*Published in : Environment and Behavior (2025), p. 1–29*
*DOI: 10.1177/00139165251356912*
*Status : Postprint (Author's version)*

# UNDERSTANDING THE NATURE OF PRO-ENVIRONMENTAL BEHAVIORS:

# A PSYCHOMETRIC NETWORK ANALYSIS

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**Abstract**
Understanding the factors that drive pro-environmental behaviors (PEB) is critical for both research and practice. While the Theory of Planned Behavior (TPB) provides a robust framework for predicting PEBs, its findings related to PEBs remain incomplete. First, PEB diversity is still overlooked and differentiating their nature and characteristics warrants further investigation. Second, TPB does not fully account for the emotional nature of the ecological transition. This study addresses these two limitations by implementing a psychometric network study among 2,100 participants testing an improved version of the TPB incorporating climate-related emotions and applied to five distinct types of PEBs: conservation, environmental citizenship, food consumption, transportation, and waste management. Our results identified perceived behavioral control as a particularly central variable in our networks. This paper also highlights the importance of considering different types of PEBs and contributes to the development of more effective strategies for fostering sustainable behaviors and facilitating ecological transition

**Keywords**
ecological behavior, emotion, norms, attitudes, proenvironnemental behavior

## Introduction

Dealing with climate change and the 1.5°C global warming objective are among the most pressing global challenges. The 2022 IPCC report emphasizes the long-standing consequences of inaction and identifies governments and individuals as key actors in achieving the necessary mitigation to avoid significant public health impacts (IPCC, 2022). From an individual perspective, household consumption habits, as shown by

Song et al. (2019), contribute approximately 20 tons of carbon dioxide equivalent per person annually, highlighting the importance of individual behavior.

A substantial body of research has sought to understand the factors that drive pro-environmental behaviors (PEBs). Among these, the Theory of Planned Behavior (TPB; Ajzen, 1991) has emerged as a widely adopted framework for examining PEBs. Key variables within the TPB, namely perceived behavioral control (i.e., the perceived ability to perform PEBs; de Leeuw et al., 2015; Jain et al., 2020) and social norms (i.e., the belief that important relatives approve and support PEBs; de Groot et al., 2021; Lucarelli et al., 2020), demonstrate the strongest influence on behavioral intentions, which, in turn, have the strongest effect on PEBs. Some researchers have integrated personal norms (i.e., feelings of moral obligations to engage in PEBs) into the TPB and demonstrated that personal norms also play a substantial role in influencing PEBs (Ateş, 2020; Morren & Grinstein, 2021). A recent scoping review by Yuriev et al. (2020) analyzed 126 recent articles drawing upon the TPB to investigate PEBs. Their review revealed that the average predictive power of the TPB on PEBs was 34.2%, with important variation depending on the specific PEB under study (6%–81% of predictive power). The conclusions of their review were twofold. First, PEBs are not a homogeneous set of actions and encompass a diverse array of behaviors, thus warranting a more detailed investigation to finely capture the boundary conditions of TPB with different types of PEBs. Second, the TPB remains incomplete and requires further expansion to fully understand PEBs, especially regarding emotions (Yuriev et al., 2020).

In the remainder of this introduction, we address both gaps in turn, highlighting a potential missing link in PEBs literature between the diversity of PEBs, and their emotional nature.

## The diversity of PEBs

TPB is a framework generally used to explain precise behaviors. The more specific the behavior is, the more effective the TPB model is in its predictions. Yet, research using TPB to investigate PEBs widely varied on the nature and specificity of PEBs (Yuriev et al., 2020). Clarification is therefore needed on the depiction of PEBs' diversity. We can postulate that the factors composing TPB will not have the same impact on different categories of PEBs. This assumption was also supported by several authors who highlighted that PEBs are not a consistent whole and argued that different variables influence the categories of PEBs (de Leeuw et al., 2015; Lange & Dewitte, 2019; Yuriev et al., 2020).

Some research analyzed specific PEBs such as switching off the computer when unused (Moussaoui et al., 2020) or choosing non-plastic rather than plastic materials when buying new products (Kovacs et al., 2020). Yet, the high behavioral specificity of their results hinders the generalizability of their findings and compromises practical implications for policy-makers. Several studies therefore support an intermediate level of specificity by identifying categories of PEBS (Lange & Dewitte, 2019; Larson et al., 2015; Stern, 2000; Yuriev et al., 2020). Those categories of PEBs are specific enough to precisely understand their predictive factors and global enough for policy-makers to identify global and relevant actions to support their change in the population.

Many instruments measuring PEBs have been developed in the literature. In the present study, we rely upon the work of Markle (2013), who conducted a systematic review of the existing scales and validated an updated PEB scale. In his work, he distinguished four dimensions of PEBs: Conservation, Environmental Citizenship, Food, and Transportation. **Conservation** refers to behaviors that mainly aim at reducing electricity (e.g., turning off the lights and the TV), water (time in the shower), and fuel consumption (e.g.,

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cooling and heating habits) of the household. **Food consumption** gathers the behaviors that reduce meat consumption (beef, pork, and chicken) and relates to buying organic or local fruits and vegetables. **Transportation** refers to behaviors such as carpooling, using public transportation, or cycling instead of driving. **Environmental citizenship** encompasses behaviors such as membership in an environmental, conservation, or wildlife organization, donating money to such an organization, signing petitions to protect the environment, striking for climate, or supporting politicians who support environmental issues. This last dimension refers to the collective and political nature of PEBs. The distinction of this category of PEBs is supported by several authors (Ogunbode et al., 2022; Oinonen & Paloniemi, 2023; Stanley et al., 2021). The scoping review of Yuriev et al. (2020), based upon 126 papers on PEBs, confirmed the distinction of two of the abovementioned dimensions. The first dimension identified in the literature is traveling and commuting (private vehicles, public transportation, carpooling, bicycles, etc.), which is conceptually close to transportation. The second dimension is energy saving (turning off taps, toilet flushing, etc.), which taps into Markle's (2013) notion of Conservation. Yet another dimension was depicted: waste management (e-waste, food waste, etc.; Yuriev et al., 2020). This dimension relates to reducing trash production, repairing instead of throwing away, buying sustainable products, recycling materials, and buying recycled packaging. Subsequent research supports the importance of adding a **Waste management** dimension to PEBs (Larson et al., 2015; Menardo et al., 2020). It globally taps the three R's, "Reduce, Reuse, Recycle" paradigm for waste management by consumers (Steinhorst & Beyerl, 2021).

Despite the acknowledgment of the heterogeneity of PEB types in the extant literature, these behaviors are predominantly analyzed as a monolithic construct in their nomological network. Research thus overlooked the nuanced differences that may arise when considering specific behaviors individually (de Leeuw et al., 2015; Lange & Dewitte, 2019; Yuriev et al., 2020). Such an approach is incongruent with the tenets of the TPB, which emphasizes the need to examine the interplay of attitudes, norms, and control in shaping distinct behaviors (Ajzen, 1991). In the context of climate change, behavioral predictors may diverge substantially: While economic considerations and habitual patterns might heavily influence transportation-related behaviors, sensory preferences (e.g., attitudes) may predominantly guide food consumption choices, established routines, and health-related beliefs and norms. From our perspective, it is critical to disentangle types of PEBs to better scrutinize the varying contributions and predictive power of each TPB component. Adopting such a nuanced lens not only adheres more closely to the theoretical framework of TPB but also contributes significantly to a better understanding of the drivers of types of PEBs, thereby offering important avenues for targeted and effective interventions.

## Emotional nature of PEBs

While decision-making was initially seen as a cognitive process in which people evaluate the potential fallout of their choices and opt for the course of action that will maximize the utility of the consequences, it is now recognized that emotions play an important role in decision-making and behavior (Lerner et al., 2015; Parmentier, 2021). Today, emotions are increasingly integrated into decision-making theories and increasingly studied for their effect on behavior (Poels & Dewitte, 2019; Xu & Guo, 2019). The direct and indirect impact of emotions was also demonstrated on environmental behavior (Carmi et al., 2015). However, rather isolated lines of research addresses the role of emotion in this context and several questions remain unanswered.

Most studies investigating the role of emotion in the TPB have dominantly focused on *anticipated* emotions, that is, the emotions that individuals expect or anticipate following the performance of a certain behavior (Yuriev et al., 2020). Research supports that negative anticipated emotions, such as anticipated guilt, could be a positive lever for action (Adams et al., 2020), whereas others found negative effects, and supported the necessity to promote positive anticipated emotions (Schneider et al., 2017). Positive anticipated emotion could positively affect behavioral intention through the "warm glow" effect: people would initiate PEBs because acting sustainably would result in positive emotional experiences that reward their behavior (Brosch, 2021; Jia & van der Linden, 2020). The experimental research of Hurst and Sintov (2022) supported that anticipated guilt would globally motivate PEBs whereas pride would depend on the type of PEBs in which the emotion was evoked.

Another line of research has investigated how current emotions influence individuals' reactions and actions toward climate change. From a cognitive appraisal perspective (Ortony, 2022), the current emotions experienced at the prospect of future events and their consequences are referred to as anticipatory emotions (Baumgartner et al., 2008). Qualitative and quantitative research mainly demonstrated that negative emotions such as anxiety (Ogunbode et al., 2022), anger, and shock (Bieniek-Tobasco et al., 2019) would have a positive role on PEBs. Positive emotions such as optimism would also have a positive link with PEBs (Bieniek-Tobasco et al., 2019). Subsequent studies have corroborated several of these results through structural modeling (Stanley et al., 2021). Yet, Heeren et al. (2022) questioned the positive impact of negative emotions and showed that too severe experience of those emotions could impede PEBs.

However, even though substantial research has now confirmed the importance of anticipatory and anticipated emotions related to climate change, the present study addresses two of the main limitations regarding future-oriented emotions. First, few studies have incorporated both anticipatory and anticipated aspects simultaneously. Previous research shows that even though anticipated emotions have higher predictive power than anticipatory emotions (Xu & Guo, 2019), both aspects have been shown to relate to behavioral outcomes (Baumgartner et al., 2008). This limitation also pertains to existing research, which focused predominantly on anticipated emotions, overlooking the potential behavioral impact of anticipatory emotions (Rivis et al., 2009). We addressed these limitations in the present study with the objective of answering several critical questions regarding the behavioral impact of emotions: what is the combined role of anticipatory and anticipated emotions on different types of PEBs? What is the added value of emotions in TPB? What are the interactions between emotions and TPBs components?

## Aim of the study

Our study adopts an approach that recognizes the multifaceted nature of PEBs, advocating for a detailed examination of their various types. This approach is consistent with the limitations of the current literature highlighted above regarding the complexity of PEBs. Additionally, we propose an expansion of the TPB to integrate the emotional dimensions of climate change. Therefore, our research focuses on testing the validity of an enhanced TPB model across five dimensions of PEBs, contributing to a more detailed and nuanced picture of PEBs and their predictors.

To explore the multifaceted dimensions of PEBs and the distinct influences of TPB components, two complementary methods were used. First, to capture those dimensions, we used experimental vignettes (Aguinis & Bradley, 2014). Experimental vignettes are brief, hypothetical scenarios, or specific descriptions of situations, designed to elicit responses from participants that are specific to the manipulated factors (i.e., types of PEBs), and reflect distinct reactions and decision-making processes. This methodological approach is particularly aligned with our objectives as it allows for a nuanced exploration of PEBs within controlled yet realistic scenarios. By presenting participants with these structured and behavior-specific vignettes, we can more accurately study the influence of their attitudes and perceptions toward specific types of PEBs, instead of addressing these in a general, unspecified approach.

Second, we analyzed our experimental vignettes data using a psychometric network approach to elucidate the complex interactions within the TPB components. Distinct from traditional psychometric methods that often posit latent variables as the source of observable psychological phenomena, psychometric network models (Borsboom & Cramer, 2013) conceptualize psychological attributes as a system of directly interacting elements. In these models, the focus shifts to understanding how distinct components of the theory are interrelated, offering a more dynamic and interconnected view of the phenomena than in traditional path analyses. More specifically, the network perspective used in the present study allows for the exploration of how specific elements of the TPB framework—attitudes, norms, perceived control, and emotions—interact and influence each other across different types of PEBs. By using this approach, we aim to provide a nuanced map of the TPB components, highlighting pivotal interconnections and dependencies that could inform more effective and tailored interventions and strategies in promoting PEBs. We can postulate that:

- Perceived control and social norms will remain main predictors of behavioral intentions in the different PEB vignettes (de Groot et al., 2021; Jain et al., 2020; Lucarelli et al., 2020).
- Emotions are expected to be an important added value to TPB by showing a central role for the network (Brosch, 2021; Yuriev et al., 2020).
- The predictive power of TPB on the five specific dimensions of PEBs, will be greater than the average 34.2% assessed by Yuriev et al. (2020) on an aggregated measure of PEBs.

Such an approach brings the three interrelated contributions to the literature: (1) Raise the affective tone of climate change and its influence on behavior (contribution to climate change literature but also emotion literature). (2) Better understand the boundary conditions of TPB and the conditions under which it operates. (3) Shed light on the complexities of types of PEBs, both in terms of their diversity and the predicting factors.

# Method

## Participants

Data were collected through an online questionnaire, resulting in a sample of 2,100 participants (1,492 women) aged between 18 and 99 years (*M* = 39.74, *SD* = 13.86). The study was approved by the ethics committee of the Institute for Research in Psychological Sciences (IPSY) of Louvain-la-Neuve (UCLouvain, Belgium). Each participant gave informed consent before completing the survey.

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DOI: 10.1177/00139165251356912
Status : Postprint (Author's version)

## Material and procedure

Participants were assigned to experimental vignettes that manipulated the type of PEBs. Building upon the work of Markle (2013), Larson et al. (2015), and de Leeuw et al. (2015), the study consisted of five vignettes: (1) **Conservation** (how often individuals reduce their heating, cooling, hot water, and lighting consumption), (2) **Environmental citizenship** (membership of an environmental, conservation, or wildlife organization and how often they talk to others about their environmental behavior), (3) **Food consumption** (decreased consumption of beef, pork, and poultry in the past year), (4) **Transportation** (use of carpooling, public transport, walking or cycling instead of driving in the past year), and (5) **Waste management** (use recycled and recyclable products, reduce consumption, be more self-sufficient, sort, recycle, repair, etc.). The experimental conditions, therefore, correspond to a certain type of behavior (for more details, see the Supplemental Material). Prior to undertaking the subsequent analyses, we conducted chi-square tests to ensure that the demographic characteristics of the participants in each vignette were sufficiently similar. These characteristics included age, gender, education level, marital status, professional status, and political affiliation. The results of these initial analyses revealed no significant differences between the five groups (for more details, see the HTML report titled "Descriptives" in the OSF repository—https://osf.io/234fx/).

The questionnaire consisted of a total of 67 items and the questions did not differ between the experimental conditions. Unless stated otherwise, items were scored from 1 = Strongly disagree to 5 = Strongly agree. A detailed depiction of the scales used can be found in the Supplemental Material. Table 1 provides an overview of each scale, including the number of items, means, standard deviation, reliability coefficients, and examples of items.

## Data analysis

All statistical analyses were performed in R (version 4.1.2; R Core Team, 2021). The full R code and data can be found on OSF (https://osf.io/234fx/). More details on the procedures outlined below can be found in the Supplemental Material.

*Data Preparation.* In order to ensure the reliability of our measures in all vignettes and given the sensitivity of network models to measurement errors (de Ron et al., 2022), we conducted confirmatory factor analyses using Full Information Maximum Likelihood (FIML) estimation with robust estimation (MLR), from the R package "Lavaan." The confirmatory factor analysis models for the five vignettes showed adequate fit to the data (RMSEA ≤ 0.05; CFI ≥ 0.90; TLI ≥ 0.89; SRMR ≤ 0.06). Factor scores were saved from these models to be used in subsequent analyses. While factor scores do not fully control for measurement errors as in latent variable modeling, they offer a 9 partial control for measurement errors by weighing more items with lower measurement errors (Skrondal & Laake, 2001). Second, we ensured that the dataset did not contain redundant variables, following the procedure described in Heeren et al. (2021) on the set of scores calculated in the previous step. The analysis did not detect any redundant variables. Third, we checked that the variables did not violate the normality assumption according to thresholds of skewness between −2 and +2 and kurtosis between −7 and +7 (Curran et al., 1996). Since the indices did not detect a normality problem, we performed our analyses on the raw data (see Table 1).

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**Table 1.** Descriptive Statistics and Reliability Coefficients.

| No. | Variable | Mean | SD | No. of items | Cronbach's $\alpha$ | McDonald's $\omega$ | Skewness | Kurtosis | Example of item |
|---|---|---|---|---|---|---|---|---|---|
| 1. | Behavioral intention | 3.50 | 0.80 | 4 | .75 | 0.83 | −0.57 | 0.15 | In the next few weeks, I am willing to implement the above behaviors. |
| 2. | Attitudes | 3.44 | 0.80 | 4 | .67 | 0.68 | −0.13 | −0.17 | Adopting the above type of behavior would be mostly beneficial to me. |
| 3. | Perceived behavioral control | 3.75 | 0.75 | 4 | .72 | 0.74 | −0.5 | 0.29 | I am confident in my ability to implement the behaviors listed above. |
| 4. | Social norms | 3.06 | 0.94 | 4 | .92 | 0.92 | −0.37 | −0.35 | Most of the people around me implement the above behaviors. |
| 5. | Personal norms | 3.09 | 0.82 | 4 | .88 | 0.88 | −0.84 | 1.13 | It is important to me to implement the above behaviors. |
| 6. | Positive anticipatory emotions | 2.40 | 0.80 | 3 | .81 | 0.81 | 0.26 | 0.03 | How do you feel in the here and now, that is, in the present moment, about the prospect of climate change and its consequences? ("Optimistic," "Confident" and "Hopeful") |
| 7. | Negative anticipatory emotions | 2.97 | 0.91 | 3 | .82 | 0.84 | −0.03 | −0.34 | How do you feel in the here and now, that is, in the present moment, about the prospect of climate change and its consequences? ("Worried," "Anxious" and "Nervous") |
| 8. | Positive anticipated emotions | 3.24 | 0.85 | 8 | .93 | 0.93 | −0.42 | 0.32 | If you implement the above behaviors in the next few weeks, how much you think you will feel: "Satisfied," "Happy," "Proud." |
| 9. | Negative anticipated emotions | 2.77 | 1.07 | 9 | .95 | 0.95 | 0.11 | −0.62 | If you implement the above behaviors in the next few weeks, how much you think you will feel: "Disappointed," "Upset," "Guilty." |

***Unregularized Gaussian Graphical Network*** Following the recent recommendations of Williams and Rast (2020). We used an Unregularized Gaussian Graphical model to estimate network structures. We implemented this procedure with the ggmModSelect method of the R package *qgraph* (Epskamp et al., 2012). We estimated the stability of the edges using a nonparametric bootstrapping of 1,000 iterations with a 95% confidence interval using the R package *bootnet*. Then, in order to detect which nodes appear to be the most influential, we performed a centrality analysis for each variable of each network using Expected Influence indices (Robinaugh et al., 2016). To be able to interpret the differences between the centrality indices of the variables, we checked their stability by using a case-dropping subset bootstrap of 1,000 iterations, using the R package *bootnet*, and performed a bootstrapped difference test to see which nodes differ significantly from each other.

In addition, we estimated the predictability of each node) using the R package *mgm* (J. Haslbeck, 2016). This measure informs about (1) how much a given node can be predicted by all other nodes in the network and (2) whether the network is primarily self-determined (strong mutual interactions between nodes) or whether it is primarily determined by separate factors, not found in the network (J. M. B. Haslbeck & Fried, 2017). Finally, to visualize the networks, we used Fruchterman and Reingold's (1991) algorithm; the nodes with the highest centrality are drawn in the center of the network, and the number of intersecting edges is minimized. Here, the nodes embody our nine predictors, and the edges between them represent partial correlations.

*Directed Acyclic Graph (DAG).* In order to obtain information about the likely direction of relationships within our model, we used a Bayesian hill-climbing algorithm, implemented through the R package *bnlearn*. Before starting the analysis, we decided to prevent certain directions. Indeed, according to the literature, behavioral intention can be considered as the most proximal determinant of behavior (Ajzen, 1991). In this sense, it should not be the cause of any other variable included in the model. Also, in view of the conceptualization of social norms, we deemed it more realistic to exclude them as consequences of any other variable included in the model. Indeed, the literature already highlighted that social norms were stable constructs that are difficult to influence by individuals' own perceptions (Abric, 1994). The indication of unlikely directions to the algorithm, regarding the nature of the variables or the existing evidence, improves the model's precision (Epskamp, 2021). For visualization, we produced a graph of the results in which the thickness of the directed edges represents the change in BIC values when that arrow is removed from the network; the thicker the arrow, the more it contributes to the structure of the model (McNally et al., 2017).

*Network Comparison.* We compared the five networks created according to the type of behavior, with the global network, which does not make this distinction. To determine which edges were statistically different between networks, we first performed the Fisher *z*-transformation. This allowed us to transform the Pearson *r*-correlation coefficients of each edge into *z*-scores. We then performed a two-tailed *Z*-test to determine the *p*-value of the difference. We also performed a "Network Comparison Test" to compare the results obtained with the two methods. This test was done for replication purposes specifically, given the required sample size for this type of analysis.

# Results

Descriptive information (means, standard deviations, Skewness and Kurtosis indices) is available in Table 1. The results of all our analyses are available in our Supplemental Material and in our interactive HTML reports on OSF (https://osf.io/234fx/).

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*DOI: 10.1177/00139165251356912*
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## Global analyses of the network

Figure 1 shows the Unregularized Gaussian Graphical Network estimated based on the entire dataset, regardless of the type of behavior. Several associations stood out: "Personal Norms" and "behavioral Intention" (*r* = .41), "Positive Anticipatory Emotions" and "Negative Anticipatory Emotions" (*r* = −.61), "Attitudes" and "Perceived Behavioral Control" (*r* = .64), and finally "Negative Anticipatory Emotions" and "Negative Anticipated Emotions" (*r* = .40; for the correlation matrix, see Supplemental Figure S1(a)). We checked the accuracy of the estimated correlations (see Supplemental Figure S1(b)), and the bootstrapped difference test indicated that these correlations were significantly higher than most other correlations (see Supplemental Figure S1(c)).

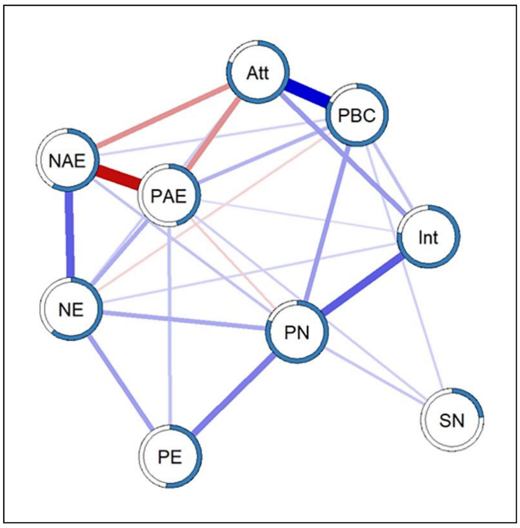


**Figure 1.** Unregularized Gaussian Graphical network on all behaviors.
*Note.* The thickness of an edge reflects the strength of the association (the thickest edge represents a value of 0.68, the thinnest edge a value of 0.11). The color of the edges represents the sign of the association; red for negative correlations and blue for positive correlations. The blue rings around the nodes indicate the proportion of variance explained in that node by all other nodes. Int = behavorial intention; Att = attitude; PBC = perceived behavioral control; SN = social norm; PN = personal norm; PAE = positive anticipatory emotions; NAE = negative anticipatory emotions; PE = positive anticipated emotions; NE = negative anticipated emotions.

Within this network, behavioral intention was significantly correlated with five variables: personal norms (*r* = .41), attitudes (*r* = .25), perceived behavioral control (*r* = .15), negative anticipated emotions (*r* = .10), and positive anticipatory emotions (*r* = .08). In terms of predictability, the average predictability of all nodes is 0.62, indicating that on average 62% of the variance of a node is explained by neighboring nodes. Social norm is the variable with the lowest predictability estimate in the network (24%). Conversely, perceived behavioral control (82%), personal norms (81%), attitudes (80%), and behavioral intention (77%) are the variables with the highest remaining predictability estimates in the network.

Figure 2 shows the Expected Influence estimates; the larger the Expected Influence value, the more central the variable (i.e., the stronger its associations with other variables). Centrality analysis provides precise information about the nodes that are essential to maintain the coherence of the network. In our network, the variables with the highest centrality values are personal

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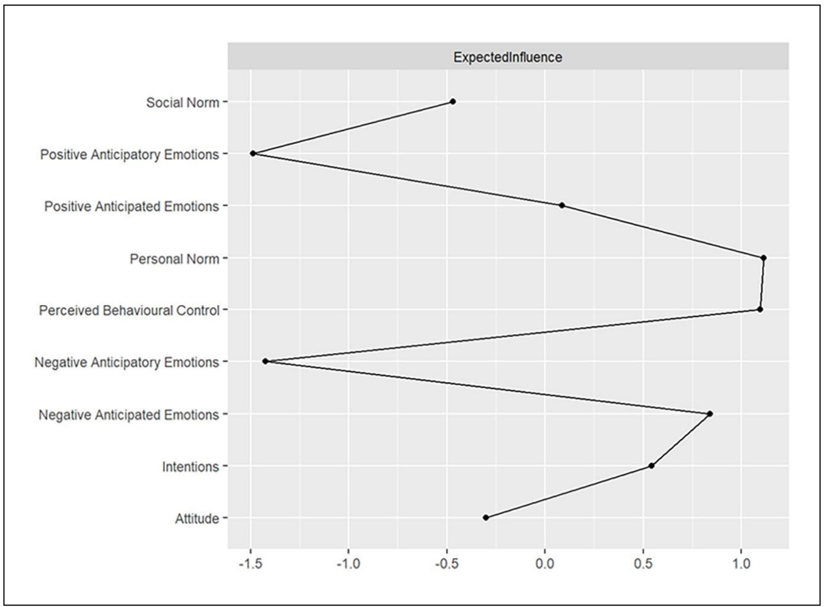


**Figure 2.** *Z*-scores of Expected Influence estimates of network variables on all behaviors.

norms and perceived behavioral control. The bootstrapped difference test indicated that these variables were significantly more central than the others (see Supplemental Figure S1(d)). Conversely, positive anticipatory emotions and negative anticipatory emotions were the variables with the lowest indices of network centrality. The bootstrap case-dropping results revealed that this centrality index appeared very stable (see Supplemental Figure S1(e)).

Figure 3 shows the directed acyclic graph (DAG). Arrows were retained in the model when their strength was found to be higher than the optimal cut-off point, consistent with Scutari and Nagarajan's (2013) procedure. The most important arrows in the network structure were "Perceived Behavioral Control" and "Personal Norm" (Δ BIC = –784.52), "Perceived Behavioral Control" and "Attitude" (Δ BIC = –774.42), "Personal Norm" and "Negative anticipated Emotions" (Δ BIC = –714.36) and "Positive Anticipatory Emotions" and "Negative Anticipatory Emotions" (Δ BIC = –511.95). The change in the BIC value and the directional probability for each arrow is shown in Supplemental Table S1. The organization within a DAG can be seen as the product of the conditional distribution of each node given its parent nodes (McNally, 2021); here, social norms and perceived behavioral control appeared to be the parent nodes of the network. Note also that negative anticipatory emotions, positive anticipated emotions and behavioral intentions appeared at the bottom of this probabilistic cascade; this means that these three variables can be thought of as probabilistically resulting from the other nodes of the model (Heeren et al., 2021). Finally, it appeared that the model that best explained the data was one in which negative anticipatory emotions and positive anticipated emotions had no influence on behavioral intentions.

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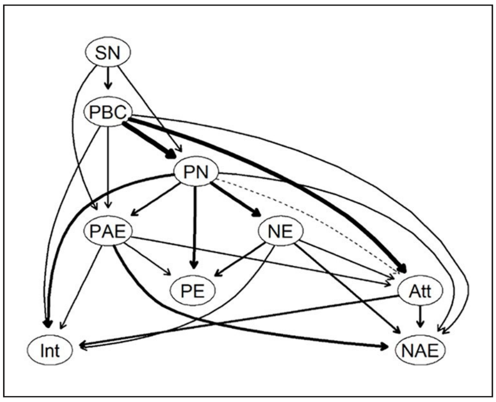


**Figure 3.** Direct acyclic graph on all behaviors.*Note.* The thickness of the edge represents the magnitude of the BIC value; the thicker an edge, the more detrimental it would be to the fit of the model to remove that edge from the network. Int = behavioral intention; Att = attitude; PBC = perceived behavioral control; SN = social norm; PN = personal norm; PAE = positive anticipatory emotions; NAE = negative anticipatory emotions; PE = positive anticipated emotions; NE = negative anticipated emotions.

## Comparisons between networks

Table 2 shows the partial correlations between each of the variables in the model and behavioral intentions, estimated in the Unregularized Gaussian Graphical network. To assess whether the differences between the partial correlations were significant, we performed a comparison z-test and a network comparison test; we compare each Unregularized Gaussian Graphical network created for each type of PEB with the Unregularized Gaussian Graphical network on all behaviors. The significance level was corrected for multiple comparisons using the Bonferroni method. The full results of these tests can be found in Supplemental Figure S2. Unregularized Gaussian Graphical networks (Supplemental Figure S3), their correlation matrices (Supplemental Figure S4) and centrality indices (Supplemental Figure S5) can also be found in the Supplemental Material.

**Table 2.** Table of Variables With a Significant Partial Correlation With Behavioral Intentions, Within the Different Unregularized Graphical Gaussian Networks.

| Type of PEB | Att | PN | SN | PBC | PAE | NAE | PE | NE |
|---|---|---|---|---|---|---|---|---|
| Conservation | 0.15 | 0.3 | 0 | 0.11 | 0 | 0 | 0 | 0 |
| Food consumption | 0.28 | 0.51 | 0 | −0.11 | 0.11 | 0 | 0 | 0 |
| Waste management | 0.21 | 0.49 | 0 | 0.2 | 0 | 0 | 0 | 0.13 |
| Environmental citizenship | 0.38 | 0.68 | 0.18* | 0 | 0.21 | 0 | −0.23 | 0 |
| Transportation | 0.2 | 0.16 | 0 | 0.13 | 0 | 0 | 0 | 0.1 |
| All behaviors | 0.25 | 0.41 | 0 | 0.15 | 0.08 | 0 | 0 | 0.1 |

*Note.* The numbers in bold represent a significantly different correlation (with both methods) from the correlation between the same pairs of variables, within the network for all proenvironmental behaviors (α = .05). Int = behavioral intention; Att = attitude; PBC = perceived behavioral control; SN = social norm; PN = personal norm; PAE = positive anticipatory emotions; NAE = negative anticipatory emotions; PE = positive anticipated emotions; NE = negative anticipated emotions.
*A significantly different correlation (with *z*-test only) from the correlation between the same pairs of variables, within the network for all pro-environmental behaviors (α = .05).

Our results suggest that a positive attitude was generally associated with higher intentions in all the PEB dimensions under study (Pearson's $r$ between .15 and .38) and that a higher level of personal norms was strongly associated with higher intentions in most dimensions of PEBs (Pearson $r$ between .16 and .68). Unlike other types of PEBs, in environmental citizenship, social norms ($r$ = .18) and anticipated positive emotions ($r$ = −.23) were directly linked to intentions. This means that for environmental citizenship

*Published in : Environment and Behavior (2025), p. 1–29*
*DOI: 10.1177/00139165251356912*
*Status : Postprint (Author's version)*

behaviors, a higher level of social norms generates more behavioral intentions and conversely, a higher level of positive anticipated emotions generates fewer behavioral intentions. Bayesian analyses (DAG) confirmed these relationships (see Figure 4). Furthermore, in all the networks, with the exception of food consumption, personal norms and attitudes were probabilistically dependent on perceived behavioral control; the more individuals feel capable of implementing PEBs, the more they have favorable attitudes to adopting these behaviors and the more important they find this (Pearson r between .15 and .68). In addition, the relationships it had with these variables appeared to be important for the structure of the different networks (see Figure 4).

Table 3 provides a summary of the most central variables in each Unregularized Gaussian Graphical network. In general, the most central variables in all the networks were personal norms and perceived behavioral control. Additionally, negative anticipated emotions were identified as a central construct in three networks: conservation, environmental citizenship, and transportation.

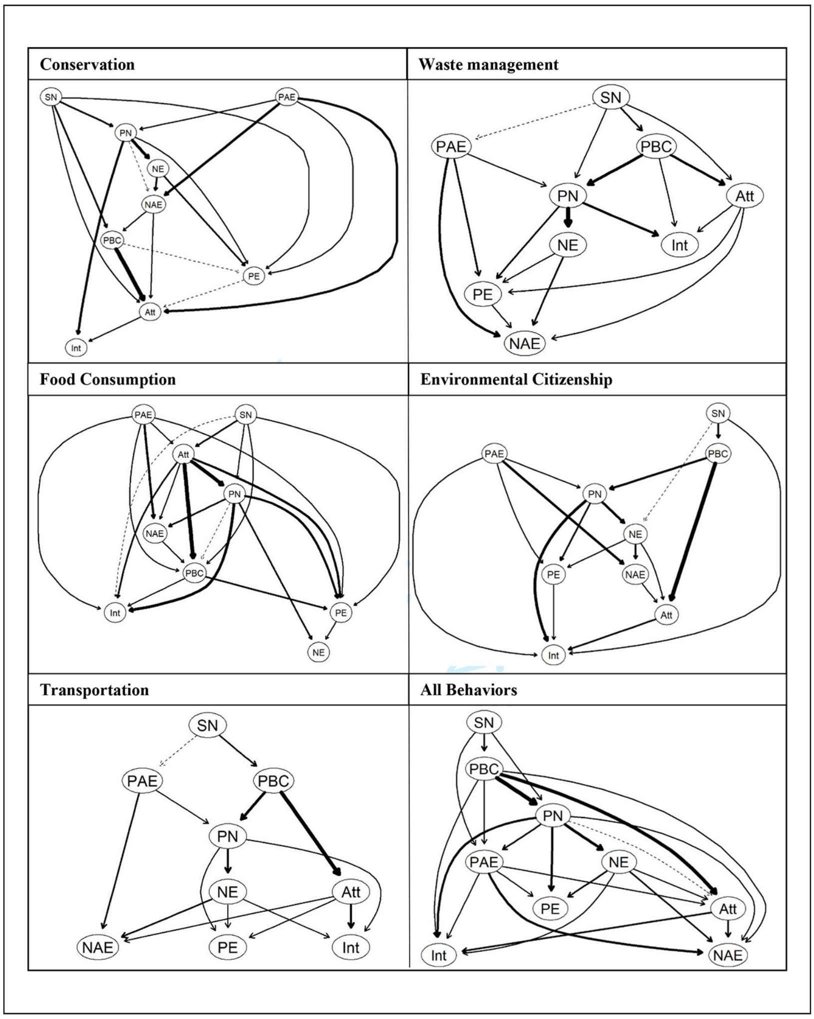


**Figure 4.** Directed Acyclic Graphs by type of pro-environmental behavior.
*Note.* The thickness of the edge represents the magnitude of the BIC value; the thicker an edge, the more detrimental it would be to the fit of the model to remove that edge from the network. The dotted arrows symbolize weaker relationships or conditional dependencies that are not as dominant. Int = behavioral intention; Att = attitude; PBC = perceived behavioral control; SN = social norm; PN = personal norm; PAE = positive anticipatory emotions; NAE = negative anticipatory emotions; PE = positive anticipated emotions; NE = negative anticipated emotions.

**Table 3.** Table of the Most Central Variables Within the Different Unregularized Graphical Gaussian Networks.

| | Most central nodes (unregularized Gaussian network) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Type of PEB | Att | PN | SN | PBC | PAE | NAE | PE | NE | Int |
| Conservation | | x | | x | | | | x | |
| Food consumption | | x | | x | | | | | |
| Waste management | | x | | | | | | | |
| Environmental citizenship | | x | | x | | | | x | x |
| Transportation | | | | x | | | | x | |
| All behaviors | | x | | x | | | | | |

*Note.* Centrality analysis provides information about the nodes that are essential to maintain the coherence of the network. The more central the variable, the stronger its associations with other variables. Int = behavioral intention; Att = attitude; PBC = perceived behavioral control; SN = social norm; PN = personal norm; PAE = positive anticipatory emotions; NAE = negative anticipatory emotions; PE = positive anticipated emotions; NE = negative anticipated emotions.

# Discussion

Recognizing the climate emergency highlighted by intergovernmental experts, including the latest IPCC report (2022), our study aimed to deepen the understanding of the mechanisms driving pro-environmental behaviors (PEBs), building upon the Theory of Planned Behavior (TPB). To achieve this, we developed an expanded model that integrates the elements from the TPB—intention, attitudes, norms, and perceived behavioral control—with future-oriented emotions (i.e., anticipatory and anticipated emotions). We applied our model to five distinct types of PEBs: conservation, environmental citizenship, food consumption, waste management, and transportation. Using a psychometric network analysis on a sample of 2,100 participants randomly assigned to the five PEB experimental vignettes, we examined which variables were most influential in determining behavioral intentions. This approach yielded several significant findings and contributions to the literature, which we discuss in the following sections.

## The predictive power of a specific approach of PEBs

Our research findings suggest that adopting a type-specific approach to PEB is advantageous. Indeed, our results reveal that the relationships between variables in our model vary across different types of behaviors. Notably, our model explains between 67% and 86% of the variance in the intention to adopt PEBs (see the HTML report titled "All Behaviors" in the OSF repository). This level of predictability is substantially higher compared to the 49.9% reported in the review by Yuriev et al. (2020), thereby supporting our initial hypothesis. One plausible explanation for this increased predictability could be the focus on highly specific behavioral components, aligning more closely with the tenets of the TPB.

## The role of PEB's diversity

While our findings demonstrate increased predictability across various behaviors, they also reveal complexities in the underlying process leading to the endorsement of PEBs. A key observation is the consistent influence of attitudes and personal norms on behavioral intentions. This pattern holds true across different types of PEBs and analytical methods employed. Specifically, we found that positive attitudes and personal norms toward PEBs are invariably linked to heightened levels of intention to engage in these behaviors. Conversely, unfavorable attitudes and personal norms lead to a reduced intention to

*Published in : Environment and Behavior (2025), p. 1–29*
*DOI: 10.1177/00139165251356912*
*Status : Postprint (Author's version)*

act. These results are also consistent with our hypothesis and with studies attesting to the benefit of adding personal norms to TPB (Klöckner, 2013; Morren & Grinstein, 2021). Personal norms—feelings of moral obligations to engage in PEBs—seem to mediate the role of social norms (measured in this study as descriptive and more external norms namely, the perceived prevalence of the PEBs among important others) on behavioral intention. According to Thøgersen's taxonomy of norms (2006), it is suggested that more integrated norms would have a stronger effect on intentions and more external ones would have a smaller effect. Our results also support that the variables leading to behavioral intentions are globally consistent across the different types of PEBs. Adoption of PEBs could be considered as a global process with slight variations from one category of PEB to another.

Additionally, our results suggest a probabilistic dependence of personal norms and attitudes on perceived behavioral control in most contexts: The more individuals feel capable of implementing PEBs, the more they have attitudes favorable to adopting these behaviors and the more they find important to adopt them. Overall, perceived behavioral control further emerged as a central variable in the network model, playing a significant role in shaping relationships with attitudes, personal norms, and intentions across different behavioral contexts. These results are consistent with the higher predictive role of PBC in TPB theory that postulates that PBC is the only one expected to directly affect behavior over and above its influence on intentions (Sheeran et al., 2003). However, notable differences were observed in the network structures pertaining to environmental citizenship and food consumption, which we discuss next.

In the case of food consumption networks, perceived behavioral control proved to have an unexpected negative and direct link with behavioral intentions, a result that deviates from previous research (Bamberg et al., 2007; Klöckner, 2013; Morren & Grinstein, 2021). This divergence may be attributed to the unique nature of these behaviors and the difficulty to change consumption habits, consistent with the literature on Environmentally Sustainable Food Consumption (ESFC; Macura et al., 2022). For example, Vermeir et al. (2020; p. 2) argued that "*food consumption goes far beyond its functional role as a means to survive. Food habits are notoriously hard to change as they are a central aspect of people's lifestyles and their socio-cultural environment*." This citation illustrates the complexity as they may not solely depend on norms and individual attitudes but are more intricately linked to lifestyle choices. In that perspective, widespread barriers to change could become very salient for people who intend to change their consumptions habits. The awareness of those widespread difficulties could hinder their perceived behavioral control. Conversely, people with no intention to change their consumption habits would not be aware of all the consequences of this behavior on their lifestyle and then express a strong initial behavioral control. Yet, the observed negative link between behavioral intentions and perceived behavioral control could also stem from statistical variance or conceptual overlap with another variable. The lack of previous psychometric network results in this regard makes the elicitation of strong explanations complex and call for further replications of these effects in future research.

Regarding environmental citizenship, our analysis revealed predominant influences from social norms and emotions. Given the public nature of environmental citizenship behaviors (e.g., joining environmental organizations, signing petitions in support of the environment, participating in climate strikes), the prominent role of social norms is consistent with the literature. It is bear reminding that we measured social norms as descriptive norms, namely to what extent important others engage in environmental citizenship behaviors. Thus, a group effect could apply to those collective behaviors: the more the ingroup participates to social behaviors the more the individual intends to do so. In the same vein, the impact of emotions aligns with findings by Verlie and Flynn (2022), who discuss the emotional drivers behind student climate strikes, explaining that an important ill-being among students initiated the large movement of strike. This ill-being and the perception of a unified concern of students about climate change led to a large mobilization in a strike to demand a radical reduction of greenhouse gas emissions. This example clearly illustrates the major role of emotion and social norms in the process leading to environmental citizenship behaviors. Surprisingly though, anticipated positive emotions were found to have a direct and negative influence on behavioral intentions: the more people imagined positive emotions when thinking about implementing environmental citizenship, the less they intended to actually implement this behavior. These results contrast with Odou and Schill's (2020) previous findings on the positive effect of these emotions on intentions and perceived behavioral control. One possible explanation could be the absence of a confounding variable in the model; for example, the more people are used to engaging in environmental citizenship, the more they intend to continue to do so, but the less they anticipate strong positive emotions. Further research is warranted to validate these findings and explore the nuances of emotional influences on environmental citizenship and PEBs in general.

## The additional contribution of emotions

Our comprehensive network analysis offers nuanced insights into the role of emotions in PEBs. Across analytical methods, we observed that emotions, in general, exerted a limited direct influence on behavioral intentions, except for anticipated negative emotions. This finding nuances their additional predictive power beyond the traditional TPB framework, especially for positive and negative anticipatory emotions, and contrasts existing findings related to behavioral effects of climate change optimism and anxiety (e.g., Heeren et al., 2022). It is worth noting, however, that anticipatory emotions are conceptually broader and less behavior-specific than anticipated emotions, as anticipatory emotions are directed at the future global consequences of climate change instead of the consequences of the specific behaviors under study. This conceptual difference can help explain that anticipatory emotions acted more as distal predictors compared to other predictors. As a consequence, this finding call for future research to better incorporate and distinguish both distal and proximal predictors of different types of behaviors. With regard to anticipated emotions, we found that negative anticipated emotions were positively correlated with intentions ($r$ = .10) and was the third most important variable when considering Expected Influence, a finding supported by the Directed Acyclic Graphs. This finding is consistent with Baumgartner et al.'s (2008) findings, suggesting that individuals are motivated to act to avoid the negative emotional consequences they anticipate in the future.

Our analysis also revealed that the influence of emotions varied significantly across different types of PEBs. Albeit inconsistently across analytical methods, negative anticipated emotions were influential on intentions only for waste management and transportation behaviors, while positive anticipatory emotions were influential only for food consumption and environmental citizenship. These findings shed light on the emotional drivers of pro-environmental behaviors, suggesting that the prospects of negative consequences and their emotional consequences are more important for certain behaviors (e.g., due to the social pressure to recycle or the clear and publicized consequences of transportation modes), while the positive consequences of other behaviors—for instance, in terms of health for food consumption, or social identity for environmental citizenship—can motivate other behaviors. These nuanced findings underscore the importance of emotions in understanding PEBs. While emotions showed a limited role in the prediction of intentions, at least for anticipatory emotions, their role in shaping intentions in particular behavioral contexts still warrants further investigation. These preliminary results call for a more thorough and detailed investigation into the role of emotion across the five dimensions of PEBs.

## Limitations

Despite the contributions of our research, our approach has certain limitations. Firstly, the network analysis is based on the estimation of partial correlations from cross-sectional data. We cannot, therefore, strongly infer potential causal relationships. The only clue we have about the direction of effects is the directed acyclic graph (DAG), which provides information about the likelihood of variables depending on each other (McNally et al., 2017). Indeed, a DAG can be seen as the product of the conditional distribution of each node present in the model, given its parent nodes; this makes it possible to indicate whether the presence of variable A implies, on average, more often the variable B, than vice versa (McNally, 2021). However, this direction does not signify the temporal precedence of node B in the model and cannot quite be interpreted as a causal effect (Bonchi et al., 2017). Furthermore, DAG assumes, by definition, that connections between nodes are directed and acyclic (i.e., it prevents loops). However, it is possible that these loops exist in reality (e.g., feedback loops). One avenue for future research that would address these limitations could be to conduct a longitudinal study and use vector autoregressive modeling on time series data (Epskamp et al., 2018).

An additional limitation of network analysis is its assumption that there are no unmeasured confounders. However, we may not have selected all the variables that may come into play in determining PEBs, which may have biased some of our results (Rohrer, 2018). Indeed, several studies have found other relevant variables to explain PEBs, such as past behavior (Lizin et al., 2017), the new ecological paradigm (Klöckner, 2013) or self-identity (Gkargkavouzi et al., 2019). Secondly, the fact that we did not measure PEBs and were only interested in the intention to adopt these behaviors can also be criticized. Indeed, although intentions are the strongest and most proximal predictor of behaviors, they do not completely predict them (Ajzen, 1991). Consequently, a study that would evaluate behaviors and add new variables potentially necessary for their prediction, as well as for the prediction of intentions, would most certainly be opportune.

Finally, we also noted some limitations in our measurements; we noted that certain items on the scale measuring attitudes are conceptually linked to the principle of perceived behavioral control. For example, if participants feel that adopting the behavior would be costly in terms of money or time, then it is highly likely that they believe that it is impossible for them to act on these behaviors, independently of their will. It cannot be ruled out that this measurement relationship may have led to some inaccuracies in our results. Moreover, we chose to focus on categories of PEBs and not on very specific ones as advocated by the TPB. While previous research supported this decision (Lange & Dewitte, 2019; Larson et al., 2015; Stern, 2000; Yuriev et al., 2020) it could have hindered the predictive power of the model investigated. Moreover, our experimental vignettes therefore exhibit different amounts of behaviors that have different levels of demand in terms of time and effort, which can bring some ambiguity in participants' answers with regards to those vignettes.

## Practical implications and future perspectives

The findings of our study hold several important implications for environmental practitioners, campaign managers and communicators, while also paving the way for future research in this field. Our research supports and extents the body of knowledge (Bamberg et al., 2007; Klöckner, 2013; Morren & Grinstein,

2021) on the influence of perceived behavioral control, attitudes, and personal norms in shaping pro-environmental intentions. Notably, our study offers deeper insights into the dynamics and structure of these relationships using experimental vignettes and a psychometric network approach.

Additionally, if our results are indicative of the dynamics trends related to PEBs, interventions aimed at increasing the perception of control over PEBs could be particularly effective. Indeed, such interventions on perceived behavioral control are likely to not only bolster pro-environmental intentions but also indirectly engender more favorable attitudes toward the adoption of PEBs, and increase the moral importance of adopting these behaviors. This suggests a cascading effect: increasing individuals' sense of control regarding pro-environmental actions may subsequently foster more positive attitudes and stronger personal norms of these behaviors. Additionally, while the role of emotions appeared limited, our findings offered insights into how specific behaviors may be more driven either by positive or negative emotions as a way to instantiate positive futures or avoid anticipated negative outcomes.

While our findings contribute valuable insights, they also underscore the need for further exploration in this area. Future research could focus on the differential impacts of various types of interventions on perceived behavioral control and the subsequent influence on PEBs. Additionally, investigating the specific mechanisms through which information and awareness campaigns translate into increased behavioral control perception and intention would be beneficial.

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## Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

## Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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