From mitigation to adaptation: Network analysis of their interrelations with climate anxiety, pessimistic future anticipation, and intolerance of uncertainty

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Abstract

Climate change represents an unprecedented threat, with rising levels of climate anxiety widely reported. Most psychological research has primarily examined relationships between climate anxiety and mitigation behaviors while largely neglecting adaptation behaviors, which involve preparing for inevitable climate impacts. Yet, ethological and foundational anxiety theories emphasize anxiety's adaptive role in fostering preparedness and proactive coping with threats, particularly in uncertain, future-oriented situations. Based on this framework, we examined whether intolerance of uncertainty (IU) and future anticipation influence the association between climate anxiety and adaptation versus mitigation behaviors. In a preregistered fashion, we analyzed data from 968 French-speaking adults using two complementary computational network modeling approaches: (1) a graphical Gaussian model to examine conditional associations among climate anxiety, IU components (prospective and inhibitory), future anticipation, experience of climate change, and adaptation and mitigation behaviors; and (2) a directed acyclic graph to generate a data-driven model of the directional probabilistic dependencies among these variables. Results consistently highlighted prospective IU—characterized by proactive information-seeking and planning in the face of uncertainty—as central within the network, and positively linked to adaptation behaviors and climate anxiety. Conversely, inhibitory IU (characterized by paralysis in uncertainty) appeared to be peripheral. This study, which relies on new computational methods, emphasizes the essential yet overlooked role of adaptation and offers fresh, data-driven insights into its relationship with climate anxiety, future anticipations, and intolerance of uncertainty.

Keywords: Climate adaptation, mitigation behaviors, climate anxiety, intolerance of uncertainty, graph theory, network analysis, future anticipation, preregistration

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The capacity of living organisms to respond to novel threats has long constituted a foundational mechanism of biological evolution. Across human history, our ancestors have continuously faced a multitude of environmental risks that endangered their survival, positioning adaptability as a core determinant of human evolutionary success (Bateson et al., 2011). In the contemporary era, anthropogenic climate change presents one of the most acute and unprecedented threats to global ecosystems, human livelihoods, and public health (Intergovernmental Panel on Climate Change [IPCC], 2022).

Although human societies have historically adapted to climatic variability, current climate change differs in both magnitude and velocity, driven by human-induced greenhouse gas emissions and unfolding at an unparalleled pace (IPCC, 2022; Neukom et al., 2019). In response, the scientific community has reached widespread consensus that urgent and coordinated action is required—comprising both mitigation strategies (i.e., reducing carbon emissions) and adaptive responses (i.e., preparing for unavoidable consequences, e.g. Fawzy et al., 2020; Urban et al., 2021).

While mitigation is essential to slow the progression of climate change, it alone cannot reverse the warming already underway. Even under the most ambitious mitigation scenarios, global temperatures are projected to continue rising, with cascading effects on environmental, economic, and psychosocial systems (IPCC, 2022). Therefore, adaptation—defined as the process of adjusting behaviors, systems, and policies to reduce harm from climate-related hazards (IPCC, 2022)—has emerged as a parallel imperative. Although adaptation is often discussed at the policy or infrastructure level, individual-level adaptive actions are equally vital. Such actions may include preparing emergency supplies, securing insurance for extreme weather events, seeking risk-related information, or implementing proactive evacuation strategies (Carman & Zint, 2020).

Despite the growing importance of individual adaptation, much of the existing psychological literature has focused disproportionately on the motivational and emotional antecedents of mitigation behaviors (e.g., energy conservation, recycling), often neglecting adaptation behaviors (Valkengoed & sch, 2019). Yet as the frequency and severity of extreme events—such as wildfires, floods, and heatwaves—increase (IPCC, 2022), understanding how individuals anticipate and prepare for such disruptions becomes essential. Meta-analytic findings indicate that several psychological variables, such as negative affect, are robust predictors of adaptive behavior, whereas knowledge, trust, and place attachment appear less influential (Valkengoed & Steg, 2019).

Concurrently, a growing body of research has highlighted the profound emotional toll that climate change exerts on individuals. Beyond those directly affected by climate disasters, increasing numbers of people—particularly younger generations and those attuned to ecological risk—report elevated levels of climate-related distress, anger, grief, and existential concern (Clayton, 2020; Crandon et al., 2022; IPCC, 2022). These emotional responses, often referred to as *climate anxiety*, *climate change anxiety*, or *eco-anxiety*, can be triggered by the anticipation of climate-related threats, even in the absence of direct exposure (Coffey et al., 2021; Hogg et al., 2021).

Notably, climate anxiety has been shown in some cases to reach levels that interfere with daily functioning—manifesting in difficulties with social interaction, ability to concentrate, productivity at schools or works, and well-being (Clayton and Karazsia, 2020; Gibson et al., 2020; Heeren et al., 2022; Hickman et al., 2021). Such impairments suggest that climate anxiety may, for some individuals, become a potential risk factor for mental health disorders (Heeren & Asmundson, 2023). However, an alternative perspective emphasizes the functional evolutionary role of anxiety as a future-oriented emotion that facilitates threat detection, risk prioritization, and action planning under uncertainty (Bateson et al., 2011; Morris, 2019; Öhman et al., 2001; Price, 2013). According to this view, anxiety is characterized by anticipatory cognition (e.g., worry about uncertain threats) and physiological arousal (e.g., muscle tension) that prime individuals to prepare for potential danger (Heeren, 2020; Öhman, 1996).

In this context, climate anxiety may be conceived as an adaptive psychological signal—alerting individuals to future-oriented threats and motivating protective behaviors. Indeed, several empirical studies have reported positive associations between climate anxiety and pro-environmental mitigation behaviors (Becht et al., 2024; Heeren et al., 2022; Ogunbode et al., 2022), lending credence to the functionalist interpretation. Nevertheless, findings remain inconsistent: other studies have reported null (e.g., Qin et al., 2024) or even negative associations (e.g., Stanley et al., 2021), suggesting that under certain conditions, climate anxiety may inhibit rather than facilitate mitigation. Critically, far less is known about how climate anxiety relates to adaptation behaviors—despite theoretical models predicting a strong link between anxiety and future-oriented planning (Bateson et al., 2011).

A key variable that may modulate this relationship is intolerance of uncertainty (IU)—a dispositional tendency to perceive ambiguous or unpredictable situations as distressing (Rosser, 2019). IU has been identified as a transdiagnostic factor in numerous emotional disorders and may play a central role in determining whether anxiety leads to adaptive engagement or avoidance (Zlomke & Jeter, 2014). IU comprises two components: *prospective IU* (i.e., desire for predictability and information-seeking) and *inhibitory IU* (i.e., paralysis and avoidance in the face of uncertainty) (Birrell et al., 2011; Bottesi et al., 2019; Hale et al., 2016). While the former may motivate action, the latter has been associated with avoidance, maladaptive coping, and functional impairment

(Berenbaum et al., 2008). Clarifying how these components interact with climate anxiety, pessimistic future anticipation, and adaptation and mitigation behaviors remains an open question.

Accordingly, the present study aims to map the relationships among key psychological constructs implicated in climate change adaptation and mitigation: climate anxiety, functional impairment, pessimistic future anticipation, prospective and inhibitory IU, and climate-related behaviors. Given evidence that perceptions of climate change risk are associated with emotional and behavioral responses (Heeren et al., 2023; Martin et al., 2020), we also include perceived climate change as a variable of interest.

To investigate these complex interactions, we employ network analysis, a computational approach that models psychological constructs as dynamic systems of interrelated components (Briganti et al., 2024; McNally, 2021). First, we estimate a graphical Gaussian model (GGM), an undirected network that identifies conditional associations among variables while controlling for all others (Borsboom et al., 2021). We assess centrality and predictability metrics to determine the influence of each variable within the network. Second, we explore the presence of community structures—clusters of nodes that cohere functionally—and identify potential *bridge nodes* that connect distinct psychological domains (Jones et al., 2019). Finally, we estimate a Bayesian directed acyclic graph (DAG), a probabilistic model that depicts directional dependencies among variables and facilitates causal hypothesis generation (Briganti et al., 2022, 2024).

To our knowledge, this is the first study to apply both undirected and directed network models to explore the interrelations among climate anxiety, IU, future expectations, functional impairment, and climate-relevant behaviors. By leveraging this integrative computational approach, we aim to offer a data-driven framework to clarify when and how climate anxiety may serve as a motivational force or a psychological burden in the context of climate change adaptation and mitigation.

Method

Transparency and Openness

The study design and analytic plan, including sample size and sampling rationale, were preregistered and can be consulted on the Open Science Framework at (https://osf.io/cs2h9). All study materials, including a de-identified version of the dataset and the R script are publicly available at https://osf.io/fu9zx/files/osfstorage).

Participants

A total of 968 French-speaking individuals participated in the study. Of these, 72% identified as women, 24.7% as men, 1.76% as non-binary or other genders, and 1.54% preferred not to disclose their gender identity. Participants were recruited via online advertisements disseminated on social media platforms and public forums targeting French-speaking populations in Europe. Regarding nationality, 81.1% of participants were Belgian, 9.5% were French, and 9.4% originated from other French-speaking countries or territories. Participants' ages ranged from 18 to 82 years (M = 23.36, SD = 10.64). Educational attainment post-primary school ranged from 11 to 30 years (M = 14.24, SD = 2.66). All participants provided written informed consent prior to participation. The study received ethical approval from the Institutional Review Board of the Psychological Sciences Research Institute at UCLouvain (Project IPSY#2021-12) and was conducted in accordance with the Declaration of Helsinki.

Measures

Climate Anxiety

Climate anxiety was measured using the validated French version of the Climate Change Anxiety Scale (CCAS; Mouguiama-Daouda et al., 2022), which comprises two subscales: cognitive-emotional impairment (8 items) and functional impairment (5 items).

Originally developed by Clayton and Karazsia (2020), the CCAS is a 13-item self-report instrument widely recognized for its psychometric robustness. Cognitive-emotional items included statements such as "Thinking about climate change makes it difficult for me to concentrate" and "I found myself crying because of climate change." Functional impairment items included statements such as "My concerns about climate change interfere with my ability to complete work or school assignments." Internal consistency was high for both subscales (cognitive-emotional: $\alpha = .85$, $\omega = .88$; functional: $\alpha = .86$, $\omega = .86$).

Experience with Climate Change

Consistent with Clayton and Karazsia (2020), participants' perceived personal exposure to climate change was assessed using three items from the validated French version (Mouguiama-Daouda et al., 2022): "I have been directly affected by climate change," "I know someone who has been directly affected by climate change," and "I have noticed changes in a place that is important to me due to climate change." Responses were recorded on a 5-point Likert scale (0 = Never, 5 = Almost always). The internal consistency was acceptable ($\alpha = .70$, $\omega = .71$).

Pessimistic future anticipation

Three items adapted from Hickman et al. (2021) assessed pessimistic anticipation of the future: "I think that humanity is doomed," "The future is frightening," and "The things I most value will be destroyed." Participants responded on a 7-point Likert scale (0 = Not at all, 7 = Absolutely). Internal consistency was satisfactory ($\alpha = .77$, $\omega = .77$).

Intolerance of uncertainty

IU was assessed using the validated French version of the Intolerance of Uncertainty Scale–Revised (Mouguiama-Daouda et al., 2023), adapted from Bottesi et al. (2019). The scale includes seven items for Prospective IU (e.g., "I should always be prepared before things happen") and five items for Inhibitory IU (e.g., "When things happen suddenly, I am very upset"). Items were rated on a 5-point Likert scale (1 = Not at all like me, 5 = Completely like me). Internal consistency was good for both subscales (Prospective IU: $\alpha = .86$, $\omega = .82$; Inhibitory IU: $\alpha = .86$, $\omega = .88$).

Mitigation behaviors

Mitigation behaviors were assessed using seven items from the French adaptation of the Belgian Climate Barometer survey. These items evaluated meat consumption, airplane travel frequency, low-emission mobility, household energy-saving actions, sustainable consumer practices, and engagement with circular economy behaviors. Internal consistency was acceptable ($\alpha = .67$, $\omega = .78$).

Adaptation behaviors

Adaptation behaviors were measured using 10 items from Lozano Nasi, Jans, and Steg (2023; Study 4). Items assessed anticipatory and preparatory actions, such as "Preparing a household emergency kit" and "Looking up information about whether my house is at risk of natural hazards." Internal consistency was strong ($\alpha = .87$, $\omega = .91$).

Network Analyses

Data preparation

Normality of the variables was assessed using standard thresholds (skewness > |2| and kurtosis > |7|; Curran et al., 1996). A nonparanormal transformation was applied using the "huge" package in R (Jiang et al., 2019), as recommended for network estimation (Epskamp & Fried, 2018).

Check for potential nodes redundancy

To avoid potential conceptual overlap between variables, we employed the "goldbricker" function from the "networktools" R package (Jones, 2024), applying the Hittner method (Hittner et al., 2003) to flag variable pairs with high intercorrelation (r > .75).. No redundant variable pairs were identified.

Since non-positive definite matrices can generate overly dense networks—potentially filled with spurious connections and unanticipated negative edges (Epskamp & Fried, 2018)—we also ensured that our correlation matrix was positive definite, thereby confirming that nodes were not a linear combination of one another.

Graphical Gaussian Model

We estimated a Graphical Gaussian Model (GGM) to examine associations among study variables using the *ggmModSelect* algorithm from the « qgraph » package in R (Epskamp et al., 2018). GGM is a standard approach for estimating undirected networks from cross-sectional psychological data. The algorithm iteratively adjusts edges to optimize model fit via the Bayesian Information Criterion (BIC), stopping when no further improvement is possible (Isvoranu & Epskamp, 2021). Edge stability was evaluated using 1,000 nonparametric bootstraps with the « bootnet » package (Epskamp, Borsboom, & Fried, 2018).

Node centrality was assessed using the expected influence index (Robinaugh et al., 2016), visualized with the *centralityPlot* function in « qgraph ». To verify the robustness of these estimates, we used a case-dropping bootstrap approach (Costenbader & Valente, 2003; Epskamp et al., 2018).

We then performed a bootstrapped difference test to determine whether nodes significantly differed in their centrality. Additionally, we computed the correlation stability (CS) coefficient, which quantifies the proportion of cases that can be removed while maintaining a correlation of ≥ .70 between centrality indices computed on the full and reduced datasets. Simulation studies recommend a minimum CS-coefficient of .25, with ≥ .50 preferred for interpretability (Epskamp et al., 2018).

Node predictability, defined as the variance of a node explained by its neighbors, was computed using the “mgm “package (Haslbeck & Waldorp, 2017) and visualized as pie charts in each node's outer ring. Predictability indicates whether the system is primarily driven by internal associations or external, unmeasured influences (Haslbeck & Waldorp, 2017).

To examine the network's modular structure, we applied the Walktrap community detection algorithm from the « igraph » package (Csardi & Nepusz, 2006), which identifies densely connected subclusters via random walks (Jones et al., 2018). Bridge expected influence, calculated with the « networktools » package (Jones, 2018), represents the sum of edge weights linking a node to other communities (Jones et al., 2021; Jones, Ma, & McNally, 2019). We assessed the stability of bridge expected influence using 1,000 person-dropping bootstraps and calculated the CS-coefficient with the « bootnet » package. Bootstrapped difference tests were used to evaluate between-node differences in bridge influence.

Finally, to address concerns that variability in node distributions may bias centrality interpretations (Fried, 2016; Terluin, de Boer, & de Vet, 2016), we computed correlations between each node's standard deviation and its centrality metrics. This allowed us to assess whether dispersion influenced a node's prominence in the network.

Directed Acyclic Graph (DAG)

Consistent with prior psychological research (e.g., Bernstein et al., 2017; McNally et al., 2017), we estimated a Directed Acyclic Graph (DAG) using a Bayesian hill-climbing algorithm, as described by Briganti et al. (2022). This algorithm iteratively evaluates different combinations of edges—including additions, deletions, and directional reversals—to identify the model that best fits the data according to the Bayesian Information Criterion (BIC). Following established procedures (Bernstein et al., 2017; McNally et al., 2017), we specified 50 random restarts and 100 perturbation steps.

To evaluate the stability of the resulting DAG, we generated 10,000 bootstrap samples with replacement and averaged the resulting networks. For each pair of nodes, we computed the frequency with which a given edge appeared across bootstrapped networks. Edge retention was determined using the optimal cut-point method described by Scutari and Nagarajan (2013): edges present in at least 51% of bootstrapped networks were included in the final model.

We visualized the average DAG using two complementary approaches. In the first, edge thickness was scaled according to its relative contribution to model fit based on BIC values; thicker edges signified a greater impact on overall network structure. In this visualization, the removal of a thick edge would result in a greater degradation of model fit than the removal of a thinner edge (McNally et al., 2017). In the second visualization, edge thickness reflected directional probability, with thicker edges indicating a higher likelihood that the connection pointed in the specified direction. For instance, a thick edge from node X to node Y signifies that this directional link occurred more frequently across the 1,000 bootstrapped networks than the alternative direction (e.g., Y to X).

Results

Descriptive statistics (i.e., mean, standard deviation, skewness, kurtosis, and range) and Pearson zero-order correlations among all variables are available in the Supplementary Materials (Table S1, Figure S1).

Gaussian graphical model (GGM)

Figure 1 displays the GGM network estimated using the *ggmModSelect* algorithm. Edge thickness reflects the strength of partial correlations between variables, with thicker edges indicating stronger associations. Nodes were placed using the Fruchterman-Reingold layout (Fruchterman & Reingold, 1991) that places nodes with highest connectivity in the center of the network.

Several connections are noteworthy. First, the strongest links were between the two IU components (r = .64) and between the two climate anxiety components (r = .61). Second, the cognitive-emotional component connected to three nodes—prospective IU (r = .13), pessimistic future anticipation ($r = .11$), and adaptation behaviors ($r = .11$)—whereas the functional component linked only to experience of climate change ($r = .16$) and mitigation behaviors ($r = .27$). Third, while prospective IU was linked to adaptation behaviors ($r = .16$), inhibitory IU showed no connections in the network.

Edge weight accuracy and reliability were confirmed using bootstrap procedures (Figure S2), and bootstrapped difference tests revealed that the strongest edges were significantly larger than most others (Figure S3). Figure 2 presents expected influence estimates, with prospective IU emerging as the most central node, and personal experience of climate change as the least. Bootstrap stability analyses confirmed the robustness of centrality estimates (Figure S4). Additionally, difference tests showed that prospective IU had significantly higher expected influence than all other nodes (Figure S5). Node predictability followed a similar trend: the cognitive-emotional component of climate anxiety showed the highest predictability (57.7%), closely followed by the functional component (57.5%), whereas personal experience of climate change showed the lowest (22.3%).

The Walktrap algorithm revealed three communities: (1) climate anxiety components, experience of climate change, and mitigation behaviors; (2) the two IU components; and (3) adaptation behaviors and pessimistic future anticipation. Figure 3 shows bridge expected influence estimates and highlights prospective IU, pessimistic future anticipation, and climate adaptation behaviors as key bridging nodes, acting like pivotal hubs connecting all the different nodes of the network system together. Bootstrapped tests confirmed these observations (Figure S6). Additional details on the accuracy and stability of these estimates, including differential variability analyses, are provided in the Supplementary Materials.

Directed Acyclic Graphs (DAGs)

The Directed Acyclic Graphs (DAGs) resulting from 10,000 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. Figures 4 and 5 present the DAGs derived from 10,000 bootstrap samples. Arrows were retained if they exceeded the optimal cut-point based on the Scutari and Nagarajan (2013) method.

In Figure 4, arrow thickness reflects BIC change when an edge is removed. Larger changes signify stronger contributions to model fit (McNally et al., 2017). The most influential arrows were from prospective IU to inhibitory IU (ΔBIC = -282.83), functional to cognitive-emotional components (ΔBIC = -223.35), mitigation behaviors to functional impairment (ΔBIC = -101.53), and functional impairment to experience of climate change (ΔBIC = -51.04). Table 1 presents all BIC changes.

In Figure 5, arrow thickness represents directional probability across 1,000 bootstrapped networks of the average 1000 bootstrapped networks in which each arrow pointed in a specific direction (i.e., the confidence in the prediction direction).The thickest arrow links prospective IU to adaptation behaviors with a directional probability of .80 (i.e., indicating that this edge pointed in that direction in 80% of the bootstrapped networks, while it pointed in the opposite direction only 20% of the time), followed by an arrow from prospective IU to pessimistic future anticipation (with a directional probability of .75). All the directional probabilities are listed in Table 1.

Finally, since DAGs encode conditional independence and joint distributions, node positioning reflects conditional dependencies (Briganti et al., 2024). The resulting DAG highlights mitigation behaviors as a foundational predictor (in-degree = 0, out-degree = 2), directly influencing the two climate anxiety components, experience of climate change, and pessimistic future anticipation—suggesting that these outcomes are more likely byproducts of mitigation behaviors than triggers. Strikingly, adaptation behaviors appeared at the bottom of the cascading network, suggesting that this node is more likely to be predicted by all other nodes than vice-versa.

Discussion

This preregistered study is, to our knowledge, the first to use computational tools from network analysis and graph theory to explore the complex relationships among climate adaptation behaviors, mitigation behaviors, climate anxiety, pessimistic future anticipation, personal experiences of climate change, and intolerance of uncertainty (IU). For the first time in this field, we distinguish between two types of IU—prospective and inhibitory—and clarify their relationships to other variables. To accomplish this, we employed two distinct computational methods: a Gaussian Graphical Model (GGM) and a Directed Acyclic Graph (DAG) using a dataset of 968 individuals. Our goal was to provide a data-driven computational model of these relationships through these analytical frameworks.

One of the most compelling findings is that both computational approaches identified prospective IU—the desire to manage uncertainty through proactive planning and information-seeking—as a pivotal pathway. This characteristic has a strong and direct association with the cognitive-emotional aspects of climate anxiety, adaptation behaviors, pessimistic future anticipation, and, unsurprisingly, inhibitory IU. In the GGM, prospective IU showed the highest expected influence, underscoring its essential role as a hub within the network. Furthermore, DAG models provide additional insights into these complex relationships. Specifically, prospective IU appears to directly predict the cognitive-emotional component of climate anxiety, adaptation behavior, and future anticipation. For these three connections, the directional probabilities—indicating the proportion of averaged 1,000 bootstrapped networks in which each arrow pointed in a specific direction—were notably high, thus ensuring a strong likelihood that these predictions are tipping in that direction rather than the opposite.

Our findings offer new insights into the psychological mechanisms underlying climate change adaptation and mitigation, aligning closely with and enhancing established theoretical frameworks. They strongly resonate with the Uncertainty and Anticipation Model of Anxiety (UAMA; Grupe & Nitschke, 2013), which suggests that anxiety is a response to uncertain future threats involving changes in cognitive, emotional, and behavioral responses. Our data supports UAMA's claim that uncertainty regarding future threats can trigger anticipatory responses. We identified prospective IU as the key factor connecting climate anxiety to adaptive outcomes. This indicates that prospective IU can help reduce anxiety by encouraging concrete actions to cope with threat. In contrast, inhibitory IU, which involves paralysis when faced with uncertainty, was found to be unrelated to these outcomes. Although we did not specifically assess “eco-paralysis” (i.e., the feeling of being overwhelmed and unable to act meaningfully in response to climate change and other environmental issues; Cianconi et al., 2023; Innocenti et al., 2023), this observation aligns with the idea that such strategies can lead individuals to disengage from both emotional processing and proactive actions, resulting in maladaptive climate anxiety. Although a critical next step in future iteration would be to further clarify the role of inhibitory IU, this distinction highlights UAMA's differentiation between adaptive and maladaptive anxiety responses based on how individuals manage uncertainty (Grupe & Nitschke, 2013).

Our findings also align completely with decades of research on IU across anxiety and related disorders. This research suggests that the inherent need for predictability associated with prospective IU contributes to the creation of "what-if" scenarios. These scenarios, in turn, intensify worries and negative emotions (Carleton et al., 2012; Morriss et al., 2023; Shapiro et al., 2020). Additionally, the role of prospective IU in predicting pessimistic future anticipations aligns with the predictions of UAMA, which suggests that in threatening situations marked by uncertainty, individuals may become overly focused on anticipatory thinking and prepare for potential threats (Boehme et al., 2014; Carlson et al., 2011).

Notably, our findings also support the Protection Motivation Theory (PMT; Rogers, 1983) and its subsequent developments, including appraisal models and the Theory of Planned Behavior. These frameworks emphasize that threat appraisal and coping appraisal are crucial factors in determining motivation. From this perspective, individuals are more likely to respond adaptively to threats when they perceive a high level of threat and have strong beliefs in their ability to cope effectively. In our study, climate anxiety can be viewed as a perceived threat, while prospective IU represents a coping orientation characterized by proactive uncertainty management through planning. The strong association between prospective IU and adaption behaviors suggests that individuals motivated by reducing IU proactively are more likely to engage in preventive measures (e.g., emergency preparedness, information gathering) consistent with PMT's danger control pathway. In contrast, anxiety without coping motivation—implied by inhibitory IU—likely leads to fear control strategies such as denial or avoidance. Although this hypothesis requires further empirical examination in future iterations, this interpretation of our findings supports the meta-analysis conducted by van Valkengoed and Steg (2019), which identified negative affect as a significant driver of adaptation behavior, particularly when paired with efficacy beliefs. While we did not directly measure self-efficacy, the proactive nature of prospective IU aligns with efficacy beliefs. This suggests that a combination of climate anxiety and proactive uncertainty reduction serves as a strong catalyst for climate adaptation actions.

Finally, our DAG unexpectedly indicates that engaging in mitigation behaviors better predicts climate anxiety and pessimistic anticipation than the reverse. While pro-environmental behaviors can help alleviate climate anxiety by fostering community support and reducing feelings of hopelessness (Schwartz et al., 2022), our findings align with a small but growing body of literature suggesting that involvement in climate mitigation might increase feelings of anxiety and pessimism, especially when individuals perceive insufficient progress. Constant exposure to climate threats can contribute to this effect (see Clayton & Parnes, 2025, for a review). Additionally, this ongoing exposure can lead to a phenomenon known as "activism fatigue" (Dwyer et al., 2019). Individuals who are already concerned about climate issues may intensify their mitigation efforts, creating a feedback loop. In this loop, taking actions heightens their climate anxiety, which in turn drives them to take even more action. Our DAG supports the idea of frequent directional reversals in the bootstrapping process, as indicated by the relatively thin arrows representing these relationships. This suggests the possibility of cycles (for further discussion, see Heeren et al., 2020; McNally et al., 2017). For example, in only 53% of the 1,000 bootstrapped networks, the edge pointed from mitigation behaviors to functional impairments related to climate anxiety, thus implying that, in 47% of the bootstrapped networks, the direction was reversed. This suggests that the prediction direction between these two variables may go both ways. Using graphical vector autoregressive modeling approaches on intensive time-series data could help reveal these bidirectional linear relationships more clearly (e.g., Contreras et al., 2024; for a review, see Blanchard et al., 2023).

The present findings also hold clinical implications for mental health practices. First, our results indicate that prospective IU serves as a key pathway that can facilitate adaptation in the context of climate anxiety. Techniques from evidence-based treatments for generalized anxiety disorder, particularly the transdiagnostic program "Making Friends with Uncertainty" (Mofrad et al., 2020), could be particularly beneficial for individuals who are eager to take climate action but feel overwhelmed by uncertainty. This intervention uses psychoeducation and behavioral experiments to help individuals learn to tolerate uncertainty, and it has shown effectiveness (Landkroon et al., 2022; Mofrad et al., 2020). Second, given the pivotal role of future anticipations in the cascading nature of the DAG networks, clinicians could also incorporate future-oriented positive mental imagery techniques to address climate anxiety.

Research by Landkroon et al. (2022) indicates that vividly imagining successfully navigating feared future scenarios can significantly reduce anxiety. These techniques are similar to exposure therapy combined with response prevention, as they encourage individuals to mentally confront their fears while practicing effective coping strategies. Studies on episodic future simulation support this method, demonstrating that imagining detailed and adaptable future scenarios can effectively reduce anxiety and enhance problem-solving skills (Jing et al., 2016). Moreover, early adaptations to climate futures have shown promising results (e.g., Engle-Friedman et al., 2022).

Our findings have important implications that extend beyond clinical practice, particularly for public health and policy. In terms of public policy and climate communication, our findings highlight a significant warning against strategies that rely solely on high-fear messaging. While such messages can increase anxiety, they may also lead to high levels of inhibitory IU and result in the paralysis they aim to overcome, especially if they do not provide clear and accessible pathways for action. Effective communication must adopt a dual approach: it should convey the urgency of the threat while also empowering individuals and communities to take actions. Some evidence indicates that framing uncertainty as a challenge to be addressed may engage people more effectively in tackling climate change than simply invoking anxiety (e.g., Goldwert, Dev, Broos, Broad, & Timpano, 2024; Nimo, Akoto-Baako, Antiri, & Ansah, 2025). Furthermore, involving communities in planning responses to climate threats can activate processes similar to prospective IU—such as information-seeking, uncertainty management, and mental rehearsal—which can enhance local adaptation strategies and reduce feelings of helplessness (Charpentier et al., 2022).

While this study provides valuable insights, several limitations warrant discussion, providing avenues for future iterations. First, our network analyses are based on cross-sectional data, limiting our ability to draw conclusions about causality or the temporal order of variables. The GGM network illustrates associations at a single point in time. Although the DAG uses Bayesian algorithms to infer directional dependencies, it cannot establish actual chronological precedence; therefore, one must not confuse these directional probabilities with actual temporal precedence (Briganti et al., 2024; Heeren et al., 2020). Therefore, the directions reported here, along with their bootstrap probabilities, should be interpreted within a hypothesis-generating framework rather than a hypothesis-testing one (Bernstein et al., 2017; McNally et al., 2017).

Second, the sample used in this study predominantly consisted of French-speaking adults from Western democracies, mainly from Belgium and France. This demographic, often referred to as WEIRD (Western, Educated, Industrialized, Rich, Democratic; Henrich, Heine, & Norenzayan, 2010), narrows the generalizability of our findings. Cultural background can shape not only climate experiences and resources for adaptation but also the expression of anxiety and tolerance for uncertainty. For example, collectivist societies may prioritize collective adaptation behaviors over individual ones. Therefore, it is crucial to replicate this type of study in more diverse samples, including those directly affected by climate change.

Additionally, recent critiques in environmental psychology emphasize that a lack of cultural diversity among research participants and authors can create blind spots (e.g., Tam & Milfont, 2020; Tam et al., 2023). Future studies should aim to gather samples from diverse continents, socioeconomic backgrounds, and cultural groups to achieve a more comprehensive understanding of the phenomenon. Beyond sampling, future research should also include culture-specific variables—such as collectivism and Indigenous ecological knowledge—to explore how they intersect with the variables in the network models we examined. These steps will enhance the validity and applicability of this research, ultimately helping to inform the development of culturally sensitive and equitable interventions.

Third, even though we took precautions to avoid redundancy (such as using the goldbricker test to ensure that no two nodes were overly collinear), one might question whether the cognitive-emotional impairment aspect of climate anxiety is truly distinct from pessimistic future anticipations. Additionally, it raises the possibility that mitigation behaviors might serve a psychological function—such as alleviating guilt and anxiety—rather than being purely pro-environmental actions. Overlapping constructs can inflate connections within a network. While our analyses for potential node redundancy did not reveal significant overlap, future research could benefit from incorporating more detailed subconstructs or employing latent variable approaches alongside networks to better delineate these nuances. For instance, distinguishing between "mitigation behaviors" that are motivated by intrinsic, value-driven reasons and those that arise from social pressure or the desire for anxiety relief may reveal different relationships with climate anxiety. Furthermore, our measure of experience with climate change was self-reported and subjective, capturing individuals' perceived exposure. It could be valuable to measure objective exposure—such as living through a confirmed disaster—to determine if it has different effects.

Finally, it is important to note that our predictability estimates in the GGM indicate that, for most nodes, a significant portion of the variance is explained by other nodes included in the model (Haslbeck & Waldorp, 2017). However, there are still portions of variance that remain unmodeled. This suggests that other factors outside our network model are influencing these variables. Future studies could incorporate variables such as trust in institutions, political ideology, or social support to explore how these factors integrate into the model. For example, trust in government may influence whether anxiety leads to adaptation. If someone trusts authorities to provide assistance, they may be more willing to invest in adaptive strategies and vice versa (e.g., Casiraghi, Curini, & Nai, 2024). Including such factors could enhance the predictability power of the network models.

In conclusion, this study can be viewed as an initial step in mapping the complex relationships between climate change anxiety, cognitive factors like uncertainty tolerance, and behavioral responses. Despite its limitations, it offers a data-driven framework that generates testable hypotheses and identifies key areas for further investigation, such as prospective IU. We encourage future research to expand on these findings by employing longitudinal designs, diverse samples, and potentially experimental manipulations to enhance our understanding of when climate anxiety motivates action versus when it becomes a hindrance. This research is not only scientifically significant but also of practical importance. As humanity faces the uncertain challenges posed by climate change, understanding these psychological dynamics will be crucial for promoting mental well-being and enabling effective adaptation on a global scale.

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

Arrow in the DAG		**Value determining arrow thickness**	
From	**To**	**ΔBIC**	**Directional Probability**
Prospective IU	Inhibitory IU	-282.83	.69
Functional	Cognitive-emotional	-223.35	.65
Mitigation behaviors	Functional	-101.53	.53
Functional	Experience of climate change	-51.04	.58
Prospective IU	Future anticipation	-50.71	.75
Prospective IU	Cognitive-emotional	-32.07	.69
Prospective IU	Adaptation behaviors	-19.17	.80
Experience of climate change	Adaptation behaviors	-7.05	.62
Mitigation behaviors	Experience of climate change	-6.52	.58
Mitigation behaviors	Future anticipation	-6.28	.64
Functional	Future anticipation	-4.86	.68
Functional	Inhibitory IU	-4.40	.57
Future anticipation	Adaptation behaviors	-3.45	.57
Cognitive-emotional	Adaptation behaviors	-2.95	.76
Experience of climate change	Cognitive-emotional	-2.79	.52
Mitigation behaviors	Cognitive-emotional	-2.76	.57

Experience of climate change	Future anticipation	-2.65	.52
Mitigation behaviors	Adaptation behaviors	0.62	.57

Note. ΔBIC = 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). 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 1,000 bootstrapped networks).

FIGURE CAPTIONS

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. Cog_Emo = The maladaptive-emotional component of climate anxiety; Funct = The functional component of climate anxiety; Adapt = Adaptation behaviors; Mitig= Mitigation behaviors; Exp = The experience of climate change; ProsIU = Prospective Intolerance of uncertainty; InhIU = Inhibitory Intolerance of uncertainty; Fut_Ant= Future anticipation.

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

Note. Cog_Emo = The cognitive-emotional component of climate anxiety; Funct = The functional component of climate anxiety; Adapt = Adaptation behaviors; Mitig = Mitigation behaviors; Exp = The experience of climate change; ProsIU = Prospective Intolerance of uncertainty; InhIU = Inhibitory Intolerance of uncertainty; Fut_Ant= Future anticipation.

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

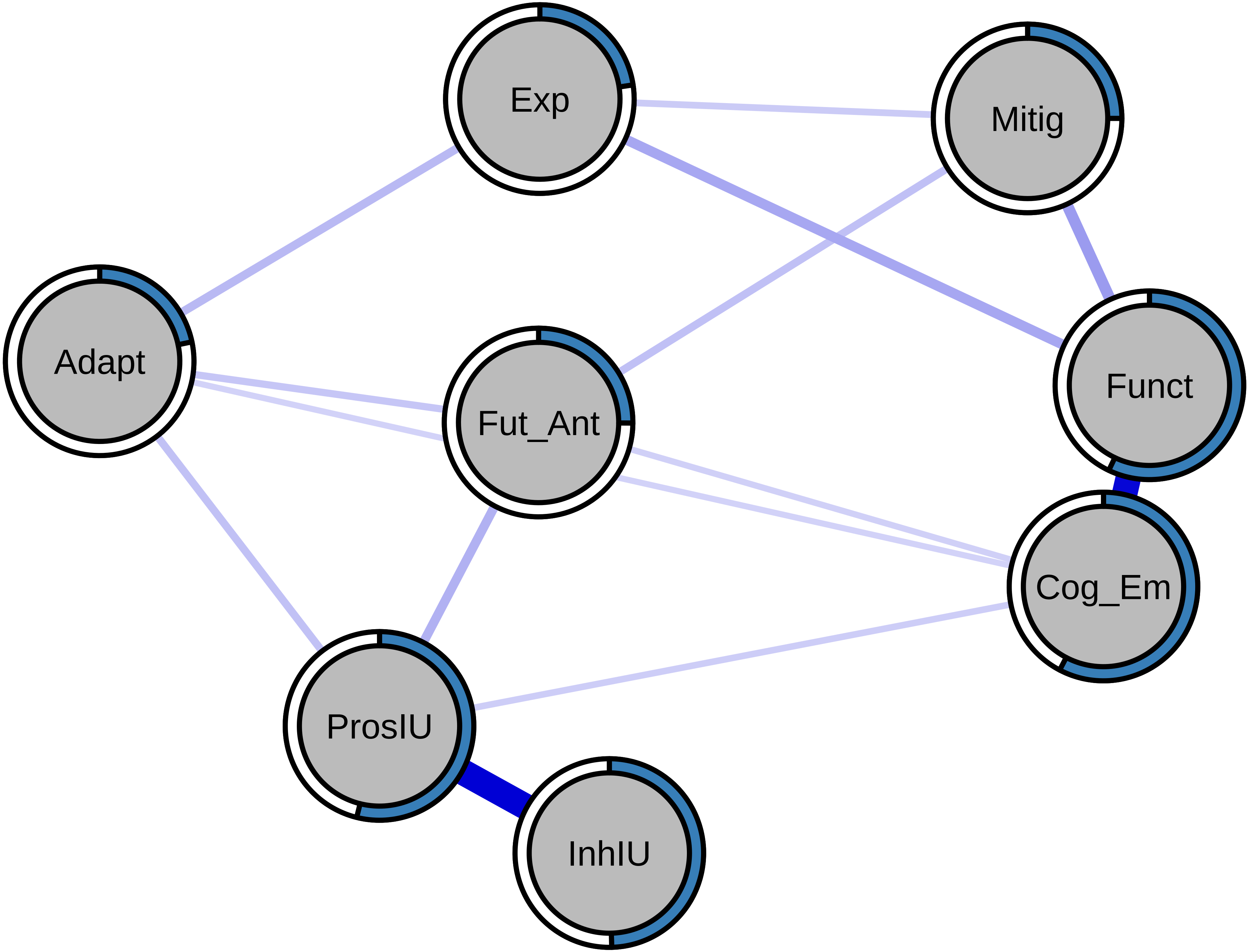
Note. Cog_Emo = The cognitive-emotional component of climate anxiety; Funct = The functional component of climate anxiety; Adapt = Adaptation behaviors; Mitig = Mitigation behaviors; Exp = The experience of climate change; ProsIU = Prospective Intolerance of uncertainty; InhIU = Inhibitory Intolerance of uncertainty; Fut_Ant= Future anticipation.

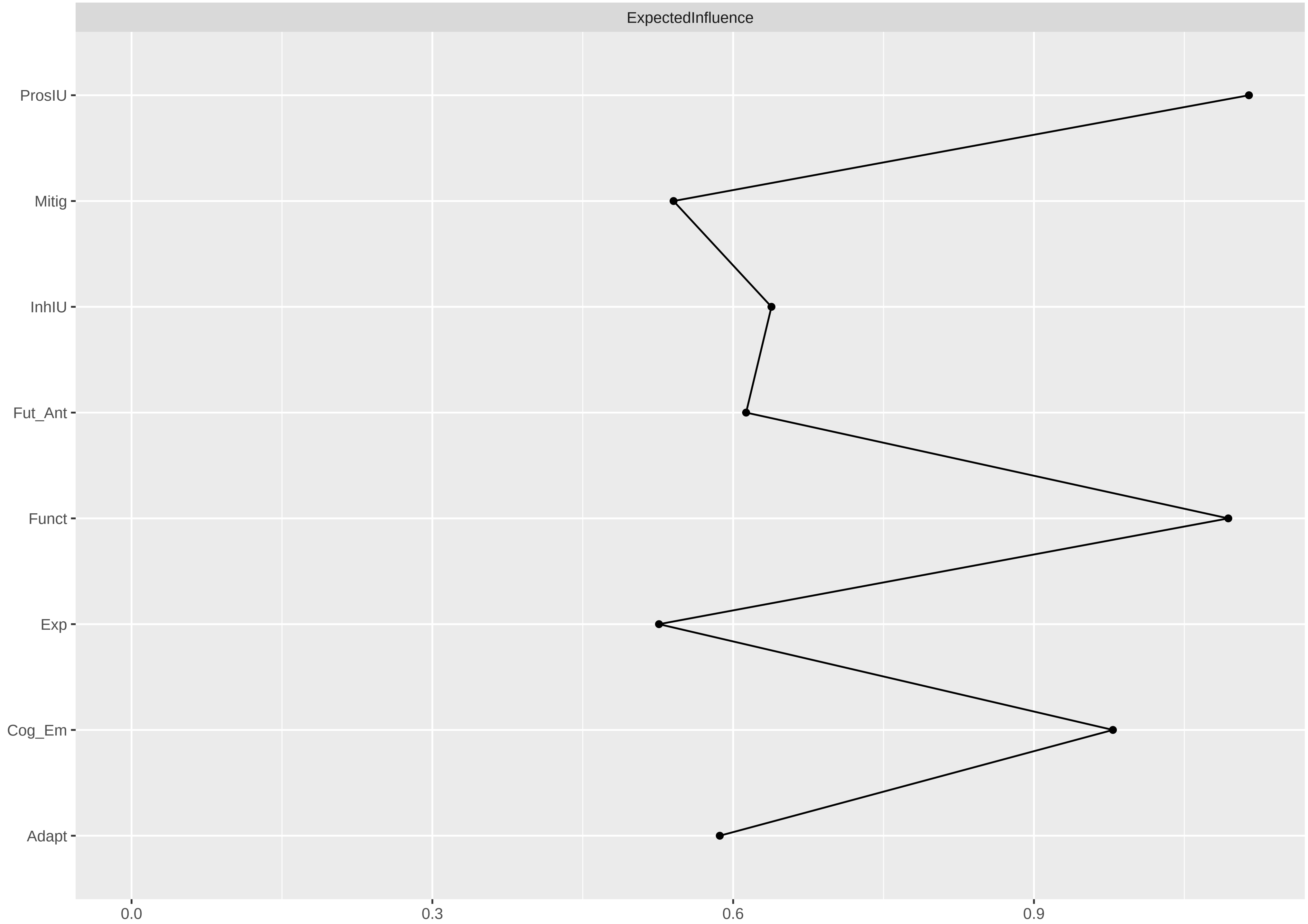
Figure 4. **Directed acyclic graphs (DAGs) With Arrow Thickness Denoting the Importance of that Arrow to the Overall Network Model Fit**

***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). Cog_Emo = The cognitive-emotional component of climate anxiety; Funct = The functional component of climate anxiety; Adapt = Adaptation behaviors; Mitig = Mitigation behaviors; Exp = The experience of climate change; ProsIU = Prospective Intolerance of uncertainty; InhIU = Inhibitory Intolerance of uncertainty; Fut_Ant= Future anticipation.

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. Cog_Emo = The cognitive-emotional component of climate anxiety; Funct = The functional component of climate anxiety; Adapt_beh= Adaptation behaviors; Mitig = Mitigation behaviors; Exp = The experience of climate change; ProsIU = Prospective Intolerance of uncertainty; InhIU = Inhibitory Intolerance of uncertainty; Fut_Ant= Future anticipation.


Exp
Mitig
Adapt
Fut_Ant
Funct
Cog_Em
ProsIU
InhIU


ExpectedInfluence
ProsIU
Mitig
InhIU
Fut_Ant
Funct
Exp
Cog_Em
Adapt
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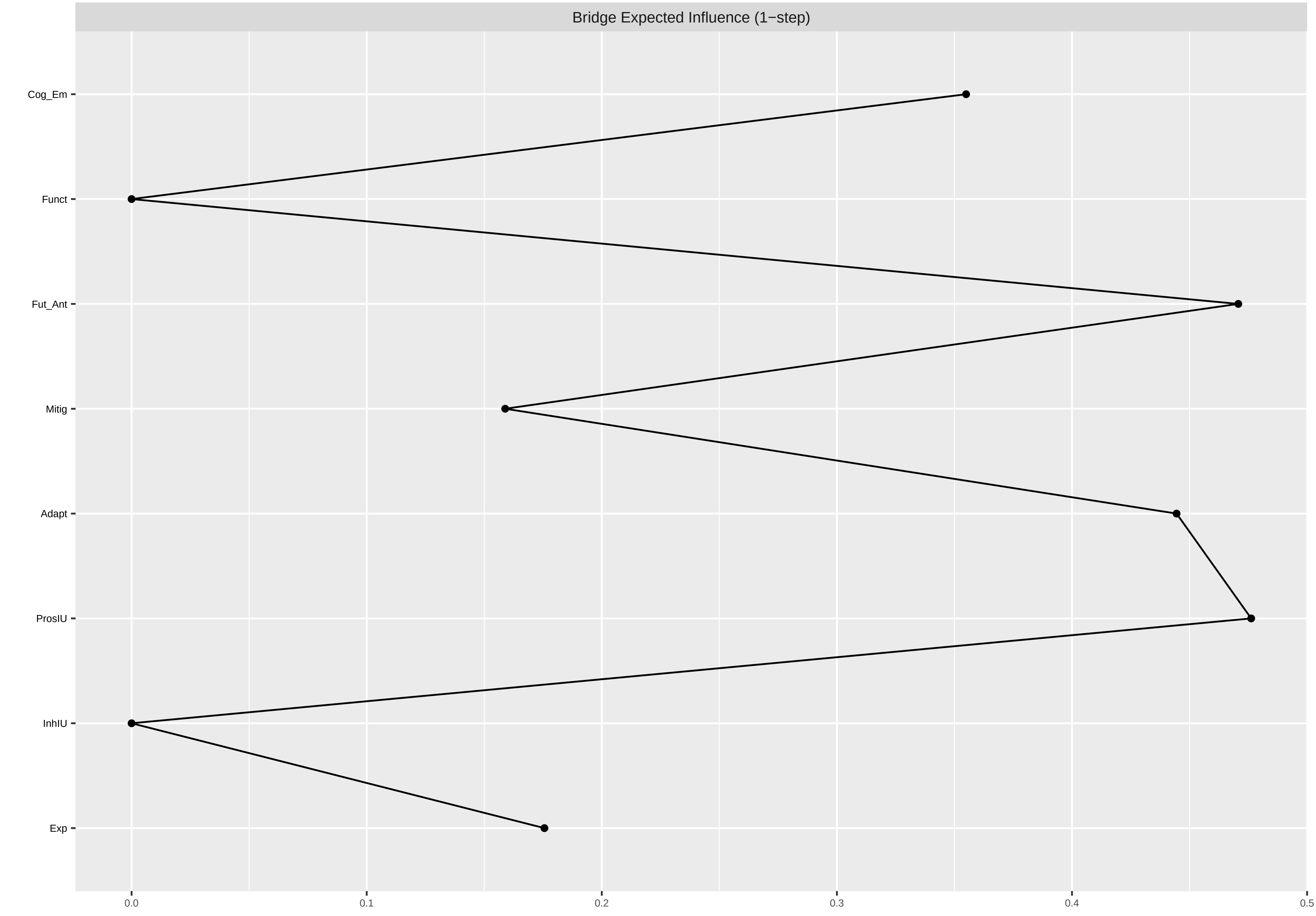
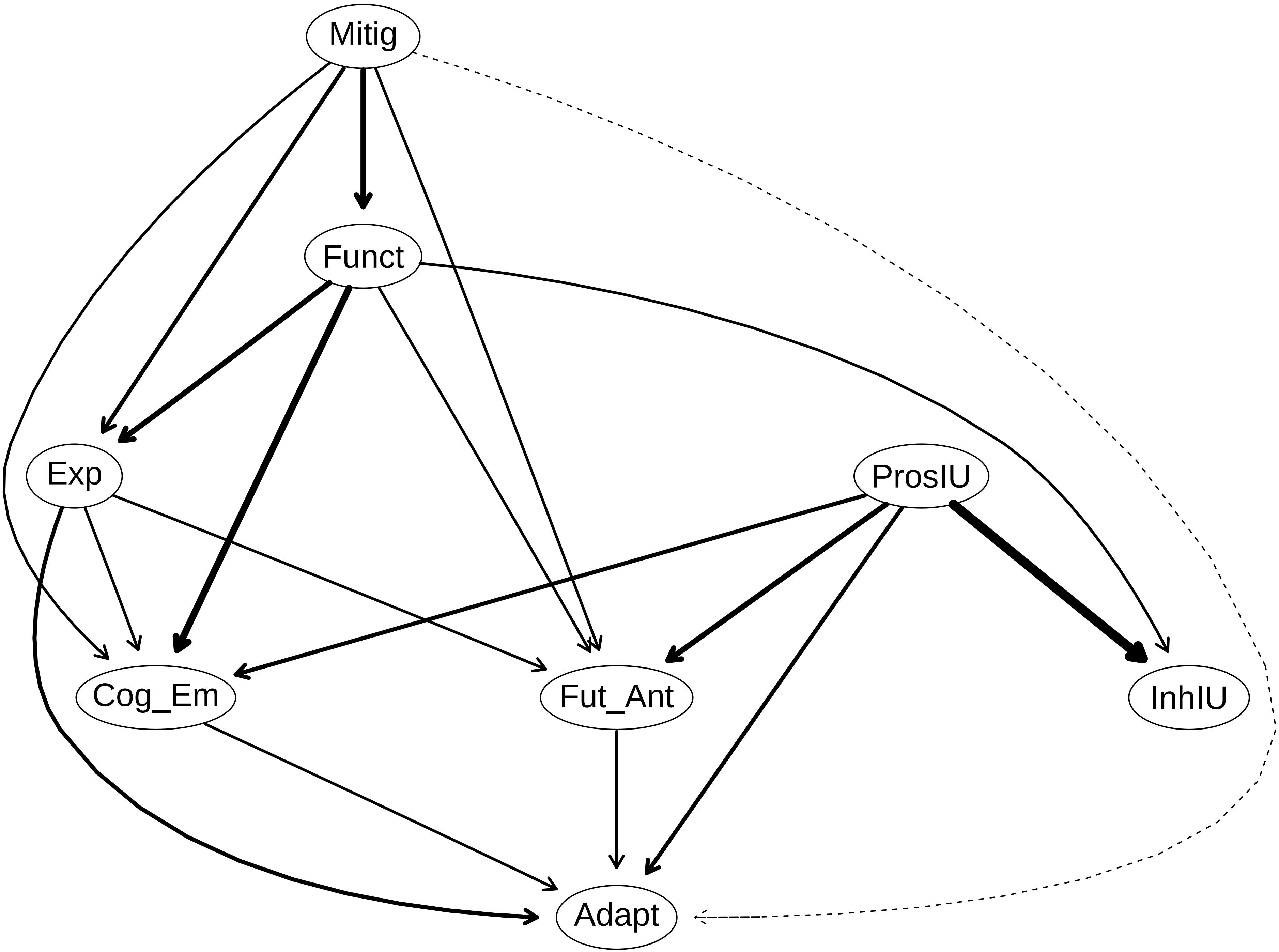
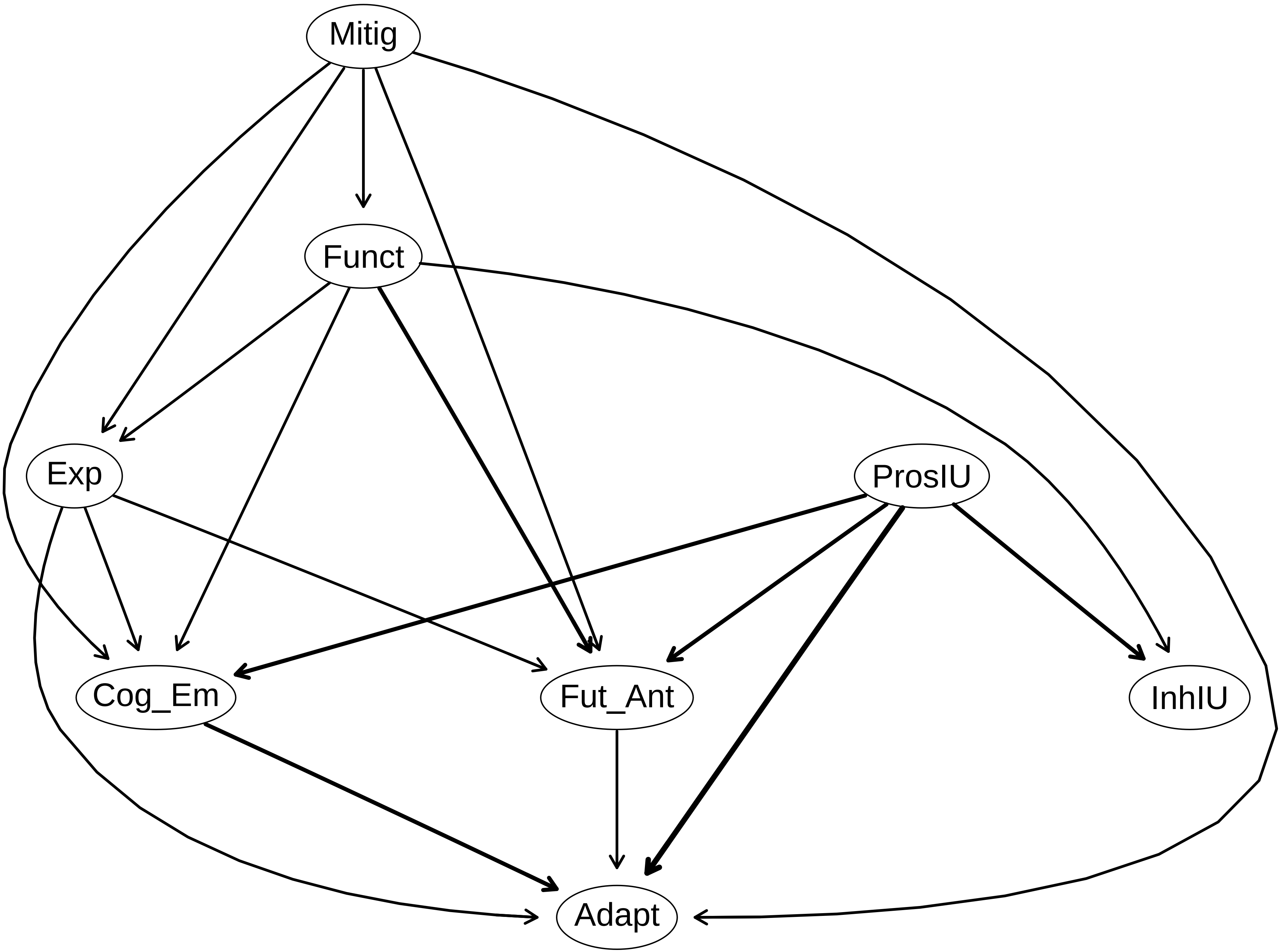
0.3
0.6
0.9


Bridge Expected Influence (1−step)
Cog_Em
Funct
Fut_Ant
Mitig
Adapt
ProsIU
InhIU
Exp
0.0
0.1
0.2
0.3
0.4
0.5


Mitig
Funct
Exp
ProsIU
Cog_Em
Fut_Ant
InhIU
Adapt


Mitig
Funct
Exp
ProsIU
Cog_Em
Fut_Ant
InhIU
Adapt