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A network approach to climate change anxiety and its key related features

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ABSTRACT

Research has pointed to startling worldwide rates of people reporting considerable anxiety vis-à-vis climate change. Yet, uncertainties remain regarding how climate anxiety's cognitive-emotional features and daily life functional impairments interact with one another and with climate change experience, pro-environmental behaviors, and general worry. In this study, we apply network analyses to examine the associations among these variables in an international community sample (n = 874). We computed two network models, a graphical Gaussian model to explore network structure, potential communities, and influential nodes, and a directed acyclic graph to examine the probabilistic dependencies among the variables. Both network models pointed to the cognitive-emotional features of climate anxiety as a potential hub bridging general worry, the experience of climate change, pro-environmental behaviors, and the functional impairments associated with climate anxiety. Our findings offer data-driven clues for the field's larger quest to establish the foundations of climate anxiety.

1. Introduction

Climate change poses one of the most significant threats to the current and future species and people living on earth, menacing their places, livelihoods, and health (Intergovernmental Panel on Climate Change, 2022). Not surprisingly, research has pointed to startling worldwide rates of people reporting considerable distress vis-à-vis climate change. For instance, in a recent 10-country study (i.e., Australia, Brazil, Finland, France, India, Nigeria, Philippines, Portugal, the UK, and the USA), 59% of a sample of 10 000 young adults declared being " very or extremely " worried about climate change. Moreover, more than 45% of the participants reported that their worries about climate change have detrimental consequences on their daily life functioning, notably because of their perception that their future is doomed (Hickman et al., 2021). Similar findings have likewise been observed worldwide among adults (e.g., Heeren et al., 2022; Ogunbode et al., 2021).

A small but growing empirical literature has termed this phenomenon climate change anxiety (also known as eco-anxiety). It refers to the experience of anxiety feelings and worries about the potential scope of the anticipated impacts of climate change and the uncertainty of their specific nature, timing, and precise location, even among people who have not personally been exposed to any direct impact (Albrecht, 2012; Clayton, 2020, 2021; Cunsolo et al., 2020; for a review, see Coffey et al., 2021). This emerging scientific focus on climate anxiety also dovetails with worldwide escalating media coverage and public interest, as reports of rising online search spikes about climate anxiety (e.g., Cunsolo et al., 2020).

However, despite the increasingly widespread recognition of climate change anxiety, uncertainties still abound regarding this phenomenon (Coffey et al., 2021). Although anxiety is likely an evolved mechanism for motivating adaptive responses to genuine threats, including ones related to the climate crisis, our concern here is with the *maladaptive* correlates of climate anxiety.

At the psychological level, Clayton and Karazsia (2020) recently proposed a measurement model of climate change anxiety encompassing two key features. The first reflects the cognitive and emotional difficulties vis-à-vis climate change, such as worrying about, crying, or

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having nightmares about climate change. The second focuses on the functional impairments that one may experience in response to climate change anxiety, such as the impact on the ability to socialize, work or concentrate at work or school (Clayton & Karazsia, 2020; Clayton, 2020). And although epidemiological research remains scarce, Clayton and Karazsia (2020) found, in two US-sample studies, that about a fifth (i.e., 17–19%) of the participants reported experiencing cognitive and emotional features of climate anxiety regularly (i.e., more than sometimes). Most strikingly, a quarter of the participants (i.e., 26–27%) reported a degree of climate anxiety interfering with their ability to function on such a basis. Similar alarming rates have been observed in different countries. For instance, in a recent study including 2080 French-speaking participants from eight African and European countries, about 11% reported experiencing the cognitive-emotional features, whereas about 21% reported experiencing daily life functional impairments (e.g., impact on the ability to go to work or socialize) because of their climate change anxiety (Heeren et al., 2022). Because functional impairments in daily life have often been envisioned as proxies for risk of psychopathology and adverse mental health outcomes (for discussion, see Boland et al., 2018; McKnight & Kashdan, 2009), these rates thus point to climate anxiety as a potential threat to mental health deserving a better understanding.

Concerning the potential triggers of climate anxiety, the perceived experience of climate change has often been suggested as a key one (e.g., Cissé et al., 2022; Clayton, 2020; Hoffmann et al., 2022). First, research has found a medium-sized correlation between participants' reported experience of climate change and the two features of climate change anxiety in culturally diverse samples (e.g., Clayton & Karazsia, 2020; Heeren et al., 2022). Second, those directly affected by climate change in their environment (e.g., Cunsolo Willox et al., 2013; Ellis & Albrecht, 2017) show more intense and prolonged emotional responses to climate change. For instance, in a study conducted in the Pacific Islands atoll nation of Tuvalu, 95% of the participants reported experiencing considerable anxiety about climate change, with this latter interfering in their daily life functioning in 87% of the cases (Gibson et al., 2020). Yet it remains unclear how the perceived experience of change respectively interacts with each of the two components proposed by Clayton and Karazsia (2020).

Another critical factor that may precondition climate anxiety is worry. Indeed, a few scholars have advanced worry (general and not specific to climate change)—i.e., a general transdiagnostic cognitive-emotional process of anxiety and related disorders — as a potential driving force of climate anxiety (e.g., Clayton, 2020; Ojala et al., 2021; Taylor, 2020). However, to date, empirical research has seldom examined this issue. Although a few studies reported medium-sized correlations between climate anxiety features and general anxiety, depression, and stress (e.g., Clayton & Karazsia, 2020; Helm et al., 2018; Searle & Gow, 2010), these studies did not focus on worry. This is unfortunate since transdiagnostic research on anxiety and related psychopathology points to worry as a potent mechanism specifically triggering anxiety feelings when one's concerns are not only broadly diffuse but also primarily future-oriented and about threats that are not immediately present and whose occurrence is uncertain (i.e., may or may not occur; American Psychological Association, 2015; Hirsch & Mathews, 2012). Given the uncertain nature, location, and timing of the forthcoming impacts of climate change, one may thus wonder about the role of worry in climate anxiety.

Finally, another key question in current climate anxiety research is whether it can prompt adaptive behavioral responses vis-à-vis climate change by motivating pro-environmental behaviors (e.g., Clayton, 2020; Ojala et al., 2021). Of critical interest, a few scholars (Higginbotham et al., 2014; Ojala et al., 2021) have grounded this question in the broader context of the potential adaptive nature of worry, wherein, under certain circumstances, worry can be seen as an adaptive problem-solving process (Sweeny & Dooley, 2017; Tallis et al., 1994). For instance, Higginbotham et al. (2014) conceptualized climate worry as a motive for pro-environmental behaviors (see also Ojala et al., 2021). Several Australian and British surveys have accordingly identified an association between climate anxiety and pro-environmental behaviors (e.g., Reser et al., 2012; Verplanken et al., 2020). However, none tested whether this association was indeed attributable to worry.

On the other hand, others have suggested that climate worry may actually inhibit people from taking adaptive steps hence producing "eco-paralysis" (Albrecht, 2011). Indeed, several studies revealed a negative—though small—association between climate anxiety and pro-environmental behaviors (e.g., Stanley et al., 2021). However, none considered the potential role of worry in this relation. Likewise, one may wonder whether the link between climate change anxiety and pro-environmental behaviors may vary as a function of the respondent's experience of climate change (e.g., Hoffmann et al., 2022). Neither did they examine whether this association may differ between the cognitive-emotional and functional features of climate anxiety. Accordingly, many questions remain unanswered regarding the adaptive and maladaptive consequences of climate anxiety, especially regarding the roles of general worry and the perception of climate change.

In the study reported here, our primary goal was thus to clarify the relations among all the variables discussed above. To do so, we relied upon network analyses, a set of computational tools to identify and analyze patterns of statistical associations between variables of interest (Borsboom & van der Maas, 2021; McNally, 2021). We first computed a graphical Gaussian Model (GGM), an undirected network model wherein nodes represent the variables of interest (i.e., the two components of climate change anxiety, the perceived experience of climate change, pro-environmental behaviors, and general worry) and the edges the conditional associations between them, while conditioning on all the remaining variables (Borsboom & van der Maas, 2021; Borsboom et al., 2021). Relatedly, we also quantified each node's importance to the resulting network structure via the computation of centrality metrics and node predictability (Borsboom & van der Maas, 2021; McNally, 2021).

-SSSe-SecSs Second, we used Bayesian network methods to estimate a directed acyclic graph (DAG), which encodes the conditional independence relationships between the variables of interest and characterizes their joint probability distribution. A DAG is a directed network wherein each edge has an arrow tip on one end, indicating the direction of probabilistic dependence (for a review, see Briganti et al., 2022). Hence, the resulting network is directed and possesses arrows reflecting the predicted direction of the probabilistic dependence among nodes—that is, whether the presence of node X in the network probabilistically implies the existence of node Y (node Y→node X) more than vice versa (node X→node Y), while considering the presence of all other nodes. 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 climate change anxiety and its key related variables.

To the best of our knowledge, this is the first study to begin visualizing the connections between the theory-driven key variables of climate change anxiety by using tools from network analysis. By combining both GGM and DAGs, such an approach can provide clues about a potential data-driven model of the interplay among these variables.

2. Method

2.1. Participants

We recruited 874 French-speaking participants, with 51.37% ($n = 449$) self-identified as women, 47.25% ($n = 413$) as men, and 1.37% ($n = 12$) as other. Participants were recruited from the general community via online social media and listserv advertisements. They were between the age of 18 and 81 years old ($M = 38.42$, $SD = 14.11$). Regarding their nationalities, 52.40% ($n = 548$) were from France, 44.16% ($n = 386$)

from Belgium, and 2.17% (n = 19) from Switzerland. Their years of education completed since primary school ranged from 0 to 24 (M = 16.72, SD = 3.05).

The study was approved by the UCLouvain Institutional Review Board (Reference: IPSY-Project#2021–54) and conducted according to the Declaration of Helsinki. Each participant provided written informed consent before completing the survey. De-identified data and R script have been made publicly available via the Open Science Framework at https://osf.io/2r659/.

3. Measures

3.1. Climate change anxiety

We assessed climate anxiety by using the Climate Change Anxiety Scale (CCAS; Clayton & Karazsia, 2020). The CCAS is a 13-item self-report questionnaire designed to measure climate change anxiety. We relied on the CCAS since it has become the most used instrument to assess climate change anxiety worldwide (e.g., Hickman et al., 2021; Innocenti et al., 2021; Wullenkord et al., 2021).

The CCAS includes two subscales that map directly onto the two key features of climate anxiety proposed by Clayton and Karazsia (2020): (a) eight items measuring the cognitive and emotional impairments of climate anxiety (e.g., "Thinking about climate change makes it difficult for me to concentrate"; "I found myself crying because of climate change") and (b) five items measuring the functional impairments (e.g., "My concerns about climate change interfere with my ability to get work or school assignments done," "My concern about climate change make it hard for me to have fun with my family or my friends").

For each item, participants rate their current strength of agreement with the item on a 5-point Likert-type scale, from 0 (Never) to 5 (Almost always), with higher scores reflecting greater endorsement. We used the validated French version of the scale (Mouguiama-Daouda et al., 2022). In the present study, the internal reliability of CCAS was high, with a Cronbach's alpha of.89 for the global scale score (0.81 for the cognitive-emotional impairments subscale and.82 for the functional impairments one). Accordingly, we computed separate scores because of our interest in distinguishing the respective influence of the cognitive-emotional and functional components of climate anxiety.

3.2. Experience with climate change

Following Clayton and Karazsia (2020), we assessed the experience of climate change via three items (i.e., "I have been directly affected by climate change"; "I know someone who has been directly affected by climate change"; "I have noticed a change in a place that is important to me due to climate change"). Participants rate their current strength of agreement with the item's content for each item using a 5-point Likert-type scale, ranging from 0 (Never) to 5 (Almost always). We used the validated French version of these items (Mouguiama-Daouda et al., 2022). with a Cronbach's alpha of.78, items' internal reliability was good in the present sample.

3.3. Worry

We assessed general worry via the Penn State Worry Questionnaire (PSWQ; Meyer et al., 1990). The PSWQ is a 16-item self-report questionnaire (e.g., "My worries overwhelm me"; "Once I start worrying, I cannot stop"). It is considered the gold-standard assessment instrument for worry (Kertz et al., 2014). Participants rate their current strength of agreement with the item's content for each item via a 5-point Likert-type scale ranging from 1 (Not typical at all) to 5 (Very typical). We used the validated French version of these items (Gosselin et al., 2001). In line with prior research (e.g., Gana et al., 2002), the items' internal reliability was high, with a Cronbach's alpha of.77 for the present sample.

3.4. Pro-environmental behaviors

Following prior research on climate anxiety (e.g., Clayton & Karazsia, 2020), we assessed participants' engagement in pro-environmental behaviors via the five items (e.g., "I try to reduce my behaviors that contribute to climate change"; "I feel guilty if I waste energy"; "I turn off lights") proposed by Clayton and Karazsia (2020). Each item was assessed using a 5-point Likert-type scale, ranging from 0 (Never) to 5 (Almost always). We used the validated French version of these items (Mouguiama-Daouda et al., 2022), and their internal reliability was acceptable in the present sample, with a Cronbach's alpha of.65.

4. Data analysis strategy

4.1. Data preparation

We only retained participants who had completed all items and removed those with missing values (n = 96). The analyses were thus performed on the remaining 778 participants. Moreover, although none of the variables violated normality according to benchmarks of skewness $> |2|$ and/or kurtosis $> |7|$ (Curran et al., 1996), we followed guidelines in psychological network analyses (Epskamp & Fried, 2018) and applied the nonparanormal transformation to our five variables of interest via the R package huge (Jiang et al., 2019).

4.2. Check for potential nodes redundancy

To ensure that none of the variables included in the network overlap conceptually, we implemented a data-driven method to identify potentially redundant pairs of variables. To do so, we followed the procedure described in recent publications (e.g., Bernstein et al., 2019; Heeren & McNally, 2018). First, we tested whether our correlation matrix was positive definite, ensuring that our variables were not a linear combination of other variables. Second, we implemented the Hittner method (Hittner et al., 2003) to search for potential highly inter-correlated ($r > 0.50$) pairs of variables that also correlated to the same degree with other variables (i.e., > 75% of correlations with other variables did not significantly differ for a given pair). To do so, we relied on the goldbricker function of the R package *networktools* (Jones, 2018). There were no apparent redundant variables in the present dataset.

4.3. Graphical Gaussian model

4.3.1. Network estimation

Following recent guidelines in network estimation (Isvoranu & Epskamp, 2021), we estimated our GGM network via the *ggmModSelect* algorithm, as implemented in the R package *qgraph* (Epskamp & Fried, 2018). This algorithm searches for an optimal unregularized GGM by iteratively changing the initially estimated edges until the Bayesian information criterion (BIC) can no longer be improved (Isvoranu & Epskamp, 2021). We opted for this approach since our dataset contained more participants than nodes[1] (Williams & Rast, 2020; Williams et al., 2019).

4.3.2. Node importance

We computed the expected influence centrality indices to quantify each node's importance in the GGM (Robinaugh et al., 2016). This index quantifies the cumulative importance of each node and describes the sum of the edge weights attached to this node, considering both positive and negative values (Robinaugh et al., 2016). Hence, higher values indicate greater centrality in the network and a higher node's local connectivity (McNally, 2021). The plot depicts the raw expected influence values for each node. In addition, we also estimated node predictability, which depicts the proportion of a node's explained variance by all its neighboring nodes in the GGM network (Haslbeck & Fried, 2017). To do so, we relied on the mgm R package (Haslbeck & Waldorp, 2018). Node predictability is presented as a pie chart in the outer ring of each node. Note that predictability across nodes also tells us whether a (part of a) network is primarily determined by itself through strong mutual interactions between nodes (high predictability) or whether it is determined mainly by other factors that are not included in the network (low predictability)—i.e., therefore showing a larger influence from variables external to the model (for a discussion, see Haslbeck & Waldorp, 2018).

4.3.3. Community detection

Finally, we tested whether the nodes denoting the key features of climate anxiety, the experience of climate change, pro-environmental behaviors, and excessive worrying cohere as one or multiple subnetworks ("communities"). Nodes within a community are more strongly interconnected than they are with nodes outside that community. As in previous psychological research (e.g., Billieux et al., 2021; Jones et al., 2018), we implemented the Walktrap community detection algorithm, which identifies potential densely connected subnetworks via random walks (Pons & Latapy, 2006). To do so, we used the waktrap.community function of the R package igraph (Csardi & Nepusz, 2006). We also identified important nodes that serve as bridges between communities by computing the bridge expected influence index via the bridge function of the R package networktools (Jones, 2018). Bridge expected influence is the sum of the edge weights connecting a given node to all nodes in the other community or communities (Jones, Ma, & McNally, 2021). The plot depicts the raw bridge expected influence values for each node.

4.4. Directed acyclic graph (DAG)

Following previous psychological research (e.g., Bernstein et al., 2017; Blanchard et al., 2021; Heeren et al., 2020; McNally et al., 2017), we estimated the DAGs via the implementation of a Bayesian hill-climbing algorithm (for more details, see Briganti et al., 2022). To do so, we relied on the R package *bnlearn* (Scutari, 2010). As implemented in this package, this approach relies on a bootstrap function that estimates the structural features of the model by adding edges, removing them, and reversing their direction to eventually optimize the goodness-of-fit target score, i.e., the Bayesian Information Criterion (BIC; a relative measure of a model's goodness-of-fit). This bootstrap function requires an iterative procedure of randomly restarting this process with various possible edges connecting various node pairs, disturbing the network system, and applying 50 different random restarts to circumvent local maxima (Briganti et al., 2022). As in prior research (e.g., McNally et al., 2017), we introduced, for each restart, 100 perturbations (i.e., attempts to insert, delete, or reverse an edge). As this iterative process of restart/perturbations unfolds, the algorithm returns the model with the optimal BIC value.

Following guidelines in the implementation of DAGs in psychological research (Briganti et al., 2022), we then ensured the stability of the resulting DAG as follows. We bootstrapped 10,000 samples (with replacement), estimated a network for each of the bootstrapped 10,000 samples, and ultimately averaged the resulting 10,000 networks to generate a final network structure via a two-step method. First, we determined how frequently a given edge appeared in the 10,000 bootstrapped networks. We then applied the optimal cut-point approach of Scutari and Nagarajan (2013) for retaining edges, which yields networks with high sensitivity and specificity. Second, we determined the direction of each surviving edge in the bootstrapped networks. If an edge pointed from node A to node B in at least 51% of the bootstrapped networks, then this direction was reported in the final DAG using an arrow pointing from node A to node B.

For ease of interpretation, we produced two visualizations of the resulting outputs. In the first one, the arrow's thickness represents the change in the BIC values when that arrow is removed from the network. In this way, the thicker the arrow, the more that arrow contributes to the model structure (McNally et al., 2017). In the second visualization, the arrow's thickness denotes directional probabilities—that is, the proportion of the bootstrapped networks wherein that arrow was pointing in that direction. In this way, the thicker the arrow, the larger the proportion of bootstrapped networks wherein this arrow points in the direction depicted.

5. Results

Descriptive information regarding our five variables of interest (before nonparanormal transformation), including mean, standard deviation, skewness, kurtosis, and range, can be found in the supplementary materials (see Table S1*)*. Pearson product-moment correlations of these variables are also provided in the Supplementary Materials (see Fig. S1).

5.1. Gaussian graphical model (GGM)

5.1.1. GGM estimation

Fig. 1 represents the unregularized GGM network estimated via the *ggmmodselect* algorithm.[2] 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 used the layout algorithm of Fruchterman and Reingold (1991) to determine node placement, so that nodes closer to the center of the network tend to yield the strongest associations with other nodes.

A few pairwise connections stand out. First, the largest edge weight is between the two constitutive features of climate anxiety. Second, whereas the functional feature of climate anxiety only has a direct connection with pro-environmental behaviors, the cognitive-emotional

[1] Although the graphical LASSO (Least Absolute Shrinkage and Selection Operator; Friedman et al., 2008) has emerged as the default network estimation method in psychological sciences, it was optimized in fields outside of psychology with very different needs, such as high-dimensional datasets wherein the number of nodes vastly exceeds the number of cases (e.g., genes versus subjects in genomics; McNally, 2021). Williams and his collaborators have shown that, in low-dimensional datasets (i.e., more participants than nodes; like most psychological data sets), regularizing partial correlation networks via the graphical LASSO returns sparse graphs but does so at the expense of possibly omitting genuine edges (Williams & Rast, 2020; Williams et al., 2019). Moreover, unregularized models do not assume that the true model is sparse, which might not be the case in the present dataset containing only a few variables (Epskamp, Kruis, & Marsman, 2017).

[2] Following recent publications relying on unregularized GGMs (e.g., McNally et al., 2022; Suen et al., 2022), we also estimated the GGM network by implementing the *EBICglasso* regularization algorithm. We found that the findings were almost identical to those resulting from *ggmmodselect* model (see Figs. S2 and S3 in the supplementary materials).

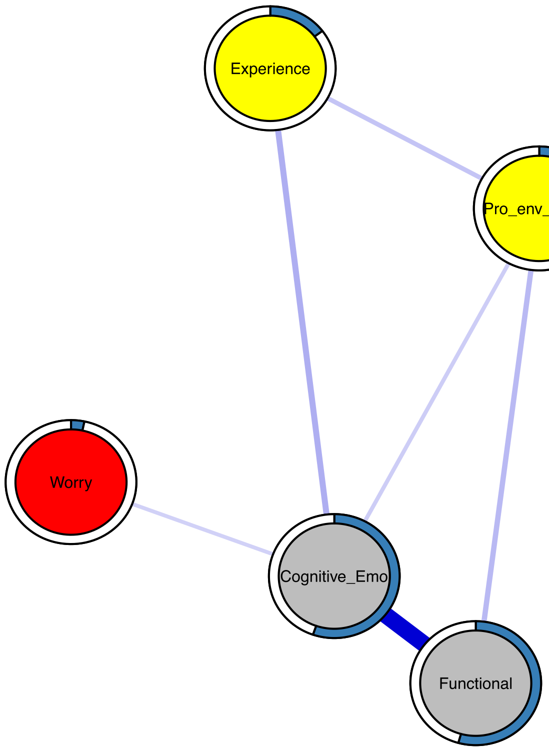

Fig. 1. Gaussian Graphical Model constructed via the ggmModSelect algorithm. *Note.* The thickness of an edge reflects the magnitude of the association (the thickest edge representing a value of.65). The blue rings around the nodes indicate the proportion of explained variance in that node by all other nodes. The color of the nodes denotes their community belonging. Cognitive_Emo = The cognitive-emotional component of climate anxiety; Experience = The experience of climate change; Functional = The functional component of climate anxiety; Pro_env_behav = Pro-environmental behaviors; Worry = General worry.

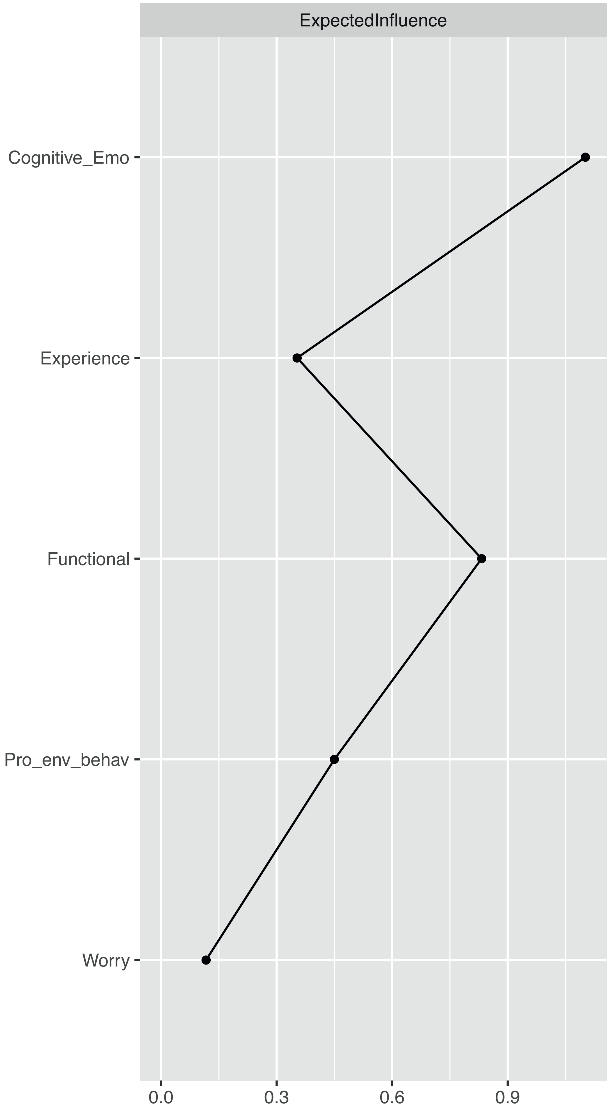

Fig. 2. Expected Influence Estimates of Gaussian Graphical Model constructed via the ggmModSelect algorithm. *Note.* Cognitive_emo = The cognitive-emotional component of climate anxiety; Functional = The functional component of climate anxiety; Pro_env_behav = Pro-environmental behaviors; Experience = Experience of climate change; Worry = General worry.

one was the only node to share a direct connection with other nodes in the network. Finally, worry had only one thin edge, shared with the cognitive-emotional feature of climate anxiety.

Following gold-standard practices in network analyses (Epskamp & Fried, 2018), we estimated the certainty and precision of the edge weights via a nonparametric bootstrapping procedure (with 1000 bootstrapped samples with replacement) to bootstrap the edge weights' confidence regions. Using a bootstrapped difference test (Epskamp et al., 2018), we also examined whether the edge weights significantly differed from one another. Results support that the edges are stable, and that the strongest and weakest edges are significantly different from one another (see Figs. S4 and S5) in the Supplementary materials.

5.1.2. *Node importance*

Expected influence values are depicted in Fig. 2. The cognitive-emotional and functional features of climate anxiety had the highest expected influence values, whereas worrying had the lowest. Following recent guidelines (Epskamp & Fried, 2018), we assessed the stability of these centrality estimates by implementing a person-dropping bootstrap procedure (with 1000 bootstrapped samples with replacement), which confirmed that these expected influence values are highly stable (Fig. S6 in the Supplementary materials). We also determined the CS-coefficient, which represents the maximum proportion of participants that can be dropped while maintaining 95% probability that the correlation between centrality metrics from the full data set and the subset data are at least 0.70. Based on a simulation study (Epskamp & Fried, 2018), a minimum CS-coefficient of 0.25 (and preferably ≥0.50) is recommended for interpreting centrality indices. In the present study, the CS-coefficient was 0.75 for the expected influence. In addition, we examined the relations between node centrality and node variance. Terluin et al. (2016) found that differential variance across variables can distort centrality estimates. That is, a variable whose variance is minimal (restricted range) is likely to have low values of centrality metrics (McNally, 2021). Here, to address this issue, we computed the correlations between the standard deviation and the centrality estimates of the five nodes to test whether differences in variances may have distorted conclusions about expected influence estimates. The two-tailed Pearson correlation between the standard deviation and expected influence centrality, $r(5) = 0.15$, $p = .80$, was not significant. Had a significant correlation emerged, this would suggest that a node's centrality in the network was affected by its variability.

We also performed a bootstrapped different test, which revealed that the two features of climate anxiety have significantly higher expected influence estimates than experience of climate change, worrying and pro-environmental behaviors (see Fig. S7 in the Supplementary materials). A similar pattern of findings was also reflected when looking at the levels of node predictability (see Fig. 1), with most explained variance for the cognitive-emotional (55.3%) and the functional (54.3%) features of climate anxiety. Note that, worry exhibited the lowest node predictability value (3.4%).

5.1.3. Community detection

Finally, the walktrap algorithm detected three communities of nodes. The first community includes the two key features of climate anxiety (i.e., cognitive-emotional and functional features); a second community only includes worry; and a third one includes pro-environmental behaviors and the experience of climate change. The three communities are represented via distinct nodes' colors in Fig. 1.

Fig. 3 shows the bridge expected influence values for all nodes, revealing that the cognitive-emotional component of climate anxiety has en especially high bridge expected influence value. We also performed a

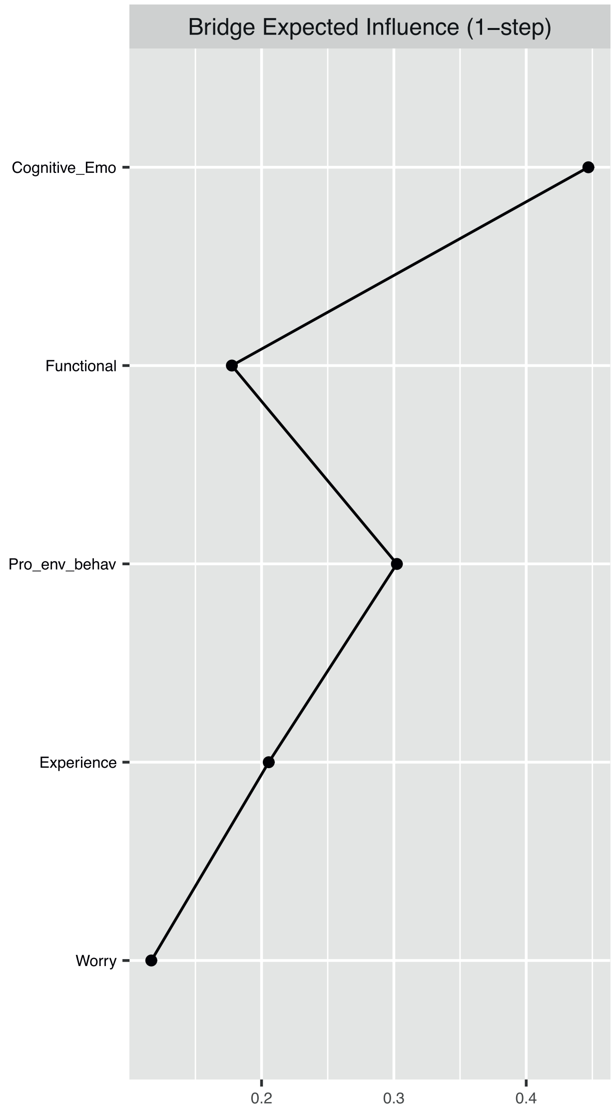

Fig. 3. Bridge Expected Influence Estimates of Gaussian Graphical Model constructed via the ggmModSelect algorithm. *Note.* Cognitive_emo = The cognitive-emotional component of climate anxiety; Functional = The functional component of climate anxiety; Pro_env_behav = Pro-environmental behaviors; Experience = Experience of climate change; Worry = General worry.

person-dropping bootstrap that indicated that bridge expected influence values were reasonably stable (see Fig. S6 in the Supplementary materials) and the CS-coefficient was 0.59. A bootstrapped different test confirmed that the cognitive-emotional component of climate anxiety had a significantly higher bridge expected value than experience of climate change and worrying (see Fig. S8 in the Supplementary materials).

5.2. Directed acyclic graphs (DAGs)

The DAGs resulting from 10,000 bootstrapped samples are presented in Figs. 4 and 5. In both DAGs, arrows that are present in the graph were retained because their strength was greater than the optimal cut-point resulting from the Scutari and Nagarajan (2013) method.

In Fig. 4, arrow thickness denotes the change in the Bayesian Information Criterion (BIC; a relative measure of a model's goodness-of-fit) when that arrow is removed from the network. In other words, the more an arrow contributes to the model fit, the thicker it is (McNally et al., 2017). In our data, the most important arrows connect the cognitive-emotional to the functional component of climate anxiety (with a change in BIC of −232.15), experience of climate change to the cognitive-emotional component (with a change in BIC of −47.58), and the cognitive-emotional component to pro-environmental behaviors (with a change in BIC of −40.92). Table 1 depicts the change in the BIC value for each arrow.

In Fig. 5, the thickness of the arrows represents directional probabilities—that is, the proportion of the averaged 10,000 bootstrapped networks wherein that arrow was pointing in that direction. Stated differently, edge thickness signifies confidence in the direction of prediction. Here, the thickest arrow points from worrying to the cognitive-emotional component (with a directional probability of .70; i.e., this edge pointed in that direction in 70% of the bootstrapped networks, and in the other direction in only 30% of the bootstrapped networks). Then, the thickest arrows point from the cognitive-emotional to the functional features of climate anxiety (with a directional probability of .63) and from the experience of climate change to the cognitive-emotional component (with a directional probability of .60).

In terms of cascading model, the DAG thus reveals a chain of nodes dependent on worry (i.e., in-degree = 0; out-degree = 1) and climate change experience (i.e., in-degree = 0; out-degree = 2), directly predictive of the cognitive-emotional components of climate change. In other words, the occurrence of the cognitive-emotional feature of climate anxiety more likely depends on the presence of worry and

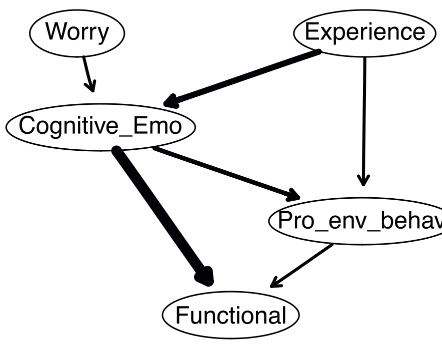

Fig. 4. Directed acyclic graphs (DAGs) With Arrow Thickness Denoting the Importance of that Arrow to the Overall Network Model Fit. *Note.* Arrow thickness denotes the importance of that arrow to the overall network model fit. Greater thickness reflects larger contribution to the model fit (i.e., Bayesian 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; Worry = General worry.

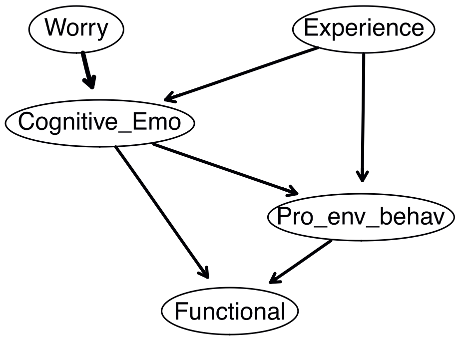

Fig. 5. Directed acyclic graphs (DAGs) With Arrow Thickness Indicating Directional Probability. ***Note.*** Arrow thickness indicates directional probability. Greater thickness reflects larger proportions of the bootstrapped networks wherein the arrow pointed in that direction. Cognitive_emo = The cognitive-emotional component of climate anxiety; Functional = The functional component of climate anxiety; Pro_env_behav = Pro-environmental behaviors; Experience = Experience of climate change; Worry = General worry.

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	-232.15	0.63
Cognitive-emotional	Pro-environnemental behaviors	-40.92	0.54
Pro-environnemental behaviors	Functional	-9.42	0.58
Experience of climate change	Cognitive-emotional	-47.58	0.60
Experience of climate change	Pro-environnemental behaviors	-5.55	0.58
Worry	Cognitive-emotional	-9.50	0.70

Note. BIC = change in Bayesian Information Criterion when that arrow is removed from the network. BIC values determine arrow thickness in Fig. 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 Fig. 5 (reflecting the frequency that arrow was present in that direction in the 10,000 bootstrapped networks).

experience of climate change than vice versa. Interestingly, the cognitive-emotional feature of climate anxiety emerged as key step in the cascading mode, with two incoming (i.e., in-degree = 2) and two outgoing arrows (out-degree = 2), including the thickest arrows of the model.

Finally, there are two parent-paths leading to the functional impairments of climate anxiety: one occurring through the cognitive-emotional feature (with a directional probability of .64) and another through pro-environmental behaviors (with a directional probability of .58), thus suggesting that the occurrence of functional impairments more likely depends on the presence of the cognitive-emotional component rather than vice versa. Table 1 depicts the directional probabilities.

6. Discussion

This is the first study to examine the network structure of climate anxiety and its related features, along with general worry. At this end, we implemented two distinct computational approaches to characterize those relations: a GGM and a DAG. One of the most remarkable findings was the convergence across the distinct approaches despite their varying assumptions and constraints. Indeed, both the GGM and the DAG pointed to the cognitive-emotional feature of climate anxiety as a potential hub bridging general worry, the experience of climate change, pro-environmental behaviors, and the functional impairments associated with climate anxiety.

First, in the GGM, the cognitive-emotional component of climate anxiety emerged as the node yielding the highest expected influence and node predictability values, thus pointing to it as a hallmark characteristic of climate anxiety. Second, in terms of community detection, both the cognitive-emotional and functional features of climate anxiety emerge a single community. In contrast, the experience of climate change and pro-environmental behaviors cohered together, while worrying formed its own community. This observation thus invites the hypothesis of worrying as related but functionally independent from all other climate change-related nodes, including climate anxiety. And interestingly, the cognitive-emotional component of climate anxiety yielded the strongest bridge centrality vis-à-vis nodes in the other communities. Finally, these patterns of findings were mirrored in the DAGs, wherein the cognitive-emotional component emerged as a critical bridge in the cascading model, with incoming arrows from worrying and the experience of climate change and outgoing ones driving not only pro-environmental behaviors but also functional impairments. The DAGs thus bolstered our confidence that the cognitive-emotional component of climate anxiety can be seen as an especially pivotal hub bridging our distinct variables of interest together.

At the theoretical level, one may interpret such a pattern of findings in light of prior work on the distinction between anxiety's adaptive and maladaptive outcomes. Indeed, for decades, basic research has been emphasizing anxiety, and particularly its cognitive and emotional features (e.g., attentional bias for threat; threat-related worries), as a potentially adaptive response vis-à-vis future-oriented uncertainty-related situations, notably in terms of anticipations of possible threats that are not immediately present and readiness for dealing with such threats should they occur (e.g., American Psychological Associations, 2015; Öhman, 2008). From this perspective, our results are thus suggestive of the cognitive-emotional component as a tipping pathway that may yield either adaptive (i.e., pro-environmental behaviors) or maladaptive responses (i.e., functional impairments) to climate change.

At the adaptive level, one may envision the behavioral engagement in pro-environmental actions emanating from the cognitive-emotional component as an anxiety-driven behavior allowing people to plan and prepare for possible climate-related threats — i.e., the adaptive responses. Our observation, in the DAG, of the cognitive-emotional component as a parent node of pro-environmental behaviors illustrates this perspective. Furthermore, this observation aligns with prior research (e.g., Reser et al., 2012; Verplanken et al., 2020), suggesting moderate-to-strong associations between climate anxiety and pro-environmental behaviors. On the maladaptive side, functional impairments in daily life (e.g., impact on the ability to go to work or school) have often been described as the ultimate proxy for identifying when psychological patterns become a threat to mental health (for discussion, see Billieux et al., 2015; Boland et al., 2018; McKnight & Kashdan, 2009). Here, the observation of the cognitive-emotional component as a parent node of the functional impairments in the DAG exemplifies this perspective. A critical next step would thus be to elucidate how people can develop functional impairments in response to climate anxiety by examining the temporal relations between these two components or experimentally manipulating the cognitive-emotional component.

In contrast to our expectations, neither worry nor the experience of climate change appeared as highly influential nodes in the network. Our findings may thus appear at odds with prior claims on the two variables as preconditions to climate anxiety (e.g., Clayton, 2020; Ellis & Albrecht, 2017; Gibson et al., 2020). Moreover, despite the DAGs pointing to both experience of climate change and worrying as the parent nodes topping the entire network, neither the GGM nor the DAGs revealed the presence of direct connections between them and functional impairments. Conversely, both variables were involved in indirect paths connecting them to functional impairments via the cognitive-emotional component. And although the DAG also revealed the presence of a path going from climate change experience to functional impairments via pro-environmental behaviors, the BIC value (i.e., the contribution to the model fit) of the arrow connecting the experience of climate change to pro-environmental behaviors was inconsequential (change in BIC of – 5.55), compared to the one going from climate change experience to the cognitive-emotional component (with a change in BIC of −47.58). Therefore, it emphasizes the likelihood that experience of climate change may primarily exert its influence on functional impairments via the cognitive-emotional component of climate anxiety.

Our results have implications. In particular, the network approach to psychopathology posits that deactivating nodes serving as hubs in the network should foster a downstream beneficial cascade (e.g., Borsboom, 2017). Consequently, if it holds for the variables investigated here, interventions directly targeting the cognitive-emotional component might help prevent the emergence of functional consequences. Moreover, this suggestion dovetails with recent but growing evidence that the cognitive-emotional features of climate anxiety (e.g., difficulty in controlling attention when thinking about climate change; difficulty in falling asleep when thinking about climate change) can be seen as a potential pathway leading to the adverse functional impact of climate change anxiety (e.g., Ogunbode et al., 2021). On the other hand, despite the extensive usage of the cognitive-emotional component of climate anxiety in today's climate anxiety literature, this component remains an umbrella construct, encompassing a wide range of potential psychological processes (e.g., attentional bias for threat; future thinking; coping strategies). Likewise, although our results suggested a tiniest—though consistent across the varying computational approaches—contribution of general worry (i.e., nonspecific to climate change), one may not exclude a more substantial impact of worry about climate-related concerns instead of general worry. A critical next step would thus be to elucidate the nature and function of all these cognitive and emotional processes in climate anxiety.

A second implication focuses on behavioral engagement in pro-environmental actions. Indeed, the DAG also identified this variable as a parent node of functional impairments. Despite recent research pointing to environmental activism as a potential strategy to help people with severe climate anxiety combating feelings of hopelessness, and promoting community connection and social support (for a discussion, see Schwartz et al., 2022), our observation aligns with a small but growing empirical literature indicating the possible damaging consequences of over-engagement on one's mental health in causes this person cares about but does not see the expected change coming (e.g., Dwyer et al., 2019; Vestergren et al., 2018)—a phenomenon dubbed "activism fatigue." In this way, practitioners may thus want to carefully audit whether engagement in pro-environmental behaviors leads to restorative or harmful consequences on the mental health of people with climate anxiety.

The present study has limitations that deserve careful consideration in future research. First, the estimation of both the GGM and DAGs relies on cross-sectional data, thus excluding any strong inference regarding the potential causal relations between the variables of interest. The only insight into the possible direction of associations is from the DAG, which uses probabilistic Bayesian learning methods to provide clues about this direction. Second, DAGs assume that connections between nodes are directed and acyclic. Yet, relationships between variables cannot always be defined as directed and acyclic relations of probabilistic dependencies (e.g., in the case of feedback loops). However, because the direction of the arrow is determined by the percentage of bootstrapped networks wherein this arrow was pointing in that direction, the degree of potential reverse directionality can be gauged from the proportion of bootstrapped networks wherein the arrow pointed in the other direction (Briganti et al., 2022; McNally, 2021). Here, a few arrows were relatively thin, indicating that the direction of the arrow was pointing in the other direction in a substantial proportion of the bootstrapped networks. For instance, the edge connecting the cognitive-emotional component to pro-environmental behaviors pointed in that direction in 54% of the 10, 000 bootstrapped networks, thus implying that it pointed in the other way in 46% of the 10,000 bootstrapped networks. The direction of the association between these two variables may thus tip in both directions. However, one cannot exclude the existence of other types of cyclicity (e. g., node A→node B→node C→node A; McNally, 2021). Further elucidating the potential bidirectional dependencies between variables would require the application of temporal network analyses on data arising from experience sampling methods (for a review, see Blanchard et al., 2022).

Third, our participants were from European countries. Since the ongoing and long-term consequences of climate change are more consequential for people living in Asian and African countries than in Europe, notably in terms of human health and safety, as well as food and water security (e.g., Collier et al., 2008; World Meteorological Organization, 2020), a critical next step would be to examine whether the present results generalize in more geographically and culturally diverse samples. Fourth, we assessed pro-environmental behaviors by using the self-reported items developed by Clayton and Karazsia (2020). Although we aimed to ensure the standardization of the measurement approach across studies, the internal reliability of these items was less than ideal. Moreover, they were restricted to self-reported individual behaviors and do not cover collective actions (e.g., political choices, environmental activism). This is unfortunate given prior research linking climate anxiety to collective actions (e.g., Schwartz et al., 2022; Stanley et al., 2021). Likewise, future iterations might want to benefit from more objective measures of pro-environmental behaviors (e.g., Lange, 2022).

Finally, although the notion of climate anxiety has been gaining traction in the media and the scientific literature over the last few years, uncertainty remains regarding the very nature of this phenomenon. In a scoping review, Coffey et al. (2021) revealed more than ten distinct operationalizations of eco/climate anxiety in the extant literature, thus suggesting a striking lack of consensus among authors regarding this notion. Here, we aligned with Clayton and Karazsia (2020) 's operationalization that focuses on anxious feelings associated with perceptions about climate change. However, other operationalizations have been proposed, and one may wonder whether the distinction between the cognitive-emotional and the functional features would remain across the plethora of different operationalizations of eco/climate anxiety. On the other hand, this issue also stresses the paucity of theoretical developments and the lack of integrative models regarding climate anxiety. As in any field of science, the absence of clearly testable and falsifiable theories thwarts scientific advancement (Borsboom & van der Maas, 2021; Eronen & Bringmann, 2021), thus urgently calling for the development of theoretical principles that can be putatively confirmed or rejected via hypothesis-driven research.

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Ethical statement

The research described in this article was approved by the UCLouvain Institutional Review Board (IPSY Project# 2021-54).

Conflict of interest

Dr. Heeren is an Associate Editor of the Journal of Anxiety Disorders. He receives financial support through payments for his editorial work on the journal mentioned above and royalties from various book publishers. The authors have no other known conflict of interest to disclose.

Data Availability

The de-identified data and R code of this study have been made publicly available via the Open Science Framework at https://osf.io/2r659/.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.janxdis.2022.102625.

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