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Leveraging AI to advance psychological research for climate policy

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Addressing climate change requires passing ambitious green policies, yet these policies often face significant public resistance. In this article, we highlight the potential of artificial intelligence (AI) to help overcome this challenge by deepening our understanding of the psychological factors influencing reasoning and decision-making about climate policy. We explore how AI can be leveraged as a tool to gain deeper insights into the factors driving public resistance, improve communication about policies, and aid the design of more effective, human-centered policies.

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Introduction

Can artificial intelligence (AI) help address the social and behavioral challenges fueling the climate crisis? At first glance, AI appears more likely to exacerbate the problem. The explosion of large-scale AI models — especially those generating human-like text and high-quality images — could strengthen the control of large corporations with little climate accountability [14,24], the very entities responsible for a significant portion of carbon emissions [23,54,62]. AI could be weaponized to propagate false narratives about climate change, threatening to further polarize the public [22,30]. On top of that, training large AI models requires vast amounts of energy, contributing to carbon emissions in its own right [35,37,63].

In light of these challenges, are there any ways AI can help rather than harm? We believe it could — if used as a *tool* to better understand the psychology of climate policymaking. Understanding how people reason about climate policies raises new psychological questions and offers a high-impact opportunity for psychologists to support progress on climate change.

Psychologists have increasingly turned their attention to climate policy, making important progress in understanding what shapes public support and what drives resistance and polarization [19,53,67,68]. This includes factors such as political identity [19], social norms [12], elite cues [53], and perceived fairness [38]. In this article, we highlight how AI can help advance this research by: (a) improving our understanding of the psychological factors that influence responses to policy solutions, (b) enhancing public understanding by clarifying complex climate policies in accessible ways, and (c) ultimately, helping to develop more human-centric climate policies informed by how people think and behave.

Why should psychologists focus on climate policy?

Policy is one of the most powerful levers for tackling climate change, yet its success depends on understanding human behavior and public opinion [67]. For example, even though policies like carbon taxes, renewable energy subsidies, and public transportation investments are proven mechanisms for reducing emissions [10,26,44], they are notoriously difficult to implement. While opposition to such policies frequently stems from powerful interest groups benefiting from the status quo [23,62], a substantial barrier lies in the public's disagreement over the best course of action [9,19,48].

Importantly, public resistance is not only driven by partisanship but also by crucial factors such as fairness and perceptions of who bears the costs of action [16]. Such concerns cut across ideological lines and can fuel backlash even against well-intentioned policies [39,42,59,61]. Understanding these beliefs is essential for designing policies that are not only effective but also responsive to public concerns and more likely to gain broad support.

Psychologists are well-positioned to help address this challenge. But doing so effectively requires deeper engagement with both policymakers — who shape and implement interventions — and social scientists, who can help contextualize behavioral insights in real-world settings. These collaborations can inform strategies to improve policy acceptance and increase the chances of successful implementation [21]. In the remainder of this article, we examine how AI tools can advance this interdisciplinary effort. Rather than replacing existing psychological research, we argue that AI can enhance it by identifying patterns in public reasoning at scale, generating and testing new policy framings, and aiding deliberative processes that can reveal common ground.

Use case 1: AI for identifying the psychological factors that influence support for policy solutions

Deciding to support or oppose a policy is fundamentally a cognitive process — it involves integrating multiple streams of information about the world and weighing psychological trade-offs that shape beliefs and actions. For example, policies like carbon taxes or EV rebates often raise concerns about economic costs, fairness, or social identity. Political scientists and psychologists have identified many psychological barriers to policy support, including mistrust, partisan cues, and social norms [12,20,52,58,67,68]. However, these factors are usually studied in isolation or through highly controlled, close-ended survey experiments, which limits our ability to understand the more nuanced ways people think about these policies. To develop more comprehensive psychological theories for climate policy, we need tools that enable fine-grained measurement of human behavior and large-scale data collection in real-world contexts.

AI can serve as an additional tool to investigate these new forms of data. By analyzing large-scale, unstructured data such as social media posts, news articles, or policy briefs, AI tools — particularly large language models (LLMs) — can be used to uncover the psychological barriers that exist in contexts beyond controlled laboratory studies [15,25,41]. This approach complements existing methods by identifying patterns in how people reason about and respond to climate policies in a variety of settings, providing a more comprehensive understanding of the psychological factors at play.

LLMs can be particularly useful in extracting structured psychological features from free-form text [49], which in turn can be used to refine existing psychological theories and develop new ones in a data-driven fashion. For example, Bhatia et al. developed an LLM-based pipeline for automatically extracting cognitive features from a natural language dataset of everyday decision dilemmas, offering a more ecologically valid method for testing cognitive models of decision-making [7]. This work demonstrates the potential in combining psychological constructs and modern AI tools to predict behavior at scale. Similarly, Chang et al. used AI to analyze search engine queries to understand the factors behind vaccine hesitancy, identifying early adopters and holdouts and enabling a more nuanced analysis of vaccine skepticism than traditional surveys could provide [11].

These case studies provide a potential template for how we might apply AI methods to the domain of climate change. By analyzing behavioral data from diverse naturalistic sources, AI can help identify patterns in sentiment, framing, reasoning, and values that shape how people conceptualize climate policies. For example, responses to carbon taxes might reveal concerns about fairness, while data on EV rebates could expose trade-offs between environmental and economic concerns (refer to Figure 1, top panel). This approach can complement existing research on public opinion and political psychology, allowing researchers to link large-scale behavioral patterns to underlying psychological mechanisms. Future studies, whether experimental or observational, could leverage these techniques to systematically analyze complex multimodal data, leading to more accurate models of policy acceptance and insights to improve public support for climate policies.

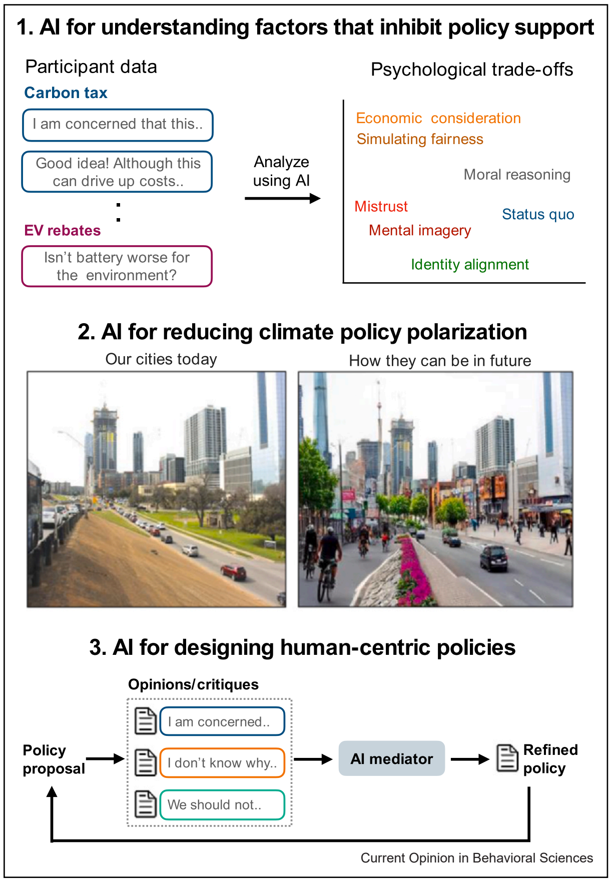
Use case 2: AI for clarifying climate policy communication

Characterizing the structure of beliefs about climate policy is an important first step toward overcoming the challenge of political polarization over proposed or existing policy. Polarization often stems from how such policies are framed and understood differently across groups. A growing body of research shows that emphasizing co-benefits, such as energy security or job creation, can broaden public support for climate policies [5,27,32,36,60,65]. AI offers new tools to complement this work by informing the development of more contextually relevant and precise climate policy communication.

Generative AI, like writing or mathematics, can be conceived of as a tool that may support learning. Viewed through this lens, AI acts as an interface to surface new factual information or the conception of alternative possibilities, making people aware of new ideas and helping them find common ground on polarizing topics [64]. In the context of climate policy communication, AI can be used to study the informational contingencies that shape people's reasoning and conceptualizations, for instance, how exposure to certain messages affects how people construe complicated, abstract phenomena like environmental policies. Importantly, AI enables these explorations at a scale and level of personalization that were previously unattainable.

For instance, Dubey et al. used text-to-image generative AI models to help people imagine the possible

Figure 1



Use cases for AI in advancing climate policy communication and design. **(1)** Building on the methodology developed by Bhatia et al. [7], AI can help analyze unstructured participant data (e.g. opinions on carbon taxes or EV rebates) to map them onto latent psychological trade-offs. Layout reflects conceptual similarity, akin to a semantic or multidimensional scaling-like space [57]. **(2)** Based on Dubey et al. [17], AI can be used to enhance support for sustainable transport policies by helping people envision the positive outcomes of proposed policies, such as greener, more walkable cities. **(3)** Using the methodology developed by Tessler et al. [66], AI mediators can synthesize public critiques of policy proposals to identify points of agreement and refine policies, making them more acceptable and effective.

consequences of increased investment in public transport [17]. The study found that when American adults across the political spectrum viewed AI-generated visualizations of car-free versions of various streets in America, they were able to more concretely understand the potential impacts of transportation policies (see Figure 1, middle panel). This study highlights AI's ability to augment human imagination about climate policy outcomes while raising important psychological questions about the role of imagination and mental simulation in decision-making.

Building on these early successes, AI has the potential to help enhance clarity in climate policy communication by making complex concepts more concrete and accessible to diverse audiences. Currently, scientists, policymakers, and politicians design their own explanations, vignettes, and arguments to communicate climate policies in a largely ad-hoc fashion. However, these explanations may fail to resonate with their intended audiences [8]. AI could help overcome these challenges by automatically identifying which explanatory approaches are most clearly understood by different groups [47,72], and in parallel, enable large-scale empirical testing of these messages [2,43,69]. This approach can help us minimize researcher-imposed biases and discover improved ways to explain policies to audiences with different knowledge backgrounds, values, and concerns.

Beyond explanation, AI could also be a valuable tool for studying the factors that drive belief change. LLMs have shown potential in identifying persuasive arguments, predicting stances based on demographic information, and predicting the appeal of specific arguments for given individuals [50]. Emerging evidence also suggests that interactions with LLMs can influence beliefs on contentious topics [13,55,70], though their effectiveness may vary depending on the context [18,64]. LLMs could thus be used to understand when and why people's construals and beliefs change in the domain of climate policy.

The preliminary successes of AI in this area raise important questions about research ethics and responsible use. While the prospect of AI as a tool for 'superhuman persuasion' has raised concerns, current evidence suggests that LLMs are not uniformly more persuasive than humans at crafting arguments [64]. We believe that instead of viewing AI as an agent for persuasion, a more constructive approach would be to treat it as a research tool for understanding how people process information and form beliefs about complex policy issues across different contexts and value systems.

Use case 3: AI for human-centered policy design

Our previous section centered on how AI can help people reach consensus over *existing* policies. Here, we explore a more speculative use case: using AI to assist in designing *new* climate policies that better integrate the perspectives of stakeholders and foster broader agreement. As with earlier examples, we emphasize AI as a tool to support human decision-making, not as an autonomous agent.

While reframing existing policies has shown some success in improving public support, it has inherent limitations. Reframing alone cannot fully circumvent deep-seated party differences, motivated reasoning, or poorly designed policies [6]. To overcome these barriers, we need new tools to help people collectively explore, evaluate, and reach consensus on policy solutions. Generative AI can serve as a component of this pipeline.

Recent work has highlighted the ability of AI to synthesize varying perspectives on political issues [4,29,31,66]. Tessler et al. demonstrated that LLMs can be trained to produce a 'group statement' that can gain maximal endorsement from groups of people with potentially diverse views on a social, political, or moral issue [66]. Participants preferred AI-mediated statements over those written by trained and incentivized humans. These AI-mediated statements balanced the majority view while giving prominence to dissenting opinions, reducing polarization by surfacing common ground. Applied to climate policy, such a system could gather public opinions on contentious proposals and iteratively refine those policies to address diverse viewpoints, akin to a digital citizens' assembly (refer to Figure 1, bottom panel).

Although these early successes are promising, real-world policy design raises additional behavioral challenges. Current AI approaches often optimize predefined objectives without modeling the populations affected by the policy. A key next step would be to integrate richer behavioral models that predict how people will respond to new policies. LLMs offer potential in this area, enabling simulation of more fine-grained and open-ended aspects of human behavior, going beyond simple economic games to more naturalistic decision-making dilemmas [45,46]. For instance, LLMs could be used for lawmakers and policymakers to better appraise constituent support for certain climate policies by simulating the opinions of the population [34]. They could also help to better anticipate the factors that cause pushback against implemented policies, for instance, by simulating public reaction to a policy conditioned on demographic information.

However, the success of these approaches hinges on the accuracy of behavioral simulators. Current LLMs exhibit some success in recapitulating public opinion, but only when conditioned on specific demographic characteristics, and they remain far from perfect proxies for real populations [56]. More broadly, given the differences in LLM and human learning mechanisms [40], we should be cautious about relying on off-the-shelf LLMs as faithful simulators of human behavior. Empirical evaluation is critical to ensure that any form of behavioral modeling accurately reflects the beliefs and behaviors of actual people. Without robust validation, the risk of misrepresentation could undermine AI's utility in policy design [3,28].

Conclusion

AI has the potential to help us explain and predict human behavior for the purposes of reducing political polarization around climate policy and designing more effective policies. The first step toward this vision is large-scale data collection, cataloging people's beliefs and construals of climate policy. This data could be aggregated from already-existing traces of internet behavior, such as web searches or social media interactions, or collected anew through large-scale experiments that allow for more open-ended expression in the form of natural language. We highlight that it is crucial to collect data from broadly sampled populations, across countries, both to understand the heterogeneity in people's construals within and across societies, and to avoid excessive flattening of the complexity of human reasoning and behavior in these contexts [33,51,71].

AI is not a panacea; by itself, AI will not solve the behavioral challenges of climate change. Its potential to improve public support for climate policies faces notable limitations. For instance, it remains uncertain whether AI can equally address the attitudes of all voters. Additionally, the same technologies that foster consensus could also be used to deepen divisions on climate issues [30]. Moreover, while public opinion is crucial, it does not necessarily translate directly into political action [1]. However, AI can serve as a tool to better predict and understand human behavior, from identifying common ground to simulating policy responses. When combined with insights from psychology, AI-enabled tools can help design policies that align with public values and drive systemic change. Used responsibly, AI could accelerate progress towards enacting policies that preserve the well-being of our planet and its inhabitants.

Data Availability

No data were used for the research described in the article.

Declaration of Competing Interest

The authors declare no conflict of interest.

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