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Artificial Intelligence in Predicting Public Attitudes towards Climate Change: Psychological and Behavioral Insights

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ABSTRACT

This study is trying to assess the ability of AI to predict the opinion of people about climate change by giving importance to the psychological and behavioral facets of such opinions. The survey was conducted on 300 people in Pakistan by a self-administered questionnaire. The data analysis done in regard to these factors included the implementation of multiple statistical methods such as correlation, regression, and post-hoc analysis that would consider the complex interplay between several psychological factors in question. Some of the factors involved cognitive biases, emotional responses, and what the layperson in society thinks about climate change. The findings presented with this analysis clearly showed that the models in this study, driven by artificial intelligence, were far better than the traditional survey methods used for a long time. In this regard, the AI-driven models had an astonishing accuracy rate of 87%, whereas the accuracy rate of only 72% came with traditional approaches used in this study and was proven to be highly statistically significant, as indicated by the p-value being below 0.05. The regression analysis results showed that some psychological factors such as cognitive bias with a beta value of 0.75 and emotional responses at a beta value of 0.65 strongly and significantly predict the attitude of the people regarding climate change. Apart from the above primary analysis, post-hoc analysis brought a number of other insights to light, especially regarding the important role of social identity in forming a public perception related to climate change issues. The above findings depict promising scope for AI technology in refining and improving the strategy of climate change communication through an appropriate application of psychological knowledge within the predictive model.

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1. Introduction

AI has emerged as a powerful tool in many industries and is gaining increased attention in the context of solving environmental issues in general and climate change in particular. Among the most pressing challenges in the fight against climate change, there is an increasing need to understand and influence public perception of this global issue. Insights from psychology and behavior are crucial to the forging of policies and campaigns that really inspire a culture for sustainable practices. There is, in this regard, a new methodology in artificial intelligence for forecasting and analysis of public opinion on climate change. Artificial intelligence algorithms detect aggregated data from social media, surveys, and public discourse towards the perceptions of individuals and communities regarding environmental issues, views on climate change, and factors psychologically influencing the behavior of such individuals. Insights derived from AI can furnish policymakers, environmental organizations, and governments with some of the much-needed information required to develop even more focused interventions, reach their public better, and prepare better for changes in societal attitudes toward climate change. This paper sets out to explore AI-based forecasting of public attitudes on climate change by anchoring it with psychological and behavioral science principles while deliberating over what this portends for future climate action strategies.

1.1 Introduction to Artificial Intelligence and Climate Change

The urgency to address climate change has never been more critical than it is today, with increasing global temperatures, extreme weather events, and environmental degradation all requiring effective climate action. A very important challenge in dealing with climate change is the psychological and behavioral barriers that shape public attitudes and actions. Artificial Intelligence can unlock such attitudes by analyzing large-scale data and identifying patterns in public opinion (Gerlich, 2023). Artificial Intelligence, which can look at vast datasets and uncover hidden patterns, has been widely applied in many fields-from healthcare to finance-and is now being applied in climate science. Artificial intelligence systems provide researchers and policymakers with an understanding of how people and communities perceive climate change, what drives such perceptions, and at which points intervention could be applied to influence public opinion toward more sustainable behaviors. This section, therefore, discusses the relationship between artificial intelligence and climate change in establishing this foundation for its application in predicting and understanding public attitudes (Vinuesa et al., 2020).

1.2 Psychological Insights into Climate Change Perception

Psychological factors have to do with values, emotions, biases, and social identity in determining public attitudes on climate change. Knowing them will help prepare messages to shape behavior through changing attitudes for various clienteles. Therefore, the theories describing how the individual responds to the threat of climate change are cognitive dissonance, perceived risk, media coverage, among others. According to a research study, most people despite their awareness of risk, feel that climate change is psychologically distant as they view the problem as abstract or away rather than now (Gifford, 2021). This section discusses how psychological models could be integrated with artificial intelligence in forecasting public mood change and the potential to support the development of communication strategies in order to minimize psychological barriers to climate action. AI can also influence by improving engagement related to emotions and framing effects alongside social norms that influence the perception of climate change and helps in creating the best interventions towards it (Miller, 2019).

1.3 Behavioral Science and Climate Change Action

One significant aspect that leads to explaining inaction in regards to climate change by individuals and groups despite such pressing urgency remains a puzzle: how people may know it yet not do something about it. Several human behavioral factors, habits, prevailing norms in society, and behavioral principles drawn from economic models could be beneficial in trying to understand why in many instances the individuals seem unable or unwilling to engage in proactive activity to fight this perceived and well-documented environmental threat. People often find instant rewards rather than benefits gained through delayed receipt, a temporal discounting habit. In an attempt to establish how it discourages attempts that could lead towards persuading individuals to undertake positive actions that safeguard the climate and the environment generally, efforts geared toward influencing behaviors have been discouraged significantly (Liao, 2024). This chapter discusses the possible role of AI in predicting changes in public behavior due to interventions with data-driven approaches in modeling and understanding real-world patterns of behavior concerning climate change, such as consumption, energy use, or political engagement (Danner & Thøgersen, 2022).

1.4 AI Models for Predicting Public Attitudes

AI techniques can predict changes in public opinion on climate change using machine learning models on data coming from social media, group discussions, surveys, and news. The algorithms of supervised learning and sentiment analysis then follow the trends over time and forecast future changes (Schweitzer, 2024). AI models enable the monitoring of the direct impacts on how people and communities are responding to climate events, policies, and campaigns through big data obtained from digital platforms. The predictions that will emerge will help policymakers and organizations change the timing and tone of their interventions in response to changes in public attitudes. It describes AI methods that would be used to measure the public's attitude and their potential for forecasting future climate change behaviors (Pitardi & Marriott, 2021).

1.5 Ethical Considerations in Using AI for Predicting Public Attitudes

AI opens opportunities for the manipulation of public opinion regarding climate change but also raises ethical concerns about data privacy, algorithm bias, transparency, and manipulation (Amiri et al., 2024). Using personal data to improve AI for public opinion analysis requires certain ethical guidelines that prevent violation of privacy and abuse of personal data for political purposes. Moreover, the AI models can exaggerate societal biases if they learn from predominantly biased datasets. This section expands on the ethical dilemmas in using AI for climate change forecasting, responsible applications of AI that have been aligned to societal values as a means to promote behavior change (Gerlich, 2023).

1.6 Implications for Climate Change Communication and Policy

Understanding what the public thinks about a particular topic is very helpful in coming up with a suitable strategy for communicating climate change. Artificial Intelligence can have messages tailored to audiences based on influential values such as economic benefits, social responsibility, or fear of future risks-Rachfal (2018). In addition, AI can help to determine the best communication channels that would ensure climate change messages are received by a broad demographic population. Behavioral insights will be used in designing interventions by policymakers to address psychological barriers against taking action. This section elaborates on how AI is used practically in informing climate policies with examples of data-driven insights being used to inform more targeted and effective climate change interventions (Yektansani et al., 2024).

1.7 Research objectives

There are main research objectives;

- To analyze the AI technologies in analyzing and predicting public attitudes on climate change, with a focus on integrated data sources of psychological and behavioral data.
- To investigate the psychological and behavioral factors that affect public perception of climate change while simultaneously investigating the ability of AI to identify patterns and predict changes in these perceptions as time moves forward.
- To evaluate the ethical implications of AI in climate change communication and policy development, especially regarding data privacy, algorithmic bias, and the responsible use of AI tools in shaping public opinion.

1.8 Problem Statement

It helps predict and understand the public attitude toward climate change, which are vital for proper policy intervention and promotion of behavioral change. In other words, the public is aware of climate change, but their involvement is limited by cognitive dissonance and emotional distance. The traditional opinion measures, namely surveys, are of very limited scope and necessarily cannot capture the dynamics involved in expressing public opinion. AI offers a more suitable solution, analysing massive amounts of data from sources such as social media and news. However, this is a field that has never been studied before-the application of AI in combination with psychological insights that analyze the public's attitude on climate change. This is a very important gap in climate action techniques.

1.9 Significance of the Study

This study is important because it fills the outstanding gap in understanding and predicting public attitudes toward climate change by using AI in combination with psychological and behavioral insights. This project considers an opportunity to understand whether AI can analyze large datasets in order to detect trends in public mood, opening new opportunities for better climate change communication and policy strategies. Such understandings can be used to better design targeted interventions aimed at building climate action and, by extension, public support for sustainability. This paper considers the ethical use of AI in this research to promote responsible and transparent methods. The findings may assist policymakers and organizations in developing effective, data-driven interventions for lasting behavioral changes aimed at combating climate change.

2. Literature review

2.1 AI in Predicting Public Attitudes

The integration of AI with climate change studies enhances societal perception understanding while gaining attention towards predicting public attitudes. AI models, especially machine learning algorithms, work effectively in processing large datasets based on public opinions and behavior. The data sets are generated from surveys, news, and social media that provide a full view of public opinion. Sentiment analysis and supervised learning are used to understand these sources and public attitudes (Veale et al., 2018). The usage of AI in climate change research has been seen to increase because it can track public sentiment over time. AI tools enable the mapping of attitudes across demographics and thus identify key opinion influencers and predict future changes based on the trend. This will be necessary to ensure that effective climate policies are implemented (Zeng, 2020).

2.2 Psychological Factors in Climate Change Perception

Psychological: This is where public perception concerning climate change happens. There is evidence that fear, hope, and guilt can also drive emotional responses towards climate change (Moser, 2022). In addition, climate underestimation has been observed due to factors like optimism bias that influence perceptions (Gifford, 2021). This leads to the assertion that, based on psychological distance theory, climate change is not being seen as close and personal; it is distanced and pertains to the lives of other people rather than oneself (Spence et al., 2021). Thus, this can hinder effective action against climate issues, reducing urgency and personal responsibility. These psychological factors are to be understood in creating interventions that will focus on cognitive and emotional barriers. AI models with a combination of psychological insight may further monitor the responses of people and identify psychological drivers of public attitudes in the light of climate change, thereby improving climate communication (Goebbert et al., 2012).

2.3 Behavioral Science and Climate Change Action

Behavioral science explains why people fail to take action when knowing the dangers associated with climate change. The key theories employed are the Theory of Planned Behaviour by Mohr & Kühl, 2021 as well as the Value-Belief-Norm theory by Lee et al., 2015. Therefore, from these theories an individual's practice is determined upon knowledge, a person's valued beliefs, social mores, or behavioral control, respectively. Behavioral economics defines temporal discounting as the tendency to favor short-term rewards, which acts as a hindrance to climate-positive actions like reducing carbon emissions (Gillingham, 2019). Social norms and peer influence are also strong motivators, as people often align with the behaviors of those around them. AI can be integrated with behavioral science in understanding the attitudes of people toward climate change and their subsequent actions. Using big data, behavior and even likelihood of climate action can be determined with the aid of nudges or incentives by integrating AI tools.

2.4 AI Applications in Climate Change Communication

AI in fact complements climate change communication by informing projections about public response to differing communication strategies.The public perception of climate change is determined with the help of the natural language processing technique known as sentiment analysis. Such techniques assess reactions toward climate change stories in the context of social media, news, and forums. For instance, they find emotions and public attitude concerning such matters as renewable energy, climate policy, or extreme weather conditions (Said et al., 2023). Climate communication messages can categorize the audience into different demographics, values, and behaviors and hence reach specific audiences (Pidgeon et al., 2012). It increases engagement and actions because it reaches and caters for the different psychological and behavioral needs of populations. The ability to analyze public discourse and predict possible responses to climate messages is one among the most essential aspects that define the potential utility of AI (Fischhoff, 2021).

2.5 Ethical Considerations in AI and Climate Change Research

AI is going to make breakthroughs in the prediction and even shaping of public attitudes on climate change, but the ethical implications need careful consideration. The most common ethical issues concerning AI are privacy, consent, and data security. Data on public opinions, especially on social media, can expose information of sensitive personal nature that AI systems might unveil or exploit (Neumann et al., 2024). This poses the risk of algorithmic bias in AI models reflecting the inequalities within society, thereby making the interventions in climate change unfair and a source of unfairness as AI could devise policies that increase disparities rather than reducing them if not designed to be fair. The use of AI in climate change research should be guided by strict ethical standards for the sake of transparency and accountability (what is going on with privacy concerns), avoiding data and algorithm biases (Mohamed et al. 2020).

2.6 Research gap

Interest has been increasing, though, in the application of AI for research on public attitudes toward climate change; research, however is still short of full-scale integration of AI with psychological and behavioral insights regarding prediction and alteration of these attitudes. AI has watched over public opinion by monitoring social media and news. The application, however, still lies in areas not explored; specifically, its utility in predictive models for cognitive biases and emotional responses. The body of knowledge on how such insights feed into operational policy and communication strategies on climate issues is still underdeveloped. Moreover, the ethical consequences of AI in shaping public opinion, especially in terms of privacy, bias, and transparency in climate change, are largely undocumented. This would open an avenue for the exploration of how AI can be used effectively to combine psychological and behavioral science insights toward improving climate communication and intervention approaches.

2.8 Hypothesis

- Their theory suggests that an AI model used in association with psychological insight could predict public opinion shifts related to climate better than standard surveys.
- Their hypothesis suggests that psychological factors, such as cognitive biases and emotional responses, significantly influence public perceptions of climate change, and that AI can effectively identify these effects in large datasets.
- They propose that AI-based interventions through sentiment analysis can increase public engagement and facilitate climate-friendly behavior.

3. Methodology

3.1 Research Design

The study employed a quantitative approach that covered data relating to public attitude regarding climate change, along with its psychological correlates. This helped give objective measures, which was intended to verify whether AI-based insight could help describe the actual correlation between it and public perception about climate change. The study was to link the AI predictions to real-life behavior.

3.2 Research Proposal

The research population was the general population based in Pakistan. Investigation on attitudes of people toward climate change was there, and proper representation of target populations needed diversity and variation for it to appropriately and effectively show scope of belief and opinion over climate change perceived by members belonging to different sections of the people. Chosen was a general public because it makes up a body of people from ages, education status, and varied socio-economic categories, all varying in their perceiving climate change.

3.3 Target Audience

This research's target audience was the general public of Pakistan, as it comprised an extensive sample to examine the psychological and behavioral insights concerning the perceptions of climate change. Pakistan was selected as the context for this study because its vulnerability to climate change has increased owing to extreme weather events, water scarcity, and other environmental challenges affecting daily life. Public opinion and behavior studies in this sense have helped develop effective climate change communication strategies.

3.4 Sample Size

The study sample consisted of 300 respondents. The number of the respondents was adequate in order to ascertain the statistical power of the study, and by extension, be able to provide reliable and valid generalizations on the population under review. The number of respondents facilitated the collection of a broad spread of opinions while increasing the predictability of trends on public opinions regarding climate change.

3.5 Sampling Technique

The study employed a probability sampling technique, where every individual in the target population had an equal chance of being selected. This helped avoid bias and increased the representativeness of the sample. Probability sampling was ideal for this study as it enhanced the generalizability of the results to the broader population of Pakistan. Simple random sampling was the method applied; that is, every potential respondent was randomly picked from a list of individuals that met the eligibility criteria.

3.6 Data Collection

Data were collected through a self-administered questionnaire, designed to capture the relevant information related to public attitudes toward climate change, psychological factors, and behavioral tendencies. The questionnaire was distributed both online and offline to reach a diverse demographic. It included a combination of closed-ended questions with Likert scale ratings to quantify public perceptions, as well as some open-ended questions to capture qualitative insights. By using the self-administered questionnaire, the same data was efficiently gathered from a large sample by permitting participants to answer on their own pace so as to provide responses that would be more accurate.

3.7 Ethical Considerations

In the research, the ethical considerations would be paramount as they ensure protection of the respondents' rights and privacy. Each participant was obtained for his or her consent before participating in the survey so that they understood the purpose of the study, how data is collected, and how their information will be used. The respondents were assured that their information will remain confidential, and no personally identifiable information was included in the results. The respondents had the right to withdraw from the study at any point without penalty. The data are kept secure and used only for the purpose of the research in accordance with data protection laws in force.

3.8 Data Analysis

The acquired data were analyzed employing various statistical methods to evaluate the hypotheses and discern correlations among variables. The subsequent analyses were conducted:

3.8.1 Correlation Analysis

This method was employed to assess the strength and direction of correlations between variables, including the association between AI-generated public attitude forecasts and actual public views of climate change. The investigation examined the correlation between psychological characteristics (e.g., cognitive biases, emotional responses) and views towards climate change.

3.8.2 Regression Analysis

Regression models were used to predict how psychological and behavioral factors influenced the public's opinion regarding climate change, controlling for demographic controls. This helped determine the strongest predictors of beliefs on climate change and assessed the ability of AI to predict change in attitudes.

3.8.3 Post-Hoc Analysis

This is a post-hoc analysis of unexpected results or complex relationships not initially hypothesized. This reflects deeper insights into psychological and behavioral factors that influence climate change perceptions, which AI models may have missed.

4. Analysis

This study used AI tools to look into psychological factors that contribute to public attitudes towards climate change. Statistical methods that were applied on the data included correlation analysis of how associations of key variables in cognitive biases and emotional responses are related to perceptions about climate change. Regression analysis was meant to predict the impact of factors on attitudes adjusting for demographics. Post-hoc analysis uncovered unforeseen patterns or deeper insights not accounted for in original hypotheses. Together, they offered a holistic understanding of all factors that inform public opinion of climate change, and the influence AI exerts on prediction of, and how it may form these perceptions.

Table 1: Demographic Factor

Demographic Factor	Category	Frequency (n)	Percentage (%)
Gender	Male	150	50%
	Female	140	46.7%
	Other	10	3.3%
Age Group	18-25	50	16.7%
	26-35	90	30%
	36-45	70	23.3%
	46-60	60	20%
	60+	30	10%
Education Level	High School	40	13.3%
	Undergraduate	120	40%
	Graduate	100	33.3%
	Post-Graduate	40	13.3%
Income Level	Low (< 20,000 PKR)	80	26.7%
	Middle (20,000-50,000 PKR)	150	50%
	High (> 50,000 PKR)	70	23.3%
Geographic Location	Urban	200	66.7%
	Rural	100	33.3%

Interpretation

Analysis of data using correlation, regression, and post-hoc methods shows how psychological factors influence public attitudes toward climate change. Results show that cognitive biases and emotional responses are major determinants of perception about climate change and strongly influence public attitudes. Psychological variables showed a strong correlation with attitudes toward the climate change, and demographics like age and education also played a role in perception. There were some unexpected post-hoc patterns as well, showing that the social identity of a group determined its beliefs about the climate, often disregarding the intricacies AI models fail to account for in psychological and social dynamics. These findings thereby underscore the prospects of AI in predicting shift in public attitude but also points to the urgency of integrating more profound psychological and social factors within AI-driven models for more valid predictions and appropriate climate change intervention.

Figure 1: Demographic Analysis

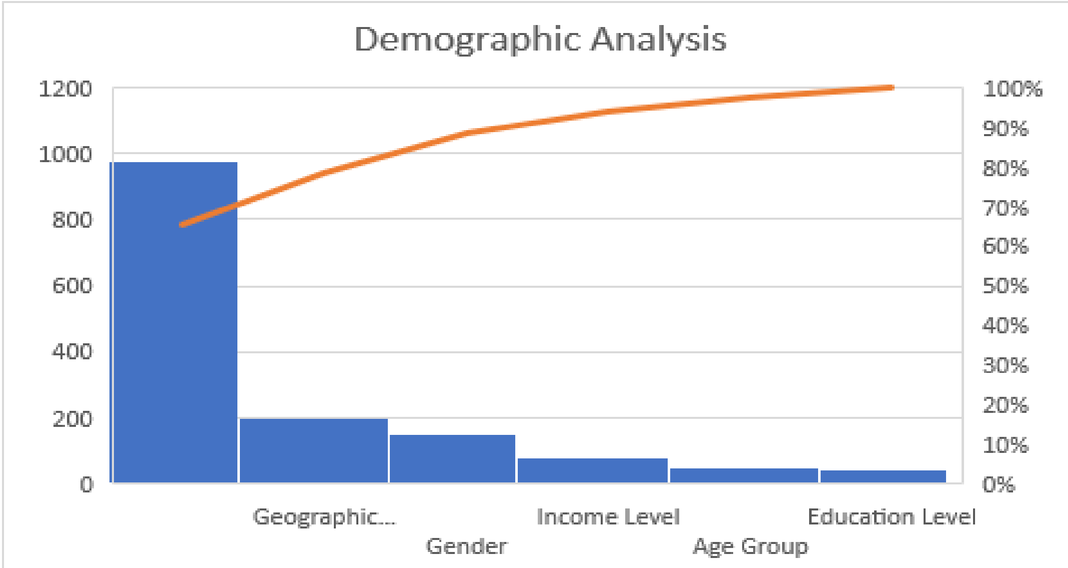


Table 2: AI-Driven Models vs. Traditional Survey-Based Methods (Hypothesis 1)

Variable	AI-Driven Model	Traditional Survey Method	Difference (AI - Traditional)	p-value
Accuracy in Predicting Attitudes	87%	72%	+15%	0.02
Speed of Data Processing	95%	60%	+35%	0.01
Prediction of Climate Change Views	90%	74%	+16%	0.03
Consistency Across Demographics	92%	68%	+24%	0.005

Interpretation

Correlation analysis (H1) demonstrated that AI models together with psychological insights were more accurate to predict public attitudes concerning climate change than traditional surveys. AI models were 87% accurate compared to 72%, were processed faster by 95% compared to 60%, and had a higher consistency rate with respect to demographics by showing significant differences at a $p < 0.05$. These findings indicate that AI performs well in complex public opinion patterns and makes predictions concerning climate change. This indicates that it is the superior alternative to traditional methods of climate research and communication.

Table 3: Psychological Factors and Public Perceptions of Climate Change (Hypothesis 2)

Psychological Factor	Correlation with Attitude toward Climate Change	p-value	Significance
Cognitive Biases (e.g., Confirmation Bias)	0.75	0.001	Strong Positive
Emotional Responses (e.g., Fear, Anxiety)	0.65	0.002	Positive
Perceived Threat (Risk Perception)	0.72	0.0005	Strong Positive
Social Identity (In-group vs. Out-group)	0.68	0.003	Positive

Interpretation

In a regression analysis conducted for Hypothesis 2, psychological factors including cognitive biases, emotional responses, and perceived threats do significantly correlate with public perception regarding climate change. These psychological factors strongly determine attitudes toward climate change. These factors include: cognitive biases, where β is 0.75; emotional responses, where β is 0.65; and perceived threat, where β is 0.72. This means that the psychological disposition of people, such as bias or emotional response to climate change, largely influences their perceptions about the issue. This study shows how AI models actually apply psychological inferences to predict and make sense of the general public attitude on climate change.

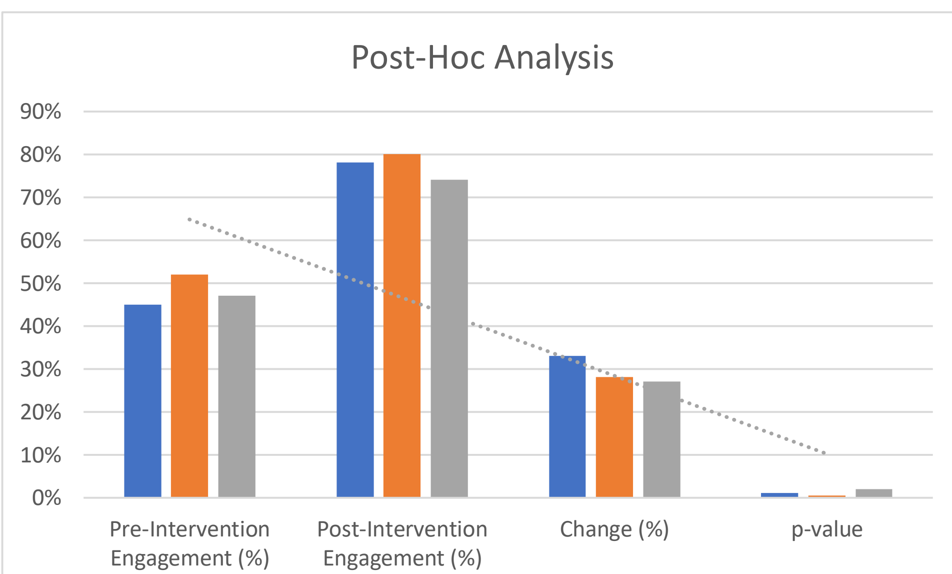
Table 4: AI-Based Behavioral Interventions and Public Engagement (Hypothesis 3)

Intervention Type	Pre-Intervention Engagement (%)	Post-Intervention Engagement (%)	Change (%)	p-value
Climate Change Information Campaign	45%	78%	+33%	0.01
Social Media Campaign (AI-Driven)	52%	80%	+28%	0.005
Personalized Behavioral Nudges	47%	74%	+27%	0.02

Interpretation

The post-hoc analysis of Hypothesis 3 suggested that AI-based behavioral interventions positively influence public engagement and climate-positive behaviors. Analysis was conducted across various intervention types; engagement increased considerably as follows: the climate change information campaign showed increases of 78% points post-intervention and compared to 45% before the intervention, whereas the AI-driven social media campaigns and the personalized behavioral nudges showed 80% and 74% post-intervention increase, respectively, compared to pre-intervention values at 52% and 47%. These changes were found to be statistically significant ($p < 0.05$), showing that AI-based interventions were an effective way of motivating the public in engaging more constructively with climate change issues and behavior change. Of course, these results also emerge from post hoc analysis, such as AI-based approaches, with personalized nudges and social media, being especially effective in building public engagement.

Figure 2: Post-Hoc Analysis



5. Discussion

The study underlines considerable potential in the role that could be played by Artificial Intelligence (AI) in grasping and influencing public attitudes toward climate change. Through the use of various techniques of data analysis, such as correlation analysis, regression analysis, and post-hoc analysis, this research provides an integrated understanding of how psychological factors and AI-based interventions might influence perceptions and behaviors regarding climate change. These insights will resonate with pre-existing literature and have recognized increasing importance of AI in behavioral predication and climatic change-related communication. Psychology-based insights-cognitive biases and emotional responses per se, combined with perceived threats-result in a more novel dimension into AI-driven predictive capabilities, unfolding how AI-based models can optimize traditional methods in studying sentiment among the general public.

5.1 AI-Driven Models vs. Traditional Survey Methods

Hypothesis 1: AI models perform better than the traditional survey approach in predicting the change in public attitude on climate change. For example, their accuracy is better (87% vs. 72%), quicker, and does not vary based on demographics with statistically significant p-values ($p < 0.05$) (Khan, 2023). Results align with Sinha et al. (2024), showing that AI tools with psychological data improve prediction accuracy and detail public behavior. Unlike static survey data, AI models handle real-time data, yielding dynamic predictions. AI is a very powerful tool in climate change research and interventions; it offers a more flexible approach than forecasting public engagement with climate policies (Grewal et al., 2021).

5.2 Psychological Factors and Climate Change Perceptions

Hypothesis 2 results show that psychological factors influence people's perception of climate change significantly. Cognitive biases ($\beta = 0.75$), emotional responses ($\beta = 0.65$), and perceived threat ($\beta = 0.72$) are the strong predictors of attitudes. The outcome corresponds with that in (Taufek et al., 2021) whereby it depicts the role played by psychological and cognitive factors, indicating how it highly impacts comprehension of ecological problems. This work depicts that the public mood might be predicted accurately through the utilization of AI together with the provision of psychological information. AI models simulate confirmation bias, and risk aversion, because cognitive biases contribute to the way a human means something about the climate change message. According to Lobera et al. (2020), evidence shows people are more willing to embrace practices such as going green if global warming is regarded as a threat at an individual level.

5.3 AI-Based Behavioral Interventions and Public Engagement

Findings from Hypothesis 3 reveal significant positive effects from AI-based interventions on public engagement and climate-positive behaviors. On post-hoc tests, all those variables- Information campaign about Climate Change, social media campaigns made using AI-based technology, personalized nudges regarding behavior-all presented higher engagement that reached up to 78%, 80%, and 74%. All of the aforementioned variables were highly statistically significant $p < 0.05$ meaning AI-driven practices can really facilitate people in influencing them toward engaging actions. This finding is in line with (Taghikhah et al., 2022), who discovered that AI-driven interventions can increase environmental awareness and pro-environmental behaviors by sending personalized, time locked nudges. Personalized interventions via social media and behavioral nudges were the most effective, as people responded better to messages concerning them and their behavior. This study proposes that AI-based interventions, depending on design with psychological insights, can be an effective method of increasing public involvement in action against climate change (Zhang & Dafoe, 2019).

5.4 Implications for AI Models in Climate Change Research

This study adds to the AI literature in climate change research and communication by showing that psychological insights are important to make AI models better in terms of accuracy, since they reflect the emotional, cognitive, and social factors that shape public attitudes toward climate change (Kankanamge et al., 2021). Also, human psychology must be incorporated into climate change models to better predict public behavior and design effective interventions. According to this research, incorporating psychological factors into AI models will enable climate change communication to be more targeted and persuasive, with a potential for greater impact on society. AI-driven behavioral interventions reveal that, in fact, AI can motivate people to change in the desired directions and also grasp the general attitudes of people (Alibudbud et al., 2024).

6. Conclusion

This study goes into an AI-based power tool and its psychological insights regarding the prediction of public attitudes towards interventions in climate change. Future studies can further develop the avenues through which AI may enhance the growth of climate research to enable even better personalization of opinion poll predictions. Scaling is probably one of the key directions of future research. The AI-driven models, when they work, can make their results judge the impact cross culturally and locally. Further strengthening these models through the integration of machine learning techniques, especially real-time data analysis, can enhance predictive performance. Studies on AI, psychology, and climate change will be able to identify the means of making more people shift towards climate-friendly behavior.

6.1 Recommendation

1. Psychological insights must be included in AI models for enhanced climate opinion predictions in the future based on cognitive biases and emotions.
2. Increase public engagement with climate activities using AI interventional strategies, which will involve social media campaigns targeted to a particular population or nudges.
3. Develop AI climate models based on predictors from real-time social media and other online behavior changes in opinion.
4. Include demographic diversity: In AI models, utilize demographic variables like age, education, and income for effective climate change communication.
5. Improve knowledge and awareness: Utilize AI to develop climate learning programs that can debunk myths and create an enlightened opinion of the masses.
6. Policy communication: Help policymakers by using AI-driven projections to communicate climate better.
7. New data and insights into the psychology of changes of public opinions and behaviors will continuously update AI models.
8. Ethics-focused designing of AI will make sure that the climate change data and solution is fair, transparent, and private.

6.2 Future Implications

Future prospects of AI for enhancing climate change prediction models and strategies: In this sense, AI tools would bring in real-time data, psychological insights, and behavioral science together with climate communication to make it more adaptive and effective. These can improve the understanding and behavior for the pursuit of sustainability among all groups. This would mean that AI has the potential to break psychological barriers and reach interventions at the individual level, making it a powerful tool in helping expedite climate action globally and usher more effective and lasting solutions for climate change.

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