Intolerance of Uncertainty and Climate Change Experience as Driving Forces of Climate Anxiety: Insights from a Network Perspective

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Abstract

Recent evidence indicates that sizeable segments of the global population experience marked anxiety about climate change. Yet important questions remain about the psychological processes that sustain climate anxiety and about how this anxiety can translate into adaptive responses (i.e., pro-environmental behaviors) versus maladaptive outcomes (i.e., impairments in daily functioning). In the present study, we explicitly build on decades of basic research identifying intolerance of uncertainty—a dispositional difficulty in tolerating the unknown—as a decisive mechanism in the emergence and maintenance of anxiety-related dysfunction. Accordingly, we investigated how intolerance of uncertainty, the experience of climate change, and climate anxiety are interconnected, along with climate anxiety's (mal)adaptive outcomes. We analyzed data from an international unselected sample (n = 728) using computational tools from the network analytical framework. Specifically, we estimated a Gaussian Graphical Model (GGM) to characterize the network's structure, identify potential clusters of variables, and detect influential nodes, and we estimated a directed acyclic graph (DAG) to examine the probabilistic dependencies among variables. Our results indicate that both intolerance of uncertainty and the experience of climate change function as driving forces within the overall network structure.

Keywords: Climate change anxiety, eco-anxiety, climate change, intolerance of uncertainty, network analysis, anxiety

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Climate change is increasingly recognized not only as an environmental and economic crisis, but also as a source of psychological strain (IPCC, 2022). Surveys across multiple countries indicate that substantial proportions of people report being very or extremely worried about climate change, and that these worries sometimes interfere with daily life (e.g., Hickman et al., 2021; Heeren et al., 2022; Ogunbode et al., 2021). This emerging phenomenon is often referred to as climate anxiety or eco-anxiety and encompasses persistent, future-oriented apprehension and emotional distress about climate change and its anticipated consequences —even among individuals who have not yet experienced any direct impact (Clayton, 2020; Heeren & Clayton, 2026; Coffey et al., 2021; for a meta-analysis, see Kühner et al., 2025).

Climate change is now widely regarded not only as an environmental and economic emergency, but also as a driver of psychological burden (IPCC, 2022). Cross-national surveys show that large segments of the population report being very or extremely worried about climate change, and that these concerns can sometimes impair everyday functioning (e.g., Hickman et al., 2021; Heeren et al., 2022; Ogunbode et al., 2021).

Despite heightened empirical attention, media coverage, and public concern, climate anxiety remains only partially understood (Heeren & Asmundson, 2023). This is particularly unfortunate from a clinical standpoint, where climate anxiety appears unusually challenging: compared with social- and death-anxiety vignettes, a climate-anxiety vignette elicits lower clinician confidence, reduced willingness to help, and higher negative affect (Williamson, King, & Raiman, 2025), underscoring an urgent need to improve our understanding so as to better equip mental health practitioners working with people experiencing debilitating climate anxiety (e.g., Croasdale et al., 2023; Heeren, 2025).

From a psychological perspective, Clayton and Karazsia (2020) proposed a model for assessing climate change anxiety that distinguishes two central components. One component captures the cognitive and emotional manifestations of climate anxiety—such as persistent worrying, crying, or nightmares about climate change. The other component targets the functional impairments that climate anxiety may induce in daily life, including difficulties with socializing, working, or concentrating in school (Clayton, 2020; Clayton & Karazsia, 2020). Initial empirical work suggests that, in two U.S. general-population samples, roughly one quarter of respondents reported levels of climate change anxiety associated with functional impairment in everyday life (Clayton & Karazsia, 2020). Similarly, a large international study conducted in European and African countries (Heeren et al., 2022) found that about one in five participants indicated that their anxiety about climate change significantly interfered with their ability to function day to day, for instance in social relationships, attention to family, and work performance. Comparable prevalence patterns have been documented in other parts of the world (e.g., Hickman et al., 2021; Tam et al., 2023).

Because disruptions in daily functioning often signal elevated risk for psychopathology (Boland et al., 2018; McKnight & Kashdan, 2009), these observations suggest that climate anxiety may represent a substantial threat to mental health and therefore warrants systematic investigation (for a discussion, see Heeren & Asmundson, 2023). Consistent with this concern, preliminary evidence indicates that climate anxiety predicts greater risk of depressive and anxiety disorders (Boluda-Verdú et al., 2022; Cosh et al., 2024), as well as increased suicide risk (Lerolle et al., 2025).

At the same time, several scholars have raised concerns about the potential dangers of “pathologizing” climate anxiety (Bhullar et al., 2022; Heeren et al., 2022; Taylor, 2020). Their position is that climate anxiety can constitute an adaptive response to a legitimate threat.

Indeed, such anxiety may spur individuals to engage in mitigation efforts, such as reducing their carbon footprint. This view is grounded in decades of research framing anxiety as a potentially adaptive reaction to uncertain future threats (for discussion, see Heeren & Asmundson, 2023). In this framework, anxiety is understood as an anticipatory process that orients individuals toward possible, not-yet-present dangers and equips them to cope effectively should these dangers materialize (e.g., American Psychological Association, 2015; Öhman, 2008). In line with this account, several studies have reported moderate to strong correlations between climate anxiety and pro-environmental behaviors (Heeren et al., 2022; Sangervo et al., 2022; Verplanken et al., 2020). Taken together, these findings suggest that, in at least some circumstances, climate anxiety is associated with constructive action. However, it remains unclear how to foster adaptive forms of climate anxiety while attenuating maladaptive responses. For example, are there specific variables that might promote adaptive responses while simultaneously constraining maladaptive ones?

Among the various triggers of climate anxiety, individuals' perceived experience of climate change has repeatedly been highlighted as a key driver (e.g., Clayton, 2020; Hoffmann et al., 2022). First, empirical studies have documented a medium-sized association between people's self-reported experiences of climate change and the two core features of climate change anxiety across culturally diverse samples (e.g., Clayton & Karazsia, 2020; Heeren et al., 2022). Second, individuals whose immediate environments have been directly affected by climate change (Cunsolo Willox et al., 2013; Ellis & Albrecht, 2017) tend to report more intense and more persistent emotional responses to climate change. For instance, in a study carried out in the Pacific atoll nation of Tuvalu, 95% of respondents reported substantial anxiety about climate change, and in 87% of cases this anxiety interfered with their daily functioning (Gibson et al., 2020). In parallel, previous work has suggested that the perceived experience of climate change may primarily foster the cognitive–emotional component described by Clayton and Karazsia (2020), without necessarily extending to the functional component (e.g., Heeren et al., 2023). That is, perceived experience of climate change might principally elicit the more adaptive facets of climate anxiety, while not directly generating its maladaptive outcomes. Accordingly, a critical next step is to establish whether, and if so how, the experience of climate change is linked to maladaptive climate anxiety, that is, to functional impairments. For example, one may ask what specific pathways could lead from perceived experience of climate change to such impairments.

Given decades of basic research regarding anxiety as a process that view threat mitigation as an increase in proactive planning and preparation for the future when confronted with uncertainty, as implied by functionalist views of anxiety (e.g., Bateson et al., 2011), one may wonder whether the way people tolerate uncertainty drives adaptative versus maladaptive climate anxiety. Dealing with the unknown is essential to survival, and intolerance to uncertainty (hereafter, IU) is a trait-like disposition reflecting the tendency to fear unacceptable and harmful future events characterized by uncertainty (for a review, see Carleton, 2016). IU affects how people perceive and react to situations wherein the risk of adverse consequences (e.g., the occurrence of a threat) is uncertain (i.e., may or may not occur), which can prevent adaptive behaviors and lead to functional impairments in daily life (e.g., Zlomke & Jeter, 2014). More specific definitions of IU include negative beliefs about uncertainty and one's ability to cope in the event of a future adverse event (Buhr & Dugas, 2002) and the tendency to view even low-probability adverse events as unacceptable or threatening (Carleton et al., 2007), mainly when ambiguous or missing information is salient or essential to the individual (Birrell et al., 2011). Uncertain threats are usually perceived as more stressful than highly predictable ones (e.g., Grupe & Nitschke, 2013; Shankman et al., 2011). For individuals with high levels of IU, more cognitive resources are used to search for certainty when threats are uncertain, leading to high psychological distress when certainty cannot be achieved (Birrell et al., 2011; Carleton et al., 2012; Dugas et al., 1998). For all these reasons, IU is now deemed as a transdiagnostic process involved in the onset and maintenance of anxiety disorders (for a review, see Rosser, 2019).

Considering that climate change entails many uncertainties, including the nature of its impacts (e.g., natural disasters, health problems, financial losses, forced migration) as well as their timing and exact locations, one may thus wonder about the role of IU in climate anxiety. Finally, IU has repeatedly been described as a core cognitive driver of worry (e.g., Dugas et al., 1998; Thielsch et al., 2015), and recent work has identified general worry as a predictor of the cognitive-emotional component of climate anxiety (e.g., Heeren et al., 2023; Parmentier et al., 2024). In a previous network study, the cognitive–emotional component emerged as the central hub in the network, with general worry acting as an important upstream node mainly connected to this component (Heeren et al., 2023). This raises the question of whether a more proximal and mechanistic construct often related to worry, such as IU, might help explain why climate-related distress tips from potentially adaptive concern into maladaptive, functionally impairing anxiety. From this perspective, one would expect IU to be closely tied to the cognitive-emotional component of climate anxiety, and, through it, to functional impairment.

Given the abovementioned points, we believe that understanding the interrelations between IU, perceptions of climate change, and climate anxiety is essential, as it may reveal pathways that lead to maladaptive outcomes (functional impairments) versus adaptive outcomes (pro-environmental behaviors). The present study builds on and extends our prior network modelling of climate anxiety (Heeren et al., 2023) by integrating IU. To do so, we used network psychometric methods to visualize the associations between these variables as nodes within a network system; a method that has become increasingly common in contemporary mental health research (for a methodological review, see Briganti et al., 2024; for a conceptual review, see Blanchard & Heeren, 2022).

In the study reported here, we had three primary goals. First, we endeavored to clarify the pairwise connections among all the variables. To this end, we computed a Gaussian Graphical Model (GGM), an undirected network model wherein the edges represent conditional independent relationships between nodes (Borsboom et al., 2021; McNally, 2021). We also quantified each node's importance to the resulting network structure.

Second, we tested whether these nodes cohere as a unitary network of interacting elements or constitute distinct communities (or subnetworks) of nodes serving different functions and, if so, whether specific nodes function as bridges, i.e., processes that connect or are shared by communities. These analyses may offer data-driven heuristics— to be followed up on and rigorously tested—in the search for especially potent nodes that may foster broader vulnerability in instigating maladaptive climate anxiety, or the mutually reinforcing interactions between IU and the experience of climate change.

Finally, we relied on Bayesian network methods to estimate a Directed Acyclic Graph (DAG), which encodes conditional independence relationships between the variables and characterizes their joint probability distribution (for a review, see Briganti et al., 2022). A DAG is a directed network wherein each edge has an arrow tip on one end, indicating the direction of probabilistic dependence among nodes—that is, whether the presence of node X implies the presence of node Y (node Y -> node X) more than vice versa (node X -> node Y). In this project, we thus relied on DAGs to examine the probabilistic dependencies between our variables of interest and generate a data-driven computational model of the interplay among our five variables of interest. Although DAGs are directed, in the present cross-sectional study the estimated graph is still derived from observational (correlational and conditional-dependence) patterns. The direction of an arrow thus reflects the orientation of probabilistic dependence that is most consistent with the observed conditional-independence structure under the assumed model, but it does not by itself establish temporal precedence or experimental manipulation (Briganti et al., 2022). Accordingly, the resulting DAG should not be interpreted as proof of causal effects; rather, it provides a compact probabilistic representation of the most plausible dependency structure among variables and is used here as a hypothesis-generating, rather than hypothesis-testing, tool.

Method

Participants

We recruited 728 French-speaking participants, among whom 48.08% identified as women, 50.55% as men, and 1.37% as non-binary or other genders. Participants were recruited through online advertisements on social media and forums targeting European French speakers.

In terms of nationality, 58.24% were from France, 38.74% from Belgium, 0.82% from Switzerland, and 2.20% from other French-speaking countries and territories around the world. Participants' ages ranged from 18 to 70 years, with a mean age of 38.36 years (*SD* = 14.23). They reported completing between 0 (i.e., no secondary education) and 27 years of education following primary school, with a mean of 16.62 years (*SD* = 3.33).

Each participant provided written informed consent before completing the survey. The study received approval from the Institutional Review Board of the Psychological Sciences Research Institute at UCLouvain (Reference: Project IPSY 2021-12) and was conducted in accordance with the Declaration of Helsinki. De-identified data, the R script used for analysis and supplementary materials are publicly available via the Open Science Framework at. https://osf.io/3a48q/overview.

Measures

Because French is the language of our participants, we used the French version of the instruments described below. All have demonstrated satisfactory psychometric properties in prior work, as detailed below.

Climate Anxiety

Climate anxiety was assessed with the 13-item Climate Change Anxiety Scale (CCAS; Clayton & Karazsia, 2020). The scale yields two subscales reflecting (a) cognitive-emotional reactions to climate change (e.g., "Thinking about climate change makes it difficult for me to concentrate") and (b) related functional impairments in everyday life (e.g., "My concerns about climate change interfere with my ability to complete work or school assignments"). Items are rated from 0 ("Never") to 5 ("Almost always"), with higher scores indicating stronger endorsement of each feature. We used the validated French version of the scale (Mouguiama-Daouda et al., 2022). In this study, Cronbach's alphas for the cognitive-emotional and the functional impairment subscales were of .82 and 82, respectively. The McDonald's omegas of these subscales were of .86 and .85, respectively.

Experience with Climate Change

Perceived experience of climate change was measured by using three brief items developed by Clayton and Karazsia (2020). These items capture the extent to which participants feel that they themselves, people they know, or places that are important to them have been affected by climate-related changes. Responses are given on a 0–5 Likert-type scale (from "Never" to "Almost always"), with higher scores reflecting greater perceived experience. We employed the validated French version of these items developed and validated in a previous study (Mouguiama-Daouda et al., 2022). The internal consistency was good in our sample, with a Cronbach's alpha of .79 and a McDonald's omega of .80.

Intolerance of uncertainty

We evaluated IU using the Intolerance of Uncertainty Scale-Revised (IUS-R; Bottesi et al., 2019), which consists of 12 items designed to assess IU. Participants rated each item on a 5-point Likert-type scale, ranging from 1 (Not at all like me) to 5 (Completely like me). We utilized the validated French version of the scale (Mouguiama-Daouda et al., 2023), which has demonstrated good psychometric properties in French-speaking samples. In the present study, the internal reliability of the IUS-R was high, with a Cronbach's alpha of .90 and a McDonald's omega of .92.

Pro-environmental behaviors

Pro-environmental behaviours were assessed with five self-report items developed by Clayton and Karazia (2020). These items index efforts to reduce one's contribution to climate change in everyday life (e.g., energy use, consumption choices), rated from 0 ("Never") to 5 ("Almost always"). We employed the validated French version of these items developed in Mouguiama-Daouda et al. (2022). In our sample, the internal reliability of the scale was acceptable, with a Cronbach's alpha of .70 and a McDonald's omega of .77.

Network Analyses

Following recent applications of network analysis to psychological processes (for a review, see Blanchard & Heeren, 2022), we formed the network at the facet-level instead of the item-level.

Data preparation

None of the variables violated normality based on to the benchmarks of skewness > |2| and kurtosis > |7| (Curran et al., 1996). However, in accordance with the guidelines for psychological network analyses (Epskamp & Fried, 2018), we applied a non-paranormal transformation to our variables of interest by using the R package "*huge*" (Jiang et al., 2019).

Check for potential nodes redundancy

To ensure that none of the variables in the network conceptually overlap, we utilized a data-driven approach to identify potentially redundant pairs of variables. Our method followed the procedure outlined in recent publications (e.g., Bernstein et al., 2019). First, we tested whether our correlation matrix was positive definite, which helped verify that our variables were not linear combinations of one another. Next, we applied the Hittner method (Hittner et al., 2003) to look for pairs of variables with high inter-correlation ($r > 0.50$) that also showed a similar correlation with other variables. Specifically, we checked that more than 75% of their correlations with other variables did not significantly differ for each pair. For this analysis, we used the goldbricker function from the R package *networktools* (Jones, 2018). Our findings revealed no apparent redundant variables in the current dataset.

Gaussian Graphical Model

Following recent guidelines for network estimation (Isvoranu & Epskamp, 2023), we estimated our Gaussian Graphical Model (GGM) network by using the *ggmModSelect* algorithm, which is implemented in the R package qgraph (Epskamp et al., 2018). This algorithm iteratively adjusts the initially estimated edges to find an optimal unregularized GGM until the Bayesian Information Criterion (BIC) can no longer be improved (Isvoranu & Epskamp, 2023). We chose this method given the low-dimensional nature of the present dataset (i.e., more participants than nodes, like in most psychological datasets), wherein the LASSO (Least Absolute Shrinkage and Selection Operator) may risk omitting genuine edges (Williams & Rast, 2020; Williams et al., 2019).

To assess the importance of each node within the GGM, we calculated the expected influence (Robinaugh et al., 2016). This index measures the cumulative importance of each node by summing the edge weights associated with it, considering both positive and negative values (Robinaugh et al., 2016). Thus, higher expected influence values indicate greater centrality within the network and enhanced local connectivity of a node (McNally, 2021). The plot displays the raw expected influence values for each node.

We also estimated node predictability for each variable. This index represents the proportion of a node's variance that can be explained by all the nodes directly connected to it in the GGM network (Haslbeck & Fried, 2017). To do so, we used the *mgm* R package (Haslbeck & Waldorp, 2018) for this analysis. Node predictability is illustrated as a pie chart in the outer ring of each node. It is important to note that predictability across nodes indicates whether a network is primarily influenced by strong mutual interactions within itself (high predictability) or by external factors not captured by the model (low predictability), suggesting a greater impact from external variables (see Haslbeck & Waldorp, 2018 for discussion).

We finally examined whether all our variables of interest are organized into one single network system or as multiple subnetworks, known as "communities". Within a community, nodes are more strongly interconnected than with nodes outside that community. To achieve this, we applied the Walktrap community detection algorithm, which identifies potentially densely connected subnetworks through random walks, as noted in previous psychological research (e.g., Billieux et al., 2021; Jones et al., 2018). This was done using the -*walktrap.community* function from the R package *igraph* (Csardi & Nepusz, 2006). We also identified nodes that act as bridges between communities by calculating the bridge expected influence index by using the *bridge* function from the R package networktools (Jones, 2018). The bridge expected influence represents the total of the edge weights connecting a specific node to all nodes in other communities (Jones et al., 2021). The plot illustrates the raw bridge expected influence values for each node.

Directed Acyclic Graph (DAG)

In line with previous psychological research (e.g., Bernstein et al., 2017; Heeren et al., 2020; Kalkan et al., 20023; McNally et al., 2017), we estimated the Directed Acyclic Graphs (DAGs) by implementing a Bayesian hill-climbing algorithm, as detailed by Briganti et al. (2022). We utilized the R package *bnlearn* (Scutari, 2010) for this purpose. This algorithm generates various combinations of edges—adding, removing, and reversing their direction—and determines the best-fitting model based on a goodness-of-fit criterion, specifically, the Bayesian Information Criterion (BIC). This iterative process is restarted randomly with different edge and node pairs to avoid local maxima and includes system perturbations, such as adding, removing, or reversing edges. Ultimately, this yields the best-fitting network through multiple iterations. Following standard practices, we set the parameters to 50 random restarts and 100 perturbations (e.g., Bernstein et al., 2017; McNally et al., 2017).

To ensure the stability of the DAG, we bootstrapped 1000 samples with replacement and averaged the networks derived from these samples. In the first step, we assessed the frequency of each edge's presence across the bootstrapped networks. We employed the optimal cut-point method suggested by Scutari and Nagarajan (2013) to establish a criterion for edge retention. In the second step, we verified that the directions of each remaining edge were consistent in the 1000 bootstrapped networks. According to the recommendations of Scutari and Nagarajan (2013), if an edge points from one node to another in at least 51% of the bootstrapped networks, we included that directed edge in the final network.

We visualized the averaged network using two methods. In the first visualization, the thickness of the edges represents relative BIC values, with thicker edges indicating greater importance to the network structure. In this context, removing a thick edge would more negatively impact the model fit than removing a thin edge (McNally et al., 2017). In the second visualization, edge thickness reflects directional probabilities, where thicker edges indicate a higher likelihood that the edge points in the depicted direction. Consequently, a thick edge from node X to node Y appears more frequently in the averaged 1000 bootstrapped networks than a thin edge from node Y to node Z.

Results

Descriptive information (i.e., mean, standard deviation, skewness, kurtosis, and range) as well as the Pearson zero-order correlations between all the variables are provided in the Supplementary Materials (see *Table S1* and *Figure S1*).

Gaussian graphical model (GGM)

Figure 1 shows the GGM network estimated using the *ggmModSelect* algorithm. The thickness of the edge denotes the strength of the pairwise association between variables, with a thicker edge denoting a larger positive partial correlation. We employed the layout algorithm developed by Fruchterman and Reingold (1991) to place the nodes, ensuring that those closer to the center of the network exhibit the strongest associations with other nodes.

Several pairwise connections are noteworthy. First, the strongest connection is between the two primary features of climate anxiety, with a correlation of $r = 0.65$. Second, although the node denoting functional impairments of climate anxiety has only one direct connection with pro-environmental behaviors ($r = 0.19$), the cognitive-emotional component has an edge with each other node—i.e. with the experience of climate change ($r = 0.21$), IU ($r = 0.19$), and pro-environmental behaviors ($r = 0.12$). Third, the node denoting pro-environmental behaviors shares an edge with the experience of climate change ($r = 0.14$). Lastly, the IU shows only one connection ($r = 0.19$), with the cognitive-emotional component of climate anxiety. We also confirmed the accuracy and reliability of the edge weight estimates (see *Figure S2* in the Supplementary Materials) using contemporary network analysis guidelines (Borsboom et al., 2021; Epskamp et al., 2018). Additionally, the bootstrapped difference test revealed that the strongest edges were significantly larger than most of the others (see *Figure S3*).

Figure 2 presents the expected influence estimates. The cognitive-emotional and the functional components of climate anxiety were the two nodes showing the highest expected influence values, while IU had the lowest. The person-dropping bootstrap procedure indicated that the estimates for expected influence are highly stable (see *Figure S4* in the Supplementary Materials). Furthermore, the bootstrapped difference test demonstrated that the most central nodes have significantly higher expected influence estimates compared to less central nodes, with the cognitive-emotional component of climate anxiety appearing as significantly more central than any other node but functional impairments (see *Figure S5* in the Supplementary Materials). Additional information regarding the accuracy and reliability of the centrality estimates are available in the supplementary materials. A similar trend was observed in the levels of node predictability (see *Figure 1*), with the cognitive-emotional features of climate anxiety explaining the most variance (55.7% of its variance is accounted for by its adjacent nodes), followed closely by the functional features (54.8%). In contrast, IU exhibited the lowest predictability value at just 0.09%, suggesting a larger influence of factors not included in the model.

Finally, the walktrap algorithm identified three distinct communities of nodes. The first community comprises the two key features of climate anxiety (cognitive-emotional and functional features); the second community consists solely of IU; and the third community includes pro-environmental behaviors along with the experience of climate change. *Figure 3* illustrates the bridge expected influence values for all nodes, highlighting that the cognitive-emotional component of climate anxiety has a particularly high bridge expected influence value. A bootstrapped difference test confirmed that this cognitive-emotional component significantly exhibits the highest bridge expected value (see *Figure S6* in the Supplementary Materials). More details regarding the accuracy and stability of the bridge's expected influence metric are provided in the supplementary materials section.

Directed Acyclic Graphs (DAGs)

The Directed Acyclic Graphs (DAGs) resulting from 1000 bootstrapped samples are shown in *Figure 4* and *Figure 5*. In both graphs, the arrows were retained based on their strength, which exceeded the optimal cut-point derived from the Scutari and Nagarajan (2013) method.

In *Figure 4,* the thickness of the arrows indicates the change in the Bayesian Information Criterion (BIC), which is a relative measure of a model's goodness-of-fit, when an arrow is removed from the network. In other words, the thicker the arrow, the more it contributes to the model fit (McNally et al., 2017). Our data reveal that the most crucial arrows connect the cognitive-emotional component to the functional component of climate anxiety (with a BIC change of -268.33), the experience of climate change to the cognitive-emotional component (with a BIC change of -42.65), and IU to the cognitive-emotional component (with a BIC change of -22.61). *Table 1* displays the change in the BIC value for each arrow.

In the *Figure 5*, most arrows were visually thin, reflecting directional probabilities that were close to .50—that is, neither orientation was strongly preferred across the bootstrapped DAGs. For example, the thickest arrow connects IU to the cognitive-emotional component of climate anxiety, with a directional probability of .56, indicating only a slight preference for this orientation over the opposite one (i.e., .44). The corresponding directional probabilities for all edges are reported in *Table 1*, which shows that, although some edges have somewhat higher directional probabilities than others, these values fall within a relatively narrow range and therefore translate into only subtle variations in arrow thickness in *Figure 5.*

Finally, because DAGs encode the conditional independence relationships and portray the joint probability distribution of each node, the organization of a node within a DAG can be seen as a product of each node's conditional distribution knowing its parent nodes in the estimated model (Briganti et al., 2024). Here, the DAG illustrates a chain of nodes dependent on the experience of climate change (with an in-degree of 0 and an out-degree of 2) and IU (which has an in-degree of 0 and an out-degree of 1), both of which directly predict the cognitive-emotional components of climate anxiety. This suggests that the cognitive-emotional component of climate anxiety is more likely reliant on the presence of IU and the experience of climate change than vice versa. Notably, the cognitive-emotional component of climate anxiety serves as a critical pathway in this cascading model, possessing two incoming arrows (in-degree = 2) and two outgoing arrows (out-degree = 2), including the thickest arrows in the model as well as the only path leading to the functional impairments of climate anxiety.

Discussion

In this study, we aimed to clarify how the two core features of climate anxiety—the cognitive-emotional component of climate anxiety and the related functional impairments — interact with climate change experiences, pro-environmental behaviors, and intolerance of uncertainty (IU). To achieve this, we conducted network analyses using two different computational methods: a Gaussian Graphical Model (GGM) and a Directed Acyclic Graph (DAG).

Although we used GGMs and DAGs as complementary tools, it is worth briefly noting how these models are related and how they differ. Both approaches belong to the broader family of probabilistic graphical models and encode conditional independence relations among variables. In a GGM, edges represent non-zero partial correlations after conditioning on all other variables, yielding an undirected network that captures symmetric conditional associations (Epskamp et al., 2018). By contrast, DAGs (Bayesian networks) represent a factorization of the joint probability distribution into conditional distributions and impose a directed, acyclic structure on the graph; edges are oriented when asymmetries in patterns of conditional dependence support one direction over another (Briganti et al., 2023; McNally, 2021). Although DAGs are often used to formalize and explore causal hypotheses, in the present context the estimated directions should be interpreted as probabilistic dependencies rather than causal effects; they are hypothesis-generating rather than hypothesis-testing. In this sense, the two approaches share a common foundation in conditional independence, but they differ in their representational constraints (undirected vs. directed acyclic graphs) and in the specific questions they address. In the present study, we therefore treated the GGM to describe the overall pattern of conditional associations among climate anxiety, IU, climate-change experience, and pro-environmental behaviors, and the DAG as a complementary tool to explore how these variables might be probabilistically ordered within the same system.

Consistent with previous research (e.g., Chan et al., 2024; Heeren et al., 2023; Ogunbode et al., 2023), both network approaches identified the cognitive-emotional component of climate anxiety as a central feature and a potential hub connecting all other processes. In the GGM, this cognitive-emotional component exhibited the highest expected influence and the largest node predictability value, emphasizing its role as a hallmark feature of climate anxiety. Moreover, while the cognitive-emotional and functional components of climate anxiety emerged as a single community in the community detection analysis, the cognitive-emotional component was the only node to have connections to all other nodes in the network. These findings indicate a strong bridging role for the cognitive-emotional component with nodes from other communities, particularly through nodes denoting climate change and IU. Although additional longitudinal research is necessary, the results suggest that activation may propagate through the network from these two nodes via the cognitive-emotional component.

These patterns were further supported by the DAGs, where the cognitive-emotional component emerged as a critical bridge in a cascading model, receiving input from both climate change experience and IU, while also exerting a strong influence on functional impairments. Thus, we are confident that the cognitive-emotional component of climate anxiety serves as a pivotal hub linking our distinct variables, particularly by tying climate change experiences and IU to functional impairments.

This pattern of findings is not surprising, as it aligns with recent evidence suggesting that the cognitive-emotional features of climate anxiety may be a pathway to its negative functional impacts (e.g., Chan et al., 2024; Ogunbode et al., 2023). For example, a recent longitudinal study found that the cognitive-emotional component of climate anxiety could predict functional impairments over time (Chan et al., 2024). Our results also align with a previous cross-sectional network study, which did not include IU though, reporting nearly identical findings in a different European sample (Heeren et al., 2023). According to Chan et al. (2024), core features of the cognitive-emotional component of climate anxiety—such as repetitive negative thinking about climate change—may increase perceived stress and distract individuals from engaging in important daily activities, ultimately impairing their daily life functioning. However, this hypothesis requires further testing in future iterations.

Perhaps our most noteworthy observation stems from the DAG's indication that individuals are less likely to experience the key aspects of climate anxiety unless they are characterized by high IU and experience climate change, since these two variables appear as top-cascading parent nodes in the entire cascade of nodes. Although our findings do not directly address the persistence of climate anxiety and its adverse functional consequences, especially given the unselected nature of our sample, this perspective aligns with a long-standing transdiagnostic tradition that considers IU and the perception of uncertain threats as central mechanisms of anxiety disorders (e.g., Birrell et al., 2011; Carleton et al., 2012; Dugas et al., 1998).

Indeed, decades of research on IU in anxiety disorders have found that IU can significantly influence how individuals perceive and respond to situations involving uncertain hazards. This can impede adaptive behaviors and lead to functional impairments in everyday life (e.g., Zlomke & Jeter, 2014), particularly when individuals believe their ability to cope with potential adverse events is low (Buhr & Dugas, 2002). Additionally, if potential threats are perceived as ambiguous or if critical information is lacking, individuals may even experience amplified anxiety, notably by triggering a cascade of uncontrollable “what if" scenarios that feed worries, and ultimately depleting cognitive resources as individuals search for certainty, leading to psychological distress and functional impairments when certainty is unattainable (e.g., Birrell et al., 2011; Carleton et al., 2012; Dugas et al., 1998; Freeston et al., 2020; Grupe & Nitschke, 2013; Pepperdine et al., 2018; Yook et al., 2010). Given that climate change encompasses numerous uncertainties, such as the nature of its impacts (e.g., natural disasters, health issues, financial loss, forced migration), their timing, precise locations, and personal consequences (e.g., Adler & Hirsch Hadorn, 2014; Fuentes et al., 2020), it is therefore not surprising that IU emerges as a potent driving force of climate anxiety, especially as a study has also pointed to IU as strongly related to the psychological responses to extreme weather and climate action (Freeston et al., 2024). A critical area for future research in climate anxiety is to explore whether IU is associated with depletion of cognitive resources, which is assumed to ultimately trigger functional impairments and psychological distress.

As with regards to the perception of climate change, preliminary research on climate anxiety reveals that how individuals perceive and experience the impact of climate change within their own environments is crucial to their emotional responses to climate change (du Bray et al., 2019; Ellis & Albrecht, 2017; Middleton et al., 2021). Notably, studies have shown a medium-sized correlation between participants' reported experiences of climate change and two specific features of climate change anxiety across culturally diverse samples (e.g., Clayton & Karazsia, 2020; Heeren et al., 2022). Furthermore, those who are directly affected by climate change in their environment exhibit more intense, prolonged and debilitating emotional reactions to climate change (Cunsolo Willox et al., 2013; Ellis & Albrecht, 2017; Maiella et al., 2020). For example, a study conducted in Tuvalu, a Pacific Islands atoll nation, found that 95% of participants reported significant anxiety about climate change, with this anxiety interfering with daily functioning in 87% of the cases (Gibson et al., 2020).

Our findings could have implications. If our observation that IU and the experience of climate change are driving forces of climate anxiety is confirmed in future longitudinal and experimental studies, one may expect, from a network perspective (e.g., Borsboom, 2017; McNally, 2021), that impeding these variables could help deactivate other nodes, potentially triggering a cascade of beneficial changes throughout the entire network.

Since IU is believed to trigger anxiety in the face of unpredictable future threats, the communication strategies employed by public health officials and government representatives regarding not only climate change itself but also the national plan to address the environmental, social, and financial challenges posed by climate change might mitigate the impact of IU and the experience of climate change on climate anxiety. Communication approaches utilized by governments and experts during other global crises, such as pandemics, have significantly influenced the perception of (un)predictability and (un)controllability of threatening situations (e.g., Frewer, 2003; Xiang et al., 2020). Given that these factors are recognized as core contributors to anxiety (for a discussion, see Heeren & Clayton, in press), careful communication strategies should be implemented by experts and nationwide representatives. Reflecting on previous crises (e.g., Frewer, 2003), promoting transparent communication efforts that limit uncertainties surrounding knowledge, decision-making processes, and action plans related to climate change mitigation and adaptation could help prepare individuals for climate change impacts and enhance emotional regulation concerning future-oriented feelings of anxiety (for further discussion, see Mheidly & Fares, 2020). However, doing so would first require a deeper understanding of the precise mechanisms of threat perception that link climate change perception with climate anxiety. Drawing on decades of basic research on fear and anxiety (e.g., Grillon, 2008; Shankman et al., 2011), factors such as the proximity, predictability, and controllability of perceived threats are likely to play significant roles. Particularly, since climate change is perceived as more threatening by economically vulnerable individuals, who are often the least equipped to adapt to a changing climate (Hornsey & Pearson, 2024), it also raises questions about how internal (e.g., feelings of hopelessness and lack of agency) and external factors (e.g., financial resource limitations) may also modulate the experience of climate change, and the possible impact on climate anxiety.

Since our DAG approach also highlighted IU as a node with several outgoing edges in the probabilistic dependency structure, a second implication concerns IU-focused interventions. Extensive research in cognitive-behavioral therapy (CBT) for anxiety disorders has demonstrated that improving tolerance for uncertainty (or reducing IU) can enhance mental health across various disorders, including social anxiety disorder, generalized anxiety disorder, and depression (e.g., Miller & McGuire, 2023; Zemestani et al., 2021). Within this broader literature, several IU-focused interventions have been developed. Most of these interventions involve classical CBT components, such as psychoeducation, problem-solving training, imaginal exposure, and behavioral exercises designed to challenge catastrophic beliefs about uncertainty (Robichaud et al., 2019), which could be beneficial for individuals experiencing debilitating climate anxiety. In addition, recent work has introduced more explicitly experiential approaches to IU. For example, the “Making Friends with Uncertainty” (MFWU) protocol developed by Mofrad et al. (2020, 2024) focuses on approaching and tolerating the felt experience of uncertainty. This protocol trains participants to tolerate—rather than avoid—uncertainty by confronting lower-stakes situations through games and playful exposure, using a pyramidal progression from low- to high-stakes situations. Recent findings show that targeting IU via MFWU leads to significant reductions not only in IU itself but also in other anxiety symptoms (Mofrad et al., 2025).

At the same time, there is accumulating evidence for more cognitive/behavioral experiment-based approaches to IU, exemplified by the program developed by Dugas and colleagues (e.g., Dugas et al., 1998, 2022). In this framework, individuals identify personally relevant beliefs about uncertainty and test these beliefs through behavioral experiments in daily life, compare their predictions (about what will happen and how they will feel) with the actual outcomes, and reflect on what they have learned. All these different approaches are best viewed as alternative yet complementary routes to addressing IU, and they expand the range of IU-based interventions that could be adapted for individuals who are eager to take climate action but feel overwhelmed by uncertainty about the future.

The present study has several limitations. First, our participants were exclusively from European countries, which affects the generalizability and inclusivity of our findings (Tam & Milfont, 2020). The ongoing and long-term consequences of climate change are more severe for individuals living in South American, Asian, and African countries than in Europe, particularly regarding human health, safety, and food and water security (e.g., World Meteorological Organization, 2024). In addition, because participants were recruited through online advertisements and social-media posts, the study relied on a self-selected convenience sample. This recruitment strategy likely attracted individuals who are relatively aware of, and engaged with, climate change and environmental issues. Consequently, our findings most directly apply to climate-change–aware and climate-change–engaged individuals, for whom climate-related distress and its links with intolerance of uncertainty, climate-change experience, and daily functioning may be particularly salient. Furthermore, because we recruited all-comers through volunteering, the recruitment process may have selected individuals already sensitized to environmental issues. Indeed, as we provided informed consent to participate in the study, our sample was not blinded to its aims. Therefore, a critical next step would be to investigate whether our results can be generalized to more geographically and culturally diverse samples, as well as to a sample unaware of the study's environmental stake. Although our sample size is relatively large for network analysis and covers a broad adult age range, the study was not designed or powered to estimate separate, stable networks across different age groups and test whether these networks statistically differ between them (van Borkulo et al., 2023). Future research with larger samples specifically stratified by age will be needed to examine whether the structure and centrality of climate anxiety, intolerance of uncertainty, and climate-change experience differ across the lifespan.

Second, both the Gaussian Graphical Model (GGM) and Directed Acyclic Graphs (DAGs) rely on cross-sectional data, which limits our ability to infer potential causal relationships between the variables (Maurage et al., 2013; Rohrer, 2018). The only insight regarding the direction of associations comes from the DAG, which employs probabilistic Bayesian learning methods to offer clues about direction of the probabilistic dependencies between variables (Briganti et al., 2024). However, when analyzing DAGs based on cross-sectional data, it is crucial not to confuse the direction of dependence with temporal precedence (e.g., McNally, 2021). DAGs provide insights into probabilistic dependencies between variables and should only be used for generating hypotheses rather than testing them (for discussion, see Briganti et al., 2022; McNally, 2021).

Third, DAGs rest on the assumption that links between nodes are both directed and acyclic. Yet, in our field, not all relations between variables necessarily fit this pattern, notably because of possible feedback loops. However, since the direction of each arrow is determined by the percentage of bootstrapped networks in which it points that way, the extent of potential reverse directionality can be inferred from the proportion of bootstrapped networks in which the arrow is oriented in the opposite direction (Briganti et al., 2022; McNally, 2021). In our analyses, many arrows appeared relatively thin, indicating that, in a substantial share of the bootstrapped networks, the association was reversed. For instance, the edge between IU and the cognitive-emotional component was oriented in that direction in 56% of the 1000 bootstrapped networks, implying that it pointed the other way in 44% of them. This pattern suggests that the direction of the association between these two variables may plausibly go in both directions. Nonetheless, other types of cyclic structures (e.g., A → B → C → A; McNally, 2021) cannot be excluded. A more in-depth investigation of such potential bidirectional dependencies would require temporal network analyses based on experience sampling data (e.g., Contreras et al., 2024; for a review, see Blanchard et al., 2023).

Fourth, we also cannot rule out that some of the non-zero edges in the GGM and DAG models may be artifacts introduced by conditioning on a collider variable (e.g., variable B in a configuration such as "A → B ← C"; Rohrer, 2018). A collider is a variable that is influenced by two other variables and typically blocks the path between them. Conditioning on this variable, however, can create an artificial association between A and C, thereby giving the impression of a relationship where none exists (for reviews, see Greenland, 2003; Munafò et al., 2018). Following prior work (e.g., Heeren et al., 2020; Lee, 2012; Munafò et al., 2018), we therefore checked that the associations between each pair of variables that remained in the GGM and DAG were already present as significant edges without conditioning on them—that is, in the zero-order correlations matrix. Supporting the absence of collider bias, every edge in the GGM and DAG corresponded to a significant zero-order correlation of medium-to-large magnitude (see Figure S1 in Supplementary Materials).

Finally, our study drew on the climate anxiety construct as defined by Clayton and Karazsia (2020). Yet, a scoping review by Coffey et al. (2021) identified more than ten different ways in which eco/climate anxiety has been operationalized in the literature. This situation underscores a substantial lack of agreement among researchers about this concept (van Dijk et al., 2025). Accordingly, it is legitimate to wonder whether our findings would hold when using the various alternative definitions and measures of climate anxiety. Moreover, although Clayton and Karazsia's (2020) cognitive–emotional dimension of climate anxiety is frequently invoked in current work, it remains a broad umbrella construct that encompasses multiple psychological processes, such as threat-related attentional biases, future-oriented cognitions, and coping strategies. The specific mechanisms involved are still far from fully understood. As we have emphasized in prior publications (e.g., Heeren & Asmundson, 2023; Heeren & Clayton, 2026), this situation points to the need for more refined theoretical developments and integrative models in the study of climate anxiety. We argue that the hypothesis-generating features of the DAG represent a crucial initial step toward such progress.

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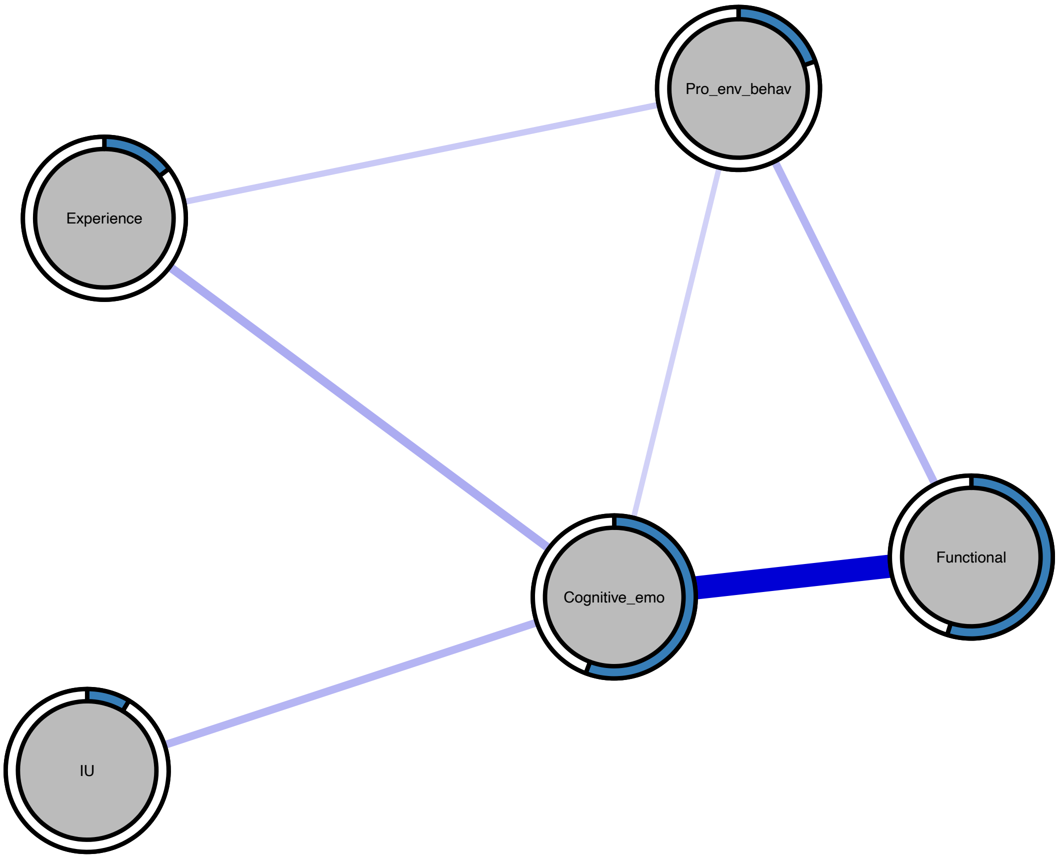
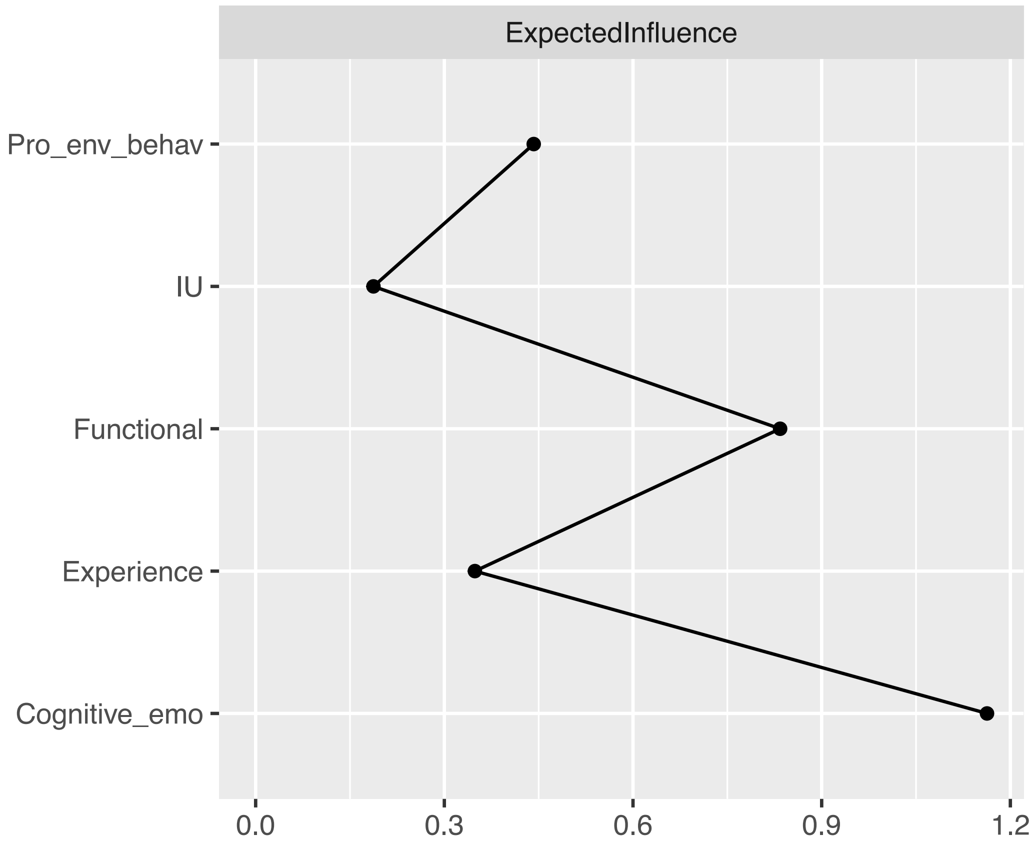
Figure 1. **Gaussian Graphical Model constructed via the ggmModSelect algorithm.**



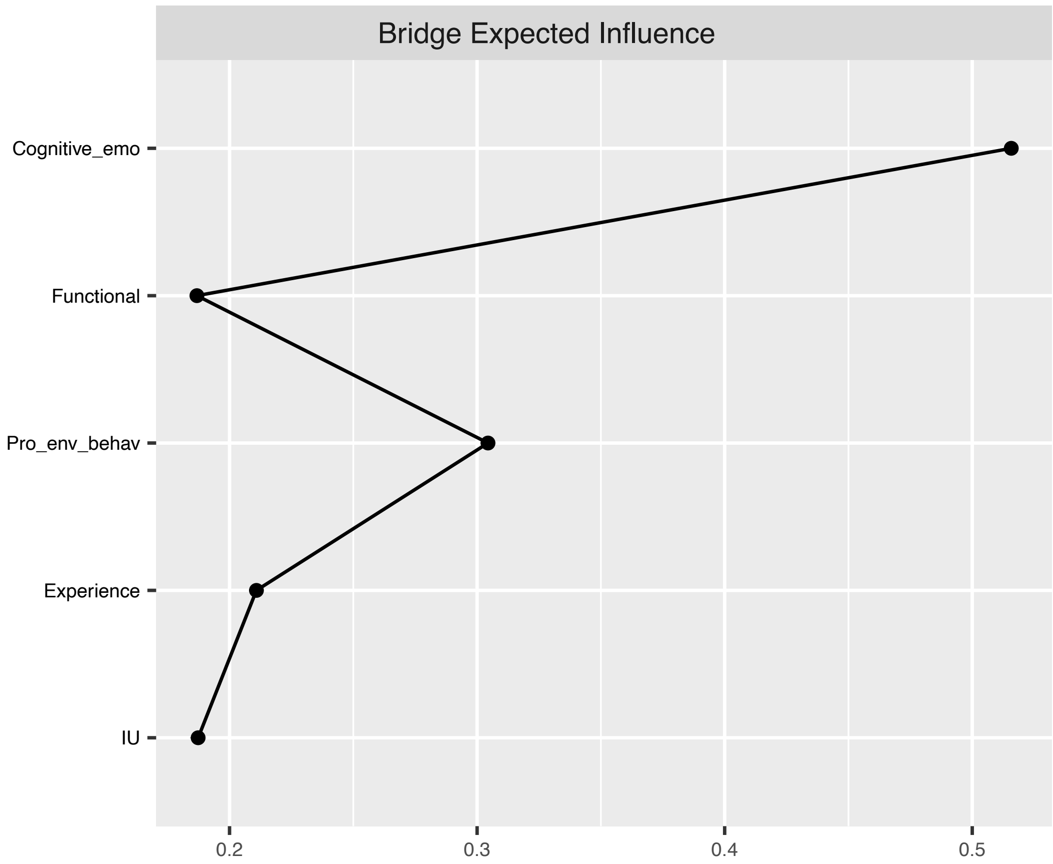
Note. The thickness of an edge reflects the magnitude of the association (the thickest edge representing a value of .65). The blue rings around the nodes indicate the proportion of explained variance in that node by all other nodes. The color of the nodes denotes their community belonging. Cognitive_emo = The cognitive-emotional component of climate anxiety; Functional = The functional component of climate anxiety; Pro_env_behav = Pro-environmental behaviors; Experience = The experience of climate change; IU = Intolerance of Uncertainty

Figure 2. **Expected Influence Estimates of Gaussian Graphical Model constructed via the ggmModSelect algorithm.**



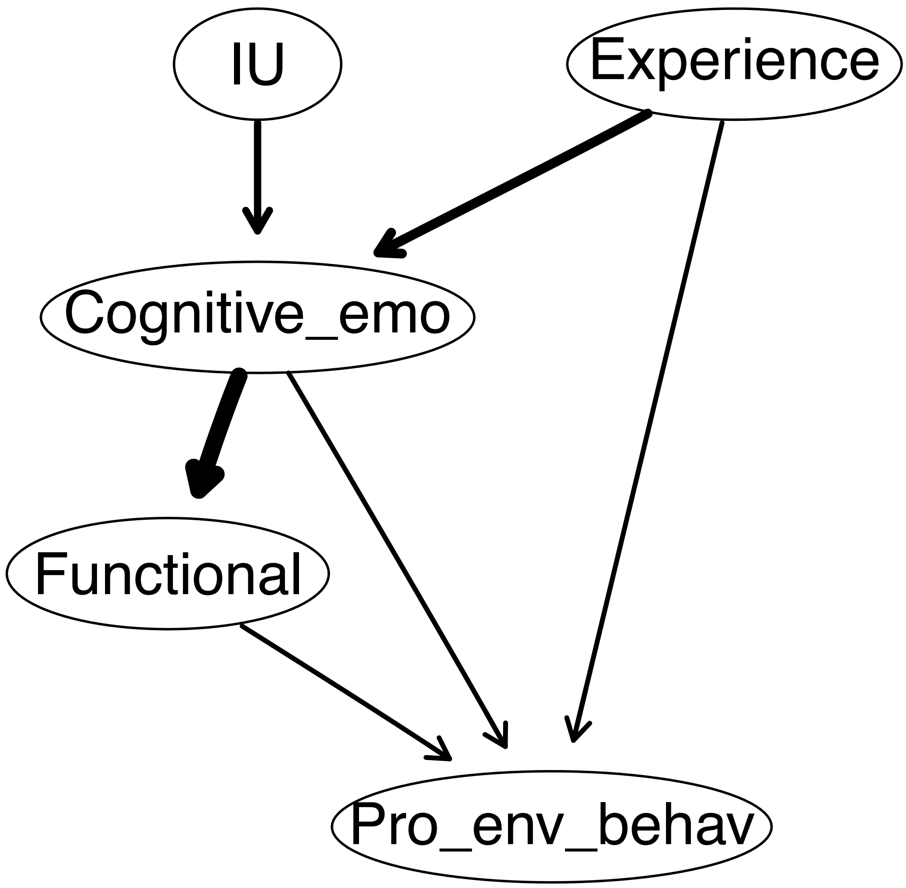
Note. The expected influence represents the cumulative importance of each node by summing the edge weights associated with it, considering both positive and negative values. In other words, higher expected influence values indicate greater centrality within the network and enhanced local connectivity of a node. The plot displays the raw expected influence values for each node. Cognitive_emo = The cognitive-emotional component of climate anxiety; Functional = The functional component of climate anxiety; Pro_env_behav = Pro-environmental behaviors; Experience = The experience of climate change; IU = Intolerance of Uncertainty

Figure 3. **Bridge Expected Influence Estimates of Gaussian Graphical Model constructed via the ggmModSelect algorithm.**



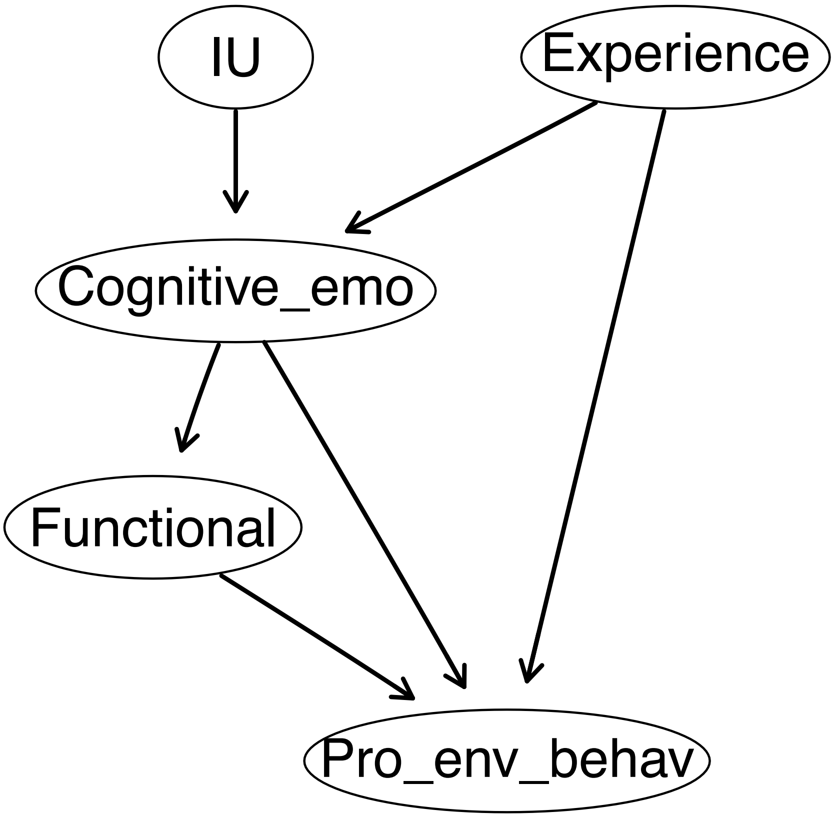
Note. The bridge expected influence represents the total of the edge weights connecting a specific node to all nodes in other communities. The plot illustrates the raw bridge expected influence values for each node. Cognitive_emo = The cognitive-emotional component of climate anxiety; Functional = The functional component of climate anxiety; Pro_env_behav = Pro-environmental behaviors; Experience = Experience of climate change; IU = Intolerance of Uncertainty.

Figure 4. **Directed acyclic graphs (DAGs) With Arrow Thickness Denoting the Importance of that Arrow to the Overall Network Model Fit**



Note. Arrow thickness denotes the importance of that arrow to the overall network model fit. Greater thickness reflects larger contribution to the model fit (i.e., Bayesian Information Criterion). Cognitive_emo = The cognitive-emotional component of climate anxiety; Functional = The functional component of climate anxiety; Pro_env_behav = Pro-environmental behaviors; Experience = Experience of climate change; IU = Intolerance of Uncertainty

Figure 5. **Directed acyclic graphs (DAGs) With Arrow Thickness Indicating Directional Probability**



Note. Arrow thickness indicates directional probability. Greater thickness reflects larger proportions of the bootstrapped networks wherein the arrow pointed in that direction. Cognitive_emo = The cognitive-emotional component of climate anxiety; Functional = The functional component of climate anxiety; Pro_env_behav = Pro-environmental behaviors; Experience = Experience of climate change; IU = Intolerance of Uncertainty

Table 1. **Directional Probabilities and BIC Values of the Arrows in the DAGs**

Arrow in the DAG		**Value determining arrow thickness**	
From	**To**	**BIC**	**Directional Probability**
Cognitive-emotional	Functional	-268.05	.54
Cognitive-emotional	Pro-environmental behaviors	-2.71	.55
Pro-environmental behaviors	Functional	-8.57	.53
Experience of climate change	Cognitive-emotional	-42.41	.54
Experience of climate change	Pro-environmental behaviors	-2.57	.58
Intolerance of uncertainty	Cognitive-emotional	-22.58	.56

Note. BIC = change in Bayesian Information Criterion when that arrow is removed from the network. BIC values determine arrow thickness in Figure 4 (reflecting the importance of that edge to the network structure). For the BIC values, negative values correspond to decreases in the network score that would be caused by the arrow's removal. In other words, negative scores mean that model fit improves with the presence of that arrow. Directional probability values determine arrow thickness in Figure 5 (reflecting the frequency that arrow was present in that direction in the 1000 bootstrapped networks).