implicitly or explicitly

– usually enact cognitive and behavioral strategies to modulate their emotional states. The less people are able to recognize and tolerate the emotions they attend to, the less likely they are able to flexibly engage in adaptive emotion regulation strategies (e.g. Gross, & Jazaieri, 2014; Sheppes, Suri, & Gross, 2015). The current finding supports both perspectives, as it suggests that both a difficulty staying in contact with uncertainty and the belief that things have to be planned might drive individuals performing behaviors to reduce, avoid, or remove uncertainty and its associated distress. Among behaviors enacted to cope with uncertainty are information seeking, distracting, or acting impulsively (Bottesi, Carraro, Martignon, Cerea, & Ghisi, 2019a). It is important to stress that, although these do not represent maladaptive behaviors *per se*, they could negatively reinforce both negative beliefs and emotions about it, thus fueling IU, if inflexibly used to manage uncertainty.

Interestingly, a general internal state aversion (i.e., “can’t stand”) rather than clearer emotional states (i.e. “upset”, node #1; “frustration”, node #2) emerged as central in the network. This evidence can be explained by the non-clinical nature of our samples: uncertainty is unpleasant in most circumstances, and the majority of people are likely to feel “uncomfortable” with uncertainty rather than “upset” or “frustrated”. From a conceptual point of view, uncertainty would begin triggering increasingly negative emotions once the individual negatively appraises the uncertain situation and repeatedly performs maladaptive coping behaviors (e.g., worry, avoidance) to cope with it, thus fostering IU. Eventually, such a mechanism would finally promote the establishment of psychopathology. In a similar way, believing that one should be able to organize everything in advance can be intended as an adaptive belief *per se*, since it reflects a desirable personality trait (i.e., conscientiousness; McCrae & Costa, 1991) and the behavior it motivates does represent a helpful strategy not to be taken by surprise. Again, individuals from the general population might endorse such belief as a culturally prescribed way of conduct; however, if constantly reinforced (both positively and negatively), adaptive action planning may escalate into pathological worry, thus assuming a relevant role in the maintenance of IU and in the development of emotional disturbances.

Specific network edges emerged as statistically stronger than the others both in undergraduates and in community individuals. For example, feeling upset when unforeseen events occur (i.e., #1) was strictly related with both the frustration due to the absence of information (i.e., #2) and the discomfort of being taken by surprise (i.e., #6), thus supporting the notion that not knowing is highly associated with aversive emotional outcomes; it is the individual context, salience, and experience that determine the specific emotional responses to an unknown (Carleton, 2016). Another interesting finding is the association between the willing to know what the future has in store (i.e., #5) and the belief about the importance of action planning (i.e., #7), which exemplifies how desiring predictability is linked to active engagement in behaviors aimed at increasing certainty and/or reducing uncertainty (Birrell et al., 2011).

Among the stronger network edges, three referred to the link between the inability to respond when facing uncertainty and the fact that uncertainty causes impairments in everyday life, so that it has to be avoided (i.e., #8 – #9; #9 – #10; #11 – #12). Coherently, this uncertainty paralysis consists in avoidance behaviors to minimize exposure to uncertainty, which precludes the disconfirmation of dysfunctional beliefs associated with uncertainty (Dugas et al., 1998). To note, avoiding uncertainty contributes increasing emotional distress both preventing exposure to feared stimuli (Foa & Kozak, 1986) and maintaining worry (Berenbaum, Bredemeier, & Thompson, 2008), thus suggesting that in the long term it might be even more impairing than worrying about uncertainty.

Findings from the community analysis outlined that, in both samples, the network of IU consists of three communities capturing negative beliefs about uncertainty, behavioral reactions to uncertainty, and emotional reactions to uncertainty. These communities are fully consistent with the initial definitions of IU (Buhr & Dugas, 2002; Freeston et al., 1994). It is worth stressing that our results held across two independent samples and four different community detection algorithms and thus to be considered as highly reliable and replicable. Interestingly, to date, factorial approaches apparently failed in detecting the distinctiveness of these components, with some studies suggesting the existence of two main dimensions – under-representing uncertainty aversiveness (e.g. Birrell et al., 2011;-Carleton et al., 2007) and recent evidence supporting the idea of IU as a univocal construct (e.g., Bottesi et al., 2019b; Hale et al., 2016;-Shihata et al., 2018). Divergent findings between factor and community analysis are not unusual (Briganti & Linkowski, 2019; Watters, Taylo, & Bagby, 2016) and could explain suboptimal fit in latent factors studies (Bansal et al., 2020). In sum, our findings suggest that IU comprises three clusters of nodes, namely negative beliefs, behavioral reactions, and emotional reactions to uncertainty, and future studies may want to directly test the structure emerged in our study.

Overall, current findings outlined that the construct of IU is highly similar in undergraduates and community individuals in terms of network similarity, global connectivity, and structure and items mean levels. A considerable amount of research about IU has been carried out on undergraduates *as if* they were equivalent to adults (Bottesi et al., 2016), and our results substantially validate such an assumption. However, the edge between nodes #1 ("*Unforeseen events upset me greatly*") and #6 ("*I can't stand being taken by surprise*") was stronger in undergraduates than in community individuals, whereas the one between nodes #3 ("*One should always look ahead so as to avoid surprises*") and #5 ("*I always want to know what the future has in store for me*") was stronger in community individuals than in undergraduates, thus suggesting that the way through which IU expresses itself may somewhat differ from college age to adulthood (Arnett, 2010). Indeed, some authors claimed that experience in emotion regulation – and, consequently, in the management of uncertainty - increase across the lifespan (Bottesi et al., 2020; Carstensen, Fung, & Charles, 2003). Taken together, these considerations may preliminary explain why uncertainty appears to be more emotionally – than cognitively – intolerable for undergraduate students; nonetheless, further additional research is warranted in order to corroborate these speculations. It is also worth mentioning that the structure of the network of IU is not substantially influenced by individual differences, such as age, gender, and marital status. Overall, only small-to-negligible differences were detected. These pieces of evidence support the idea that IU is substantially invariant across important differences between individuals (Bottesi et al., 2019b).

Finally, the predictability analysis showed that, on average, more than half of variance in IU components was not explained. This piece of evidence encourages future research where the focus should be broadened to take into account other constructs and phenomena potentially impacting IU, such as neuroticism, distress tolerance, coping styles, attachment, and negative affect (e.g. Carleton, 2016; Shihata et al., 2016; Zdebik, Moss, & Bureau, 2018).

Broader implications and future research directions can be derived. Our study based on network analysis generates specific and testable predictions, which are markedly different from those proposed by latent factor studies. From a latent factor standpoint, targeting the most central items (i.e., #6 and #7) would not have any impact on the other elements of IU. Moreover, even if such intervention could somehow influence the latent factor, its effect on all the other items would be proportional to their factor loadings. From a network analysis standpoint, varying the degree of activation of a certain node would putatively spread through the network in a fashion proportional to each edge strength, with propagation being more likely to occur within each community. For instance, targeting item #7 is likely to have a stronger impact on item #5, which belongs to the same community, than on item #9, which is grouped in a different cluster (van Bork et al., 2019). Future experimental and clinical studies could directly test these two alternative predictions, with the final goal to develop an effective therapeutic intervention on IU.

We acknowledge here several limitations. First, our study was based on cross-sectional data, which does not allow deriving directionality among items. In line with previous methodological and clinical literature (Borsboom & Cramer, 2013; Epskamp, Waldorp, Mottũs, & Borsboom, 2018), we suggest that our network model may provide clues about the causal skeleton among the elements of IU, with the caveat that other causal factors may have not been modeled, as shown by the predictability analysis. Hence, strong causal claims are to be avoided and our results should be considered as a preliminary step toward a better understanding of the internal structure of IU. Second, the IUS instruments usually measure IU as a stable trait, while network approach contends that this construct unfolds over time, by either reinforcement or inhibition of its elements. Moreover, it has been shown that IU is not exclusive to adults, but it is likely to develop from early childhood to adolescence, paralleling neurological and cognitive maturation (Osmanağaoğlu, Creswell, & Dodd, 2018). In the future, researchers may want to investigate its developmental trajectory across the lifespan, by sampling the IU elements over short periods of time (i.e., days, weeks) with state measures for IU, such as the IUS- Situation-Specific version (Mahoney & McEvoy, 2012). Third, being the 12-item IUS the most widely adopted measure of IU, several authors argue that it does not adequately capture the construct, with some encouraging refinements of the items (e.g. Bottesi et al., 2019b) and others suggesting the use of more comprehensive measures (Lauriola et al., 2018). Moreover, IU may be related also with the tendency towards emotionally motivated rash actions (Bottesi et al., 2019a; Sadeh & Bredemeier, 2019), which makes negative urgency (Whiteside & Lynam, 2001) another construct deserving integration in the conceptualization and measurament of IU. Fourth, preliminary analysis showed that three items were either poorly informative or possibly redundant, but inconsistently across the two samples. Therefore, we preferred including all the items to make our study more comparable with vast literature on IU. Although it is unlikely that such minor violations impacted our results, future studies should focus on pinpointing the necessary prerequisite at node level, in order to perform a high-quality network analysis. Fifth, our study did not rely on clinical data. The inclusion of a patients sample could have been highly informative and it may have allowed shedding light on the possible role of IU as maintaining factor in psychopathology.

5. Conclusions

Despite the limitations, we believe that our study has three major strengths. First, to our knowledge, it represents the first attempt to investigate the internal structure of IU by means of a network approach. By doing so, we have highlighted several important new pieces of information with regard to this important phenomenon and its functioning. Specifically, we found that a general internal state aversion and believing that it is essential to plan in advance to deal with uncertainty may play a pivotal role in the establishment of IU. Moreover, our findings provide preliminary, but solid evidence to the original intuition of IU as consisting of three dimensions, namely beliefs, emotions, and behaviors (Freeston et al. 1994). Lastly, current results suggest that IU may not differently express itself according to distinct life stages or individual differences. Second, the employed samples were large and highly representative of the undergraduate and community population, which makes reported findings highly generalizable to the non-clinical population. Third, we paved the way to several future studies, which could represent a major step forward in our understanding of this phenomenon. In fact, we believe that future research should expand extant results by means of longitudinal designs and by exploring the underlying structure of IU in samples of individuals experiencing symptoms of various emotional disorders. By doing so, it should be possible to shed further light on the transdiagnostic nature of IU and improve our current clinical toolbox for treating mental disorders.

Figure captions

Figure 1 Network models for the 12 items of the IUS-R.

Figure 2 Strength scores (standardized z scores).

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Table 1
Demographic data across groups.

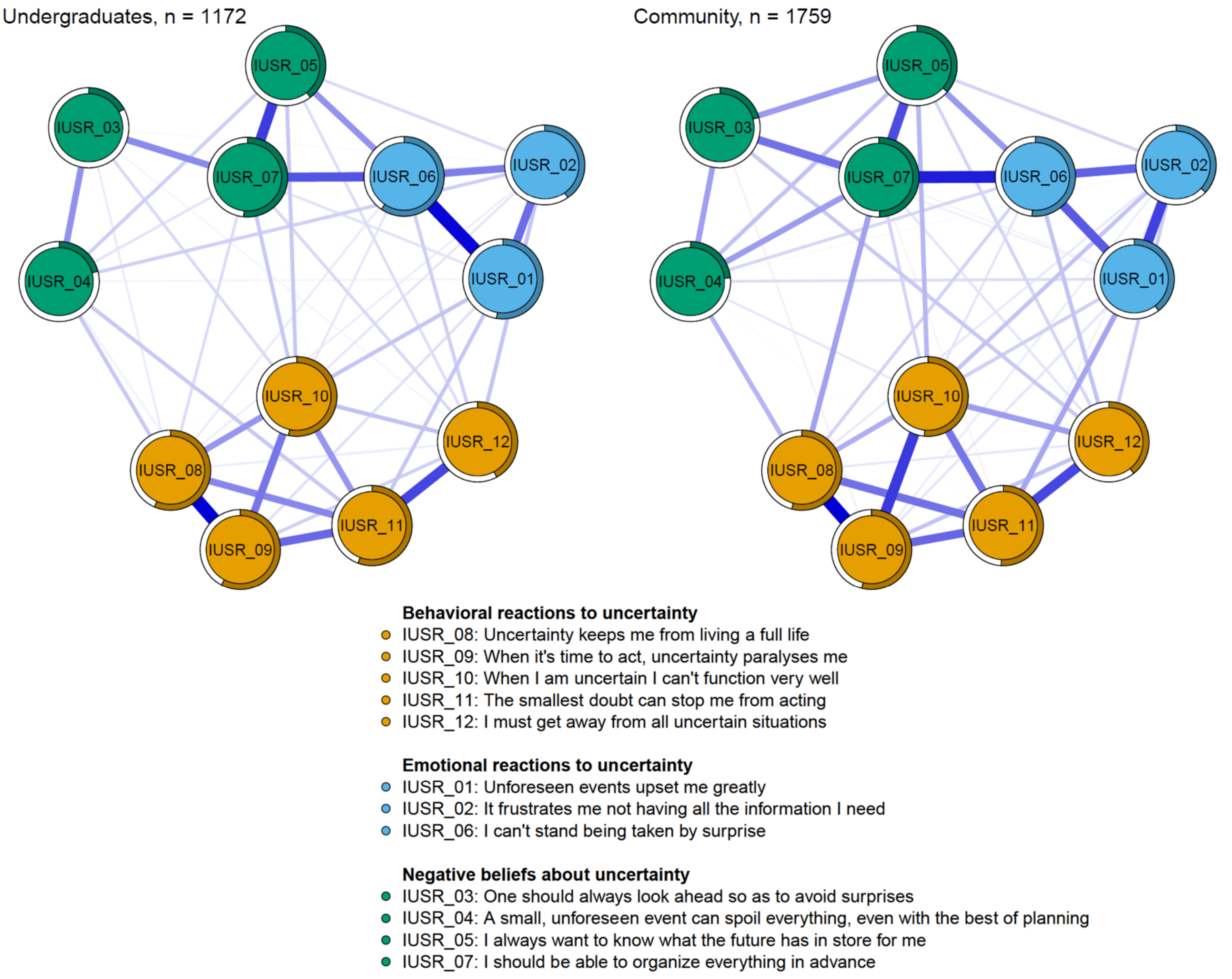
	Undergraduate sample	**Community sample**
Age (M±SD)	21.50±1.88	40.72±14.61
Years of education (M±SD)	13.97±1.60	13.67±3.83
Marital status (% single/not in a domestic relationship)	84.2	39.5
Occupation (% full-time job)	-	48.4

Table 2

Means, standard deviations, and polychoric correlations in the undergraduate samples (n = 1172) and in the community samples (n = 1759)

Variable	*UG - M*	*UG - SD*	*Comm - M*	*Comm - SD*	*t-test*	*adjusted p*	*Cohen's d*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
1. IUSR_01	2.57	1.02	2.45	1.03	3.09	0.024	0.11	-	.55	.21	.29	.41	.67	.49	.43	.44	.49	.46
2. IUSR_02	2.23	1.06	2.21	1.10	0.46	1	0.01	.50	-	.22	.29	.40	.56	.44	.38	.35	.42	.38
3. IUSR_03	2.30	1.14	2.57	1.26	6.18	<0.001	0.23	.22	.20	-	.29	.24	.25	.36	.26	.21	.28	.22
4. IUSR_04	2.87	1.11	2.98	1.23	2.52	0.14	0.09	.29	.26	.3	-	.29	.28	.32	.34	.31	.30	.34
5. IUSR_05	2.43	1.11	2.23	1.14	4.81	<0.001	0.18	.32	.35	.35	.34	-	.52	.57	.35	.34	.42	.35
6. IUSR_06	2.22	1.04	2.24	1.06	0.57	1	0.02	.52	.51	.29	.35	.47	-	.61	.44	.40	.49	.43
7. IUSR_07	2.43	1.09	2.41	1.13	0.39	1	0.01	.39	.38	.40	.40	.53	.59	-	.43	.39	.49	.42
8. IUSR_08	2.34	1.16	2.25	1.17	1.99	0.56	0.07	.43	.39	.23	.35	.34	.46	.46	-	.69	.60	.61
9. IUSR_09	1.93	1.07	1.76	1.02	4.19	<0.001	0.16	.40	.37	.16	.24	.29	.39	.35	.64	-	.61	.63
10. IUSR_10	2.07	1.00	1.93	1.00	3.68	0.003	0.14	.42	.41	.23	.31	.40	.45	.43	.56	.61	-	.59
11. IUSR_11	1.75	.98	1.69	.96	1.47	1	0.05	.43	.37	.19	.27	.3	.39	.33	.58	.59	.57	-
12. IUSR_12	1.40	.72	1.55	.85	5.26	<0.001	0.19	.35	.37	.26	.25	.35	.42	.38	.45	.47	.50	.54

Note. UG = undergraduate sample; *Comm* = community sample. Polychoric correlations in the undergraduate sample are reported above the diagonal, while polychoric correlation in the community sample are reported below the diagonal.



Undergraduates, n = 1172
Community, n = 1759
IUSR_01
IUSR_02
IUSR_03
IUSR_04
IUSR_05
IUSR_06
IUSR_07
IUSR_08
IUSR_09
IUSR_10
IUSR_11
IUSR_12
Behavioral reactions to uncertainty
IUSR_08: Uncertainty keeps me from living a full life
IUSR_09: When it's time to act, uncertainty paralyses me
IUSR_10: When I am uncertain I can't function very well
IUSR_11: The smallest doubt can stop me from acting
IUSR_12: I must get away from all uncertain situations
Emotional reactions to uncertainty
IUSR_01: Unforeseen events upset me greatly
IUSR_02: It frustrates me not having all the information I need
IUSR_06: I can't stand being taken by surprise
Negative beliefs about uncertainty
IUSR_03: One should always look ahead so as to avoid surprises
IUSR_04: A small, unforeseen event can spoil everything, even with the best of planning
IUSR_05: I always want to know what the future has in store for me
IUSR_07: I should be able to organize everything in advance

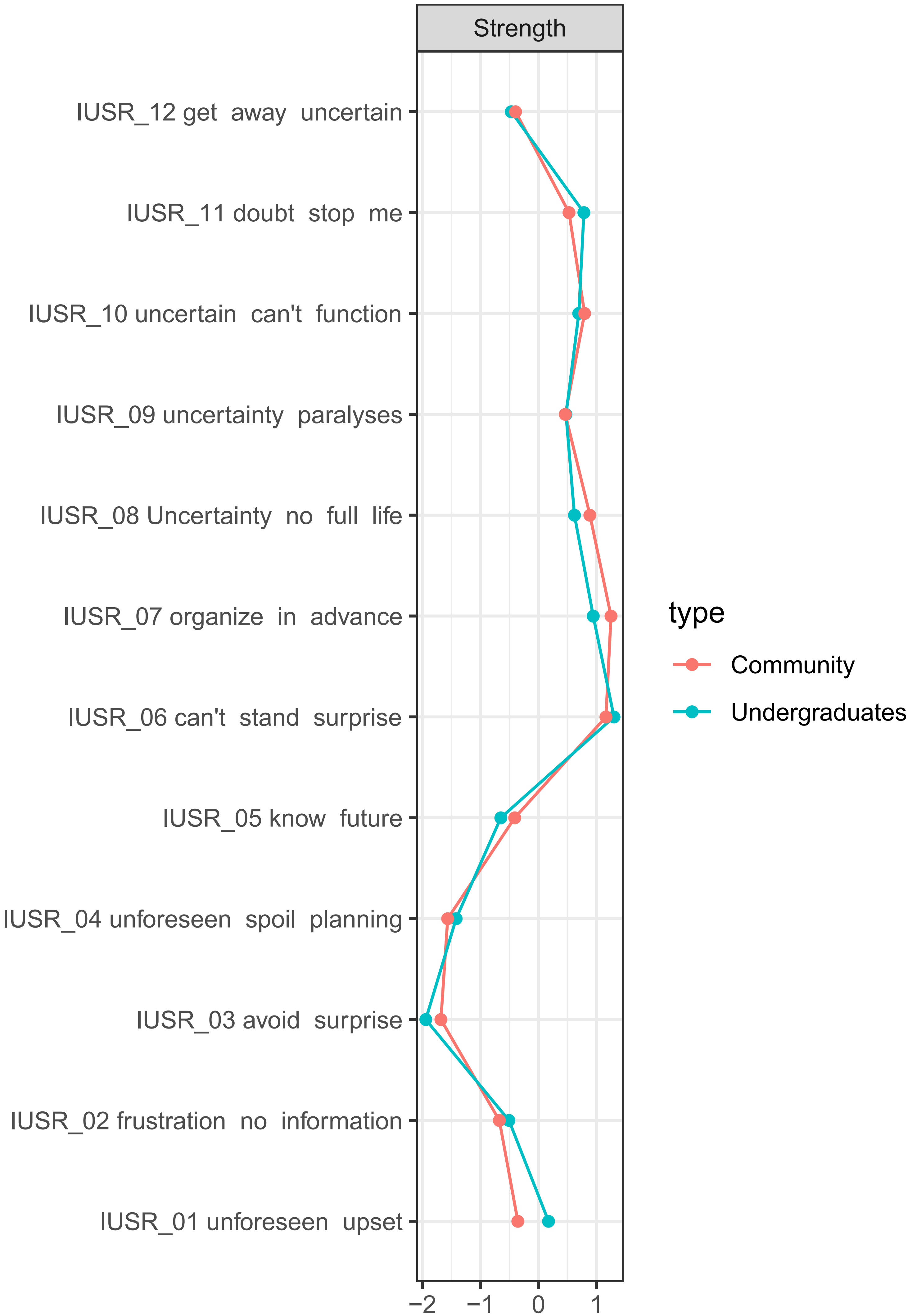
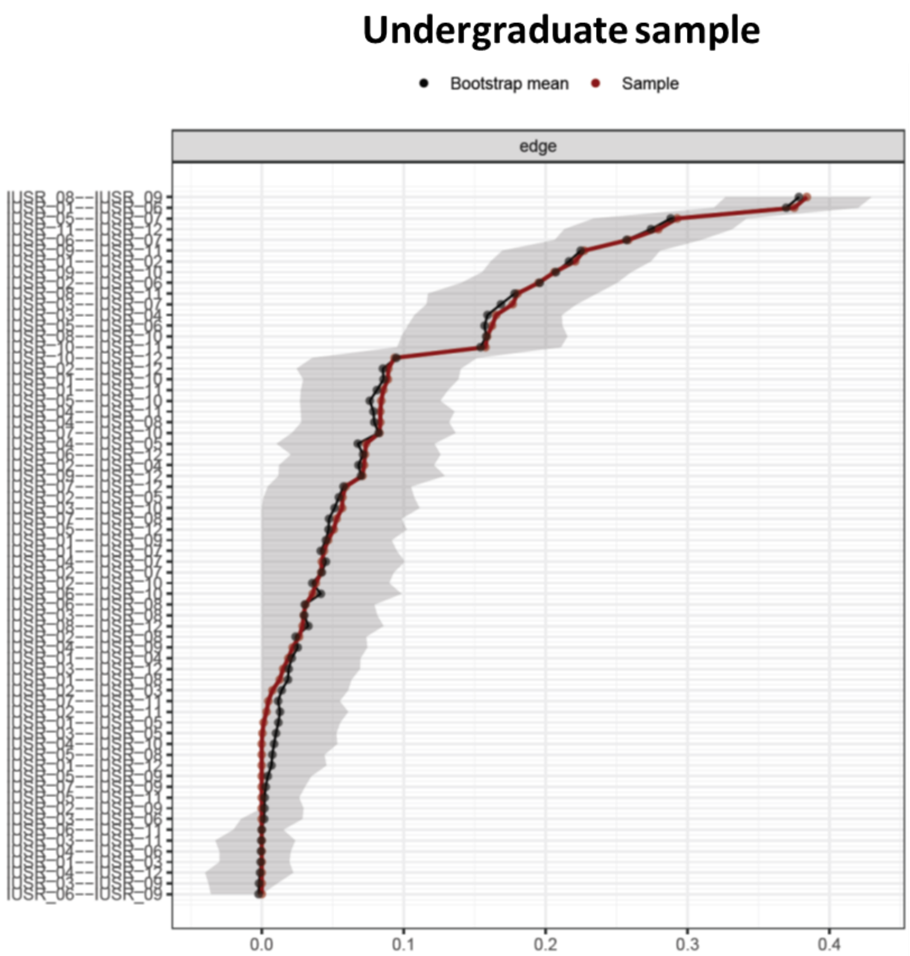

Strength
IUSR_12 get away uncertain
IUSR_11 doubt stop me
IUSR_10 uncertain can't function
IUSR_09 uncertainty paralyses
IUSR_08 Uncertainty no full life
IUSR_07 organize in advance
IUSR_06 can't stand surprise
IUSR_05 know future
IUSR_04 unforeseen spoil planning
IUSR_03 avoid surprise
IUSR_02 frustration no information
IUSR_01 unforeseen upset
−2
−1
0
1
type
Community
Undergraduates

Table S1. *Community detection analysis across the spinglass, walktrap, leading eigenvector, and fast greedy algorithms.*

	Undergraduate sample				Community sample			
Variable	*Spinglass*	*Walktrap*	*Leading eigenvector*	*Fast greedy*	*Spinglass*	*Walktrap*	*Leading eigenvector*	*Fast greedy*
1. IUSR_01	Emot	Emot	Emot	Emot	Emot	Emot	Emot	Emot
2. IUSR_02	Emot	Emot	Emot	Emot	Emot	Emot	Emot	Emot
3. IUSR_03	Belief	Belief	Belief	Belief	Belief	Belief	Belief	Belief
4. IUSR_04	Belief	Belief	IUSR_04	Belief	Belief	Belief	Belief	Belief
5. IUSR_05	Belief	Emot	Belief	Belief	Belief	Belief	Belief	Belief
6. IUSR_06	Emot	Emot	Emot	Emot	Emot	Emot	Emot	Emot
7. IUSR_07	Belief	Emot	Belief	Belief	Belief	Belief	Belief	Belief
8. IUSR_08	Behav	Behav	Behav	Behav	Behav	Behav	Behav	Behav
9. IUSR_09	Behav	Behav	Behav	Behav	Behav	Behav	Behav	Behav
10. IUSR_10	Behav	Behav	Behav	Behav	Behav	Behav	Behav	Behav
11. IUSR_11	Behav	Behav	Behav	Behav	Behav	Behav	Behav	Behav
12. IUSR_12	Behav	Behav	Behav	Behav	Behav	Behav	Behav	Behav

Note. Behav = Behavioral reactions to uncertainty; *Belief* = Negative beliefs about uncertainty; *Emot* = Emotional reactions to uncertainty. Single-item communities are labelled with the item name (i.e., IUSR_04).

Figure S1. *Nonparametric bootstrapped confidence intervals of estimated edges for the two samples. The red line represents the estimated edge, while the dark area indicates the 95% bootstrap confidence interval.*



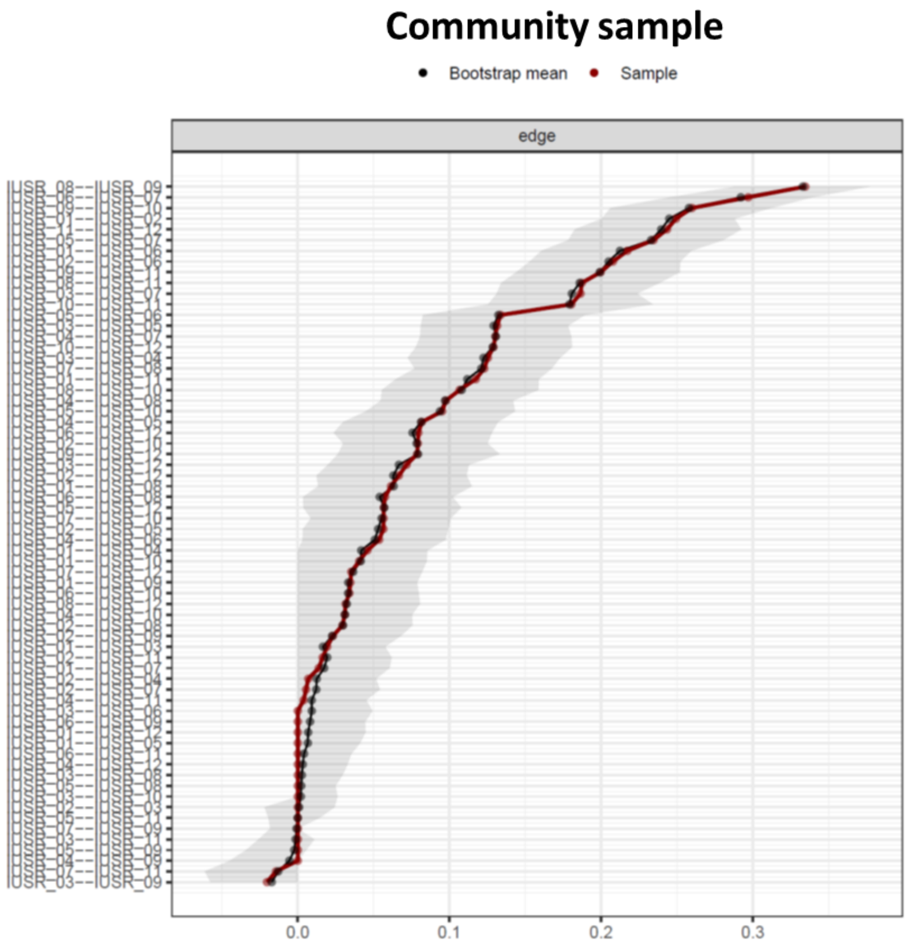


Figure S2. *Nonparametric bootstrapped difference test for edges, across the two samples. Gray boxes indicate no significant difference, whereas black boxes indicate statistically significant difference (p < 0.05). Diagonal color and saturation represent the magnitude and direction of each estimated edge.*

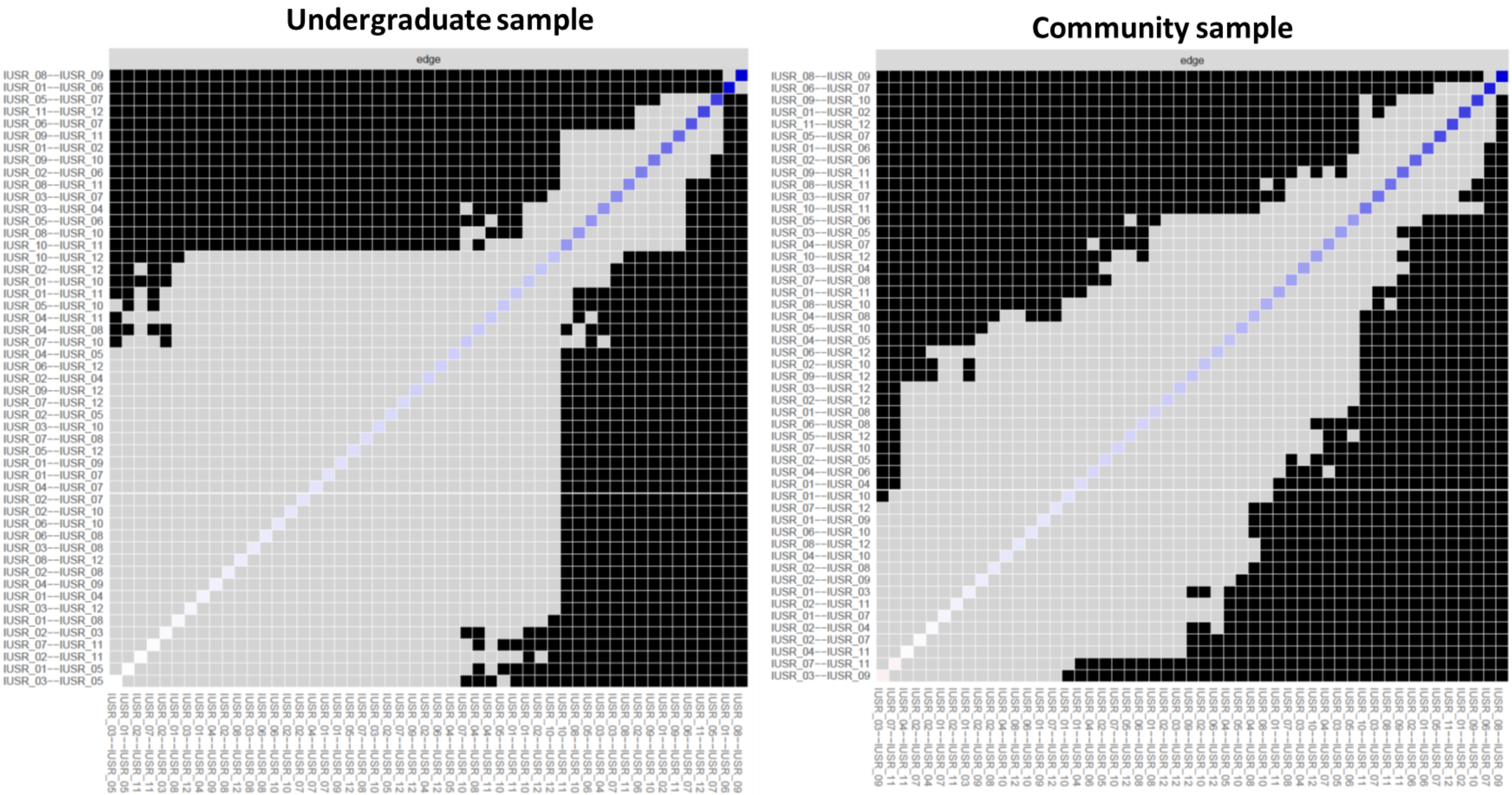


Figure S3. *Representation of the correlation of the strength in the original network with the strength of the networks sampled while dropping participants, across the two samples.*

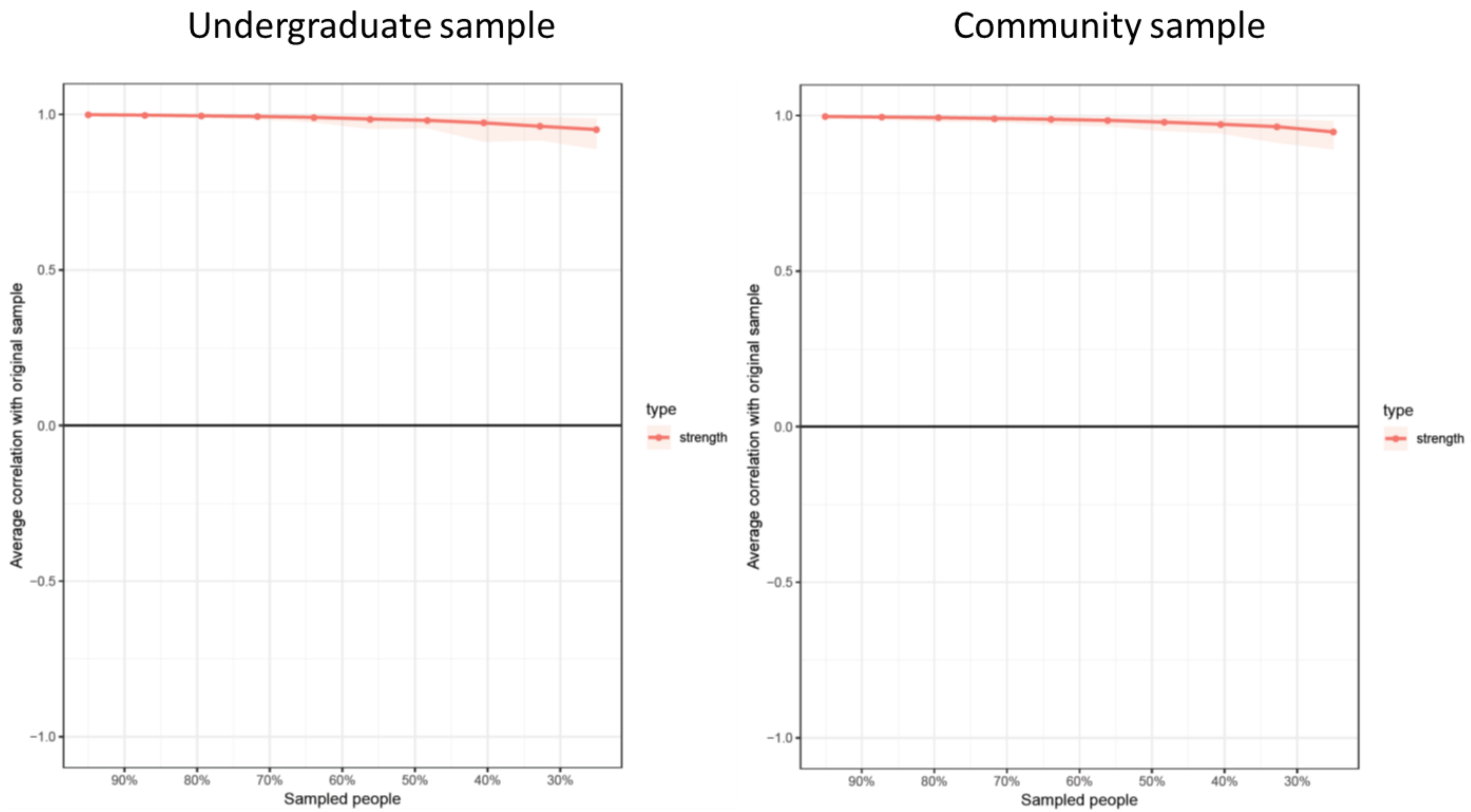


Figure S4. *Nonparametric bootstrapped difference test for strength across the two samples. Gray boxes indicate no significant difference, whereas black boxes indicate statistically significant difference (p < 0.05). Diagonal values represent the strength score of each node.*