

Article

A Role for Artificial Intelligence (AI) in Qualitative Research? An Exploratory Analysis Examining New York City Residents' Perceptions on Climate Change

Nadav L. Sprague ^{1,2,3,*} , Gabriella Y. Meltzer ^{4,5,6} , Michelle L. Dandeneau ⁷, Daritza De Los Santos ⁸ , Drew B. O'Neil ⁷, Andrew K. Kim ³, Alejandra Parisi ⁹, Shane Araujo ⁷, Christine C. Ekenga ¹⁰, Eva L. Siegel ¹¹  and Diana Hernández ⁷ 

- ¹ Department of Global Health and Social Medicine, Harvard Medical School, Boston, MA 02115, USA
 - ² Center for Climate, Health and the Global Environment (C-CHANGE), Harvard T.H. Chan School of Public Health, Boston, MA 02115, USA
 - ³ Department of Epidemiology, Mailman School of Public Health, Columbia University, New York, NY 10032, USA
 - ⁴ Department of Environmental Science, American University, Washington, DC 20016, USA
 - ⁵ Department of Health Studies, American University, Washington, DC 20016, USA
 - ⁶ The Collaborative for Women's Environmental Health, Department of Obstetrics and Gynecology, Columbia University Irving Medical Center, New York, NY 10032, USA
 - ⁷ Department of Sociomedical Sciences, Mailman School of Public Health, Columbia University, New York, NY 10032, USA
 - ⁸ Nelson Institute for Environmental Studies, University of Wisconsin, Madison, WI 53706, USA
 - ⁹ Department of Counseling Psychology, Teachers College, Columbia University, New York, NY 10027, USA
 - ¹⁰ Gangarosa Department of Environmental Health, Rollins School of Public Health, Emory University, Atlanta, GA 30322, USA
 - ¹¹ Department of Environmental Health Sciences, Mailman School of Public Health, Columbia University, New York, NY 10032, USA
- * Correspondence: nadav_sprague@hms.harvard.edu



Academic Editors: Hossein Bonakdari, Ebrahim Ghaderpour and Silvio José Gumiere

Received: 26 September 2025
Revised: 13 November 2025
Accepted: 18 November 2025
Published: 21 November 2025

Citation: Sprague, N.L.; Meltzer, G.Y.; Dandeneau, M.L.; De Los Santos, D.; O'Neil, D.B.; Kim, A.K.; Parisi, A.; Araujo, S.; Ekenga, C.C.; Siegel, E.L.; et al. A Role for Artificial Intelligence (AI) in Qualitative Research? An Exploratory Analysis Examining New York City Residents' Perceptions on Climate Change. *Sustainability* **2025**, *17*, 10459. <https://doi.org/10.3390/su172310459>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Abstract

As artificial intelligence (AI) advances, there is growing interest in leveraging this technology to enhance climate change research and responses. While AI has been applied in quantitative climate research, its role in qualitative research remains underdeveloped. Yet, qualitative inquiry is essential for understanding how individuals perceive and experience the effects of climate change. This study aimed to both (1) gain a deeper understanding of New York City residents' perceptions and lived experiences of climate change and (2) evaluate the suitability of AI for analyzing qualitative data. Using StreetTalk, a qualitative method involving street-intercept video interviews and social media dissemination, research teams analyzed interview transcripts through four approaches: human-only, human-then-AI, AI-then-human, and AI-only. Co-authors were then provided with anonymized (blinded) versions of the final theme sets that they did not contribute to and evaluated them using a standardized rubric developed for this study. The AI-then-human approach produced the most comprehensive and contextually accurate results, yielding nine key themes: (1) personal responsibility and action, (2) community unity and support, (3) government and corporate responsibility, (4) concern for future generations, (5) climate change impact, (6) climate-related conspiracy theories, (7) low literacy around local climate change, (8) helplessness, and (9) competing interests around climate change. These findings provide valuable local perspectives to guide evidence-based strategies for climate mitigation and community engagement. This research also represents an initial step toward establishing best practices for integrating AI into qualitative data analysis.

Keywords: control trial; climate change perceptions; StreetTalk; street intercept interviews; ChatGPT; qualitative analysis evaluation tool; public health; environmental change; global warming

1. Introduction

As climate change accelerates and continues to pose significant threats to ecosystems and human livelihoods globally, advancements in artificial intelligence (AI) are simultaneously reshaping industries by enhancing communication, streamlining workflows, and transforming interactions with technology [1–5]. The impacts of climate change on human life and wellbeing are severe and devastating, whereas the impacts of AI are more nuanced, promising both incredible advancements and profound ethical considerations for the future of humanity. While the energy-intensive processes behind AI raise valid concerns about its environmental sustainability and justice [6,7], its integration into research and daily life is inevitable [8]. To ensure AI's role in combating climate change, rather than exacerbating, we must adapt early and critically assess its capabilities to create sustainable solutions for the future [9].

1.1. The Importance of Qualitative Research on Climate Change Perceptions

Climate change is the human-induced acceleration of alterations to the Earth's long-term climate patterns, primarily attributed to the emission of greenhouse gases [10]. The impacts of climate change are dire. Such impacts include the destabilization of ecosystems, worsening natural disasters, and threats to food and water security, which will present significant challenges to human health, infrastructure, sociodemographic equity, and geopolitical stability [3,11–13]. Despite climate change's global reach, its impacts differ inter- and intra-regionally and vary from macroclimates to microclimates [12,14,15].

As climate change transpires within communal boundaries, we must gain a nuanced understanding of its local impacts through people's lived experiences. Current research on climate change perspectives is dominated by quantitative surveys that capture broad political environmental typologies and generalized demographic information [16,17]. However, these surveys fail to capture personal knowledge gained from individuals' and communities' lived experiences coping with climate change [17,18]. Incorporating qualitative research is imperative to understand individuals and communities' perspectives and lived experiences and develop culturally appropriate mitigation strategies.

1.2. Societal and Environmental Impacts of AI

The exponential evolution of AI has coincided with the rapid escalation of climate change. The use of AI has marked a paradigm shift across virtually every sector—from national and personal security to school bullying, quantitative research, and celebrity gossip—reshaping the landscape of modern society [19–22]. By optimizing workflows, enhancing communication, and enabling breakthroughs in fields like healthcare and energy, AI has demonstrated transformative potential [23,24]. However, these advancements are accompanied by significant societal and environmental costs that must not be overlooked.

One of the most pressing concerns is the ecological footprint of AI. Training large-scale models, such as those used for natural language processing (NLP) and image recognition, demands vast computational power and energy resources. For instance, training GPT-3 consumed approximately 1287 megawatt-hours (MWh) of electricity [25]. However, the inference phase of AI models—where trained models are deployed for practical use—may have an even greater energy demand [6,25]. For example, supporting ChatGPT was

estimated to require 564 MWh of electricity per day, underscoring the substantial ongoing costs of AI applications [25]. Furthermore, broader integration of generative AI, such as incorporating AI into every Google search, could result in daily electricity consumption of up to 80 GWh, equating to 29.2 TWh annually [25]. These figures illustrate the growing energy demands associated with AI deployment at scale. The environmental costs of AI extend beyond energy usage. The production of AI hardware, such as GPUs, relies on rare earth materials, which are resource-intensive to extract and process [6,25]. This contributes to habitat destruction, pollution, and a growing global e-waste problem.

As AI becomes inevitably becomes increasingly integral to modern society [26], it is imperative to prioritize Green AI—the development and deployment of AI systems designed with sustainability in mind [27]. Briefly, Green AI, also referred to as Sustainable AI, seeks to reduce the environmental impact of AI technologies by improving energy efficiency and encouraging the adoption of sustainable resources [27,28]. By adopting sustainable practices, AI can potentially contribute to addressing climate change rather than exacerbating it. For instance, AI has the potential to advance climate science by enabling sophisticated predictive models for climate patterns, enhancing disaster response strategies, and optimizing renewable energy systems [29–32]. Simultaneously, efforts to make AI itself more sustainable, such as streamlining the computational requirements for training and inference, can reduce its environmental impact [33]. By critically leveraging AI in this manner, we can attempt to ensure its transformative capabilities are aligned with the global imperative to combat climate change.

1.3. Leveraging Artificial Intelligence (AI) for Qualitative Research

While AI should be handled with concern and caution, it has the ability to optimize workflow processes and streamline human interactions [23,24]. In various fields of research, AI has allowed for advancements in quantitative methodologies by processing and analyzing big datasets with unprecedented speed and accuracy [34,35]. AI-powered tools, such as machine learning algorithms and natural language processing, enhance efficiency and scalability in quantitative research by enabling predictive modeling, pattern recognition, data visualization, and streamlined data collection and analysis [36,37].

While AI has already transformed the landscape of quantitative research methodologies, its impact on qualitative research remains limited. Like quantitative approaches, qualitative research is an intensive, detail-oriented process that demands systematic rigor, iterative reflection, and contextual sensitivity. As such, AI can serve as a powerful tool for qualitative research (just as it has for quantitative work) by supporting the organization, synthesis, and exploration of complex datasets [38]. Integrating AI into this process, however, raises both practical and theoretical questions about how meaning is constructed, interpreted, and represented. From an interpretivist perspective, qualitative analysis seeks to uncover patterns of meaning through the interaction between data, researcher, and context [39]. Large language models (LLMs) operate by detecting and summarizing patterns across vast collections of text—a process that, while computational, conceptually parallels human thematic abstraction at scale [40]. Testing AI within qualitative analysis thus provides a theoretical opportunity to examine whether algorithmic pattern recognition can augment or approximate human interpretive reasoning.

The application of AI into qualitative research has been primarily limited to auto-coding or identifying key words. Briefly, auto-coding in qualitative analysis begins with human researchers creating codes through thematic analysis [41]. Subsequently, qualitative analysis software (like NVivo and ATLAS.ti) identifies patterns within the data and assigns codes accordingly to the detected themes [41,42]. Other studies have leveraged AI to generate keywords in attempt to reduce the time and financial burdens of qualitative

analysis. For example, one study that used a natural language processing program on Python 3.7.4 64-bit to identify keywords found that this process reduced project time by a minimum of 120 h and reduced costs by \$1500 [40]. However, this study did not have a rigorous assessment evaluating the accuracy and quality of the AI- and human-generated data compared to the fully human-generated data. Moreover, the methods employed in this study utilized coding in Python for qualitative analysis. As such, to replicate this study would necessitate qualitative researchers to possess Python coding skills—a proficiency often lacking among both qualitative and quantitative researchers [43,44]. It is important to note that while the existing examples focus primarily on improving efficiency in terms of time and financial savings, there is potential for AI to also enhance the quality and depth of thematic analysis. In large, qualitative research has overlooked the potential of leveraging existing knowledge accessible within now mainstream AI applications, such as contextualizing data within previously published works and identifying subtle patterns and nuances, which could potentially enrich thematic analysis. Harnessing these capabilities would enable researchers to develop comprehensive codes and themes in interview transcripts more effectively, thereby enhancing the depth and richness of qualitative data analysis.

1.4. Integrating Artificial Intelligence to Qualitative Data Analysis on Climate Change Perceptions

Despite the looming threat of climate change, there is limited scientific research that qualitatively investigates individuals' personal perceptions on how climate change impacts their lives [45–47]. To date, AI has been underutilized in qualitative research, as it has not yet been employed to develop specific thematic codes. With this in mind, our interdisciplinary team explored personal perceptions on climate change impacts while at the same time testing a novel use of AI by utilizing it to help develop themes. Given that climate change is a pressing issue impacting all living beings on the planet we aimed to add to the limited body of qualitative, field-based research on the subject.

In this study, we examined New York City (NYC) residents' experiences and perceptions of climate change and its societal impacts. We did so by implementing the StreetTalk methodology, a strategy developed by this research team to conduct rapid street intercept interviews and an associated social media dissemination strategy [48]. The StreetTalk research methodology entails engaging passersby in public settings and asking questions on a given topic, thereby eliciting spontaneous and dynamic responses from those willing to talk to strangers on camera. A key element of this approach is to post those interviews on social media platforms to enable widespread and timely dissemination.

The present study aimed to (1) gain a deeper understanding of NYC residents' perceptions and lived experiences of climate change and (2) evaluate the suitability of AI for analyzing the qualitative data generated via street intercept interviews. As such, this paper offers new substantive and methodological insights by tackling the intersection of two major burgeoning societal issues: climate change and AI.

2. Methods

Using the novel StreetTalk research method, we examined NYC residents' experiences, knowledge, and perceptions of climate change. Then, during our thematic analysis, we conducted a blinded control trial to assess the suitability of currently available AI technologies as a tool for developing themes in a qualitative analysis. The Columbia University Institutional Review Board approved this study [AAAU3071]. Prior to participating in this study, participants signed informed consent and media release forms approved by Columbia University.

2.1. Positionality Statement

The interdisciplinary research team comprised individuals from diverse racial, ethnic, and socioeconomic backgrounds, all of whom had firsthand experiences with climate change while residing in NYC. This team consisted of students, trainees, and faculty from numerous disciplines, including epidemiology, biology, anthropology, environmental science, sociology, environmental health, public health, psychology, and sociomedical sciences. Our team's principal investigator (D.H.) is a NYC-native (South Bronx) Latina sociologist and public health researcher. Every author participated in the data collection and analysis stages of this study.

The research team developed the current project to normalize and publicize NYC residents discussing the impacts of climate change through a new method that records and disseminates individuals' experiences and challenges living in the time of climate change. We wanted to understand the perspectives of everyday residents on this topic as these high-level conversations were occurring throughout NYC to engage the public in climate change discourse and publicize those perspectives on social media and the academic literature.

2.2. StreetTalk Data Collection

The team identified Central Park/Midtown, Greenwich Village/Washington Square Park, Harlem, and Washington Heights as ideal locations for data collection, as they are areas within Manhattan that represent NYC's diverse population.

In September 2023, groups of two to four research team members went into the field to recruit participants and then interview willing participants on-the-spot. Researchers approached people on the sidewalk, at bus stops, in parks, as well as other public outdoor locations to ask passersby whether they would be interested in participating in this study. Once a person demonstrated interest, they were then screened into the study based on whether they currently lived in one of NYC's five boroughs. Then the researchers reviewed the consent and media release forms to the participants, highlighting the social media nature of the project and answering any questions. Participants were informed that they were allowed to drop out of this study at any point or retract a statement from the recording. Those who agreed to participate then signed both forms before the interview was initiated.

Immediately after the researchers received the signed consent and media release forms, one researcher began conducting the interview, while the other video and audio recorded the discussion. Table 1 presents the interview questions and supplementary probes.

Table 1. Questions and Probes for StreetTalk Interviews.

Question	Probe
What comes to mind for you when you think about climate change?	
What concerns do you have about climate change?	
Climate change has been shown to cause heat waves, flooding, forest fires, tropical storms, and other natural disasters. In what ways have you personally experienced the effects of climate change?	How does climate change impact your daily life? (If at all)
	Have you had to adjust or change your behavior accordingly? How so?
	What about during this summer specifically?
	How has the air pollution from the Canadian wildfires affected you?
Our area is prone to heavy rain in part due to climate change. Has that affected you in any way?	Were you directly impacted by Hurricanes Ida or Sandy? If so, what was that experience like for you?
In your opinion, what steps should the government and local authorities, and/or corporations take to address climate change and its impacts in New York City?	
What actions can you and other individuals take to reduce the effects of climate change in our everyday lives?	

All interviews were conducted in English and lasted approximately 10–15 min. Participants received a \$10 gift card as compensation.

2.3. *StreetTalk Data Analysis Control Trial*

For this study, we conducted a blinded control trial on the thematic analysis of the StreetTalk video transcripts where analysts were randomly assigned to one of the following thematic analysis groups: human-only, human-then-AI, AI-then-human and AI-only. Co-authors were provided with anonymized versions of the final set of themes that they did not contribute to, along with a predetermined rubric for grading. Co-authors' scores were averaged to determine whether AI is a suitable option for developing themes in qualitative analysis as compared to traditional methods.

In addition to understanding NYC residents' perceptions of climate change, the research aimed to test the utility of leveraging AI to develop themes. In contrast to previous studies that required complex Python coding skills, we opted to use Open AI's TeamGPT (the team version of ChatGPT) running the GPT-4 Turbo model because it offered a user-friendly interface and the ability to rapidly process and analyze large amounts of text data. TeamGPT also has advanced data privacy protection and enhanced control over data handling. All data was non-sensitive and transcripts were de-identified prior to unloading transcripts to the TeamGPT platform.

2.3.1. Testing AI- Versus Human-Generated Qualitative Analysis

To test the efficacy of AI in creating themes, we divided the research team into three groups, each responsible for developing a set of themes, while the fourth version was solely generated by TeamGPT. Each group was given a template to fill out that included theme name, theme description, and sample quotes (Supplementary S1).

The first group was the fully human-generated themes (co-authors G.Y.M., M.L.D., S.A., and D.B.O.). This group followed the same thematic analysis process that we used and described in greater detail in our prior paper [48]. Briefly, using an interpretivism paradigm [49], this team conducted the qualitative thematic analysis through Braun and Clarke's six phases codebook approach to thematic analysis [50]. The six phases were (1) familiarizing themselves with the data, (2) generating preliminary codes, (3) searching for themes connecting preliminary codes, (4) reviewing potential themes, (5) defining and naming themes, and (6) producing a report [50]. The group took four weeks to analyze the data (weeks 1–4 of data analysis).

The second group conducted the human-then-AI-generated thematic analysis (co-authors N.L.S., A.K.K., D.H.). This group randomly selected 25% of the transcripts and followed the same steps as the fully human-generated thematic analysis group for those transcripts to create a preliminary set of themes. The group then entered all the StreetTalk video recorded transcripts and the prompt, which included the preliminary set of themes, presented in Supplementary S2 to TeamGPT. TeamGPT then generated a report with a finalized set of themes that incorporated all the transcripts and the knowledge gained from the preliminary set of human-generated themes. The group took one week to analyze the data (week 1).

To produce the fully AI set of themes, the first author (N.L.S.) uploaded all StreetTalk video transcripts along with the prompt in Supplementary S3. This step was completed after the human-then-AI team developed their preliminary set of themes, but before the preliminary set of themes were inputted into TeamGPT. This timing was strategic to ensure that neither the fully AI or human-then-AI set of themes influenced each other on the platform. TeamGPT then produced a final report that incorporated all the transcripts. This took one day to complete (last day of week 1).

The third group conducted the AI-then-human-generated thematic analysis (co-authors E.L.S., P.A., D.D.L.S.). This group revised the fully AI-generated themes based on the transcripts and video recordings of the StreetTalk interviews. The team followed the following steps: (1) familiarizing themselves with the transcripts and video recordings of the StreetTalk interviews and the TeamGPT-produced themes, (2) identify gaps in the TeamGPT-produced themes, (3) revise TeamGPT-produced themes based on interview transcripts, (4) double check and update the quotes provided by TeamGPT to ensure none were made up, and (5) producing a report. The group took three weeks to analyze the data (weeks 2–4 of data analysis).

2.3.2. Thematic Analysis Scoring

The research team could not find a high-quality tool to assess the quality and accuracy of thematic codes. As such, the first and senior author of this study (N.L.S. and D.H.) worked together to develop the rubric presented in Table 2 based on accepted standards in qualitative research [50–53]. Before scoring, all reviewers were trained on the rubric and completed a calibration exercise using a practice set of themes to align expectations and ensure consistent application of the scoring criteria. During training, reviewers discussed example ratings and reached consensus on how to interpret each rubric dimension, which improved scoring reliability and minimized individual bias. The first author of this study (N.L.S.) blinded each of the finalized thematic reports. Each report was labeled by a random identifier, and reviewers were unaware of which analytic approach produced which set of themes. The first author then sent each group the thematic reports generated by the other groups with accompanying rubrics to evaluate the set of themes' quality and representation of the data (Table 2). The human-then-AI theme group graded every thematic report, as they never saw the final version of what TeamGPT generated and those themes were substantially different than what was inputted. Once the first author received the scores from the entire research team, the sets of thematic scores and ranks were averaged to determine which thematic analysis strategy was superior.

Table 2. Rubric to assess the thematic analyses.

Criteria	Description	Scoring *
Theme Definition	Clear and concise definition of each Theme.	0–10
Theme Saturation	Adequate coverage of all relevant themes in the data.	0–10
Contextual Understanding	Demonstrated understanding of the context when assigning themes.	0–5
Theme Integration	Integration of themes into a cohesive analytical framework.	0–5
Theme Independence	Absence of overlap or redundancy between themes.	0–5
Thematic Depth	Depth of analysis within each theme.	0–5
Theme Relevance & Utility	Relevance of theme to research questions or objectives, and practical usefulness for research purposes.	0–5
Total		/45

* Higher scores indicate higher quality, so that 45/45 is a perfect score and 0/45 is the worst possible score.

3. Results

3.1. Thematic Analysis Results by Group

From 10 to 28 April 2023, a total of 20 StreetTalk interviews were recorded, with 22 participants interviewed (two videos had two participants). Of the 22 participants, 7 were recorded in Washington Heights, 5 in Harlem, 5 in Greenwich Village/Washington Square Park, and 5 in Central Park/Midtown. While information on age, race, ethnicity, gender, and sexual identity was not collected, there appeared to be a diverse range within the sample.

Presented in Figure 1 are the resulting themes generated by each analytic workflow, illustrating similarities and divergences across human, hybrid, and fully AI approaches.

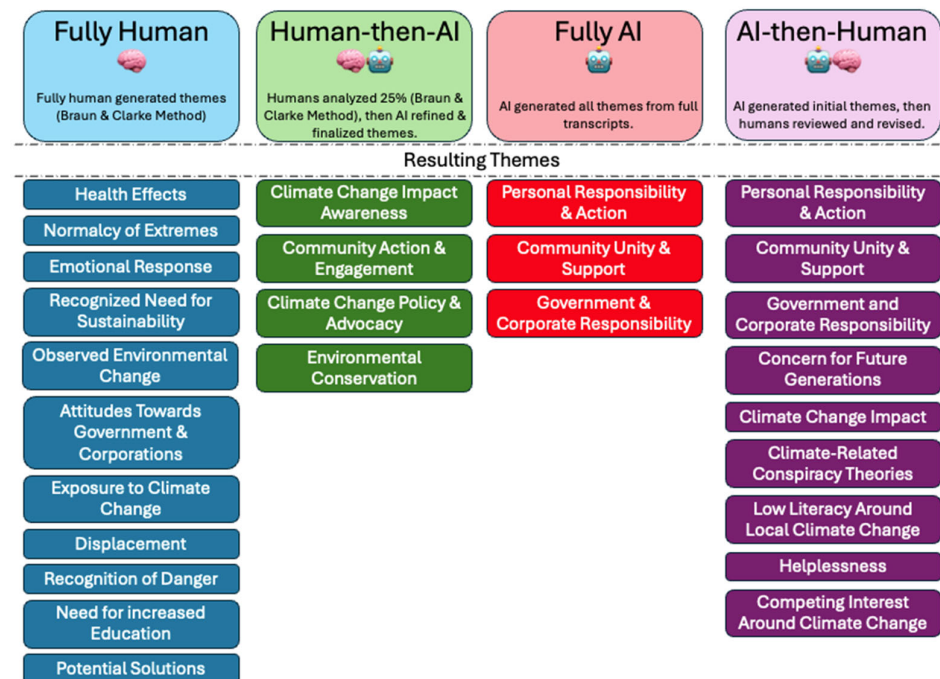


Figure 1. Resulting themes across analytic workflows varying in human and AI (Artificial Intelligence) involvement.

3.1.1. Fully Human-Generated Thematic Analysis

The fully human-generated thematic analysis group identified 11 themes on NYC residents' perceptions and thoughts surrounding climate change. The 11 themes were (1) health effects, (2) normalcy of the extremes, (3) emotional response, (4) recognized need for sustainability, (5) observed environmental changes, (6) attitudes towards government and corporations, (7) exposure to climate change, (8) displacement, (9) recognition of danger, (10) need for increased education, and (11) potential solutions (Figure 1). The definitions of the themes as well as exemplary quotes for each developed from this group are presented in Supplementary S4.

3.1.2. Human-Then-AI-Generated Thematic Analysis

Figure 1 presents the four themes generated by the human-then-AI analysis. Included in Supplementary S5 are the theme definitions and exemplary quotes. Briefly, the four themes were (1) climate change impact awareness, (2) community action and engagement, (3) climate change policy and advocacy, and (4) environmental conservation. TeamGPT generated the majority of exemplary quotes presented, extrapolating from the sentiment of participants' interviews, rather than taking the quotes directly from the transcripts. These quotes were not directly stated by participants; rather, TeamGPT broke protocol and developed exemplary quotes that encapsulated participants' perceptions or sentiments, summarizing and streamlining the quotes to be more clearly connected to the theme. This was not anticipated; however, the research team decided not to fix these quotes or identify the issues before the grading process, as it should be part of how it is graded. When grading, people would have to decipher on their own whether a quote was fake, which is a necessary skill as AI expands. If this analysis were to be chosen as the best, we would then fit exemplary quotes from participants. The exemplary quotes presented in Supplementary S5 are the ones selected and generated by AI.

3.1.3. Fully AI-Generated Thematic Analysis

As depicted in Figure 1 and Supplementary S6, the fully AI-generated themes were (1) personal responsibility and action, (2) community unity and support, and (3) government and corporate responsibility. Just like in the human-then-AI-generated themes, the quotes were not directly from participants, but were instead summarized and streamlined to be more closely connected to the theme.

3.1.4. AI-Then-Human-Generated Thematic Analysis

As presented in Figure 1, the AI-then-human-generated thematic analysis identified 9 themes: (1) personal responsibility and action, (2) community unity and support, (3) government and corporate responsibility, (4) concern for future generations, (5) climate change impact, (6) climate-related conspiracy theories, (7) low literacy around local climate change, (8) helplessness, (9) competing interests around climate change. The definitions of the themes as well as exemplary quotes for each thematic category developed from this group are presented in Supplementary S7. Just like in the other AI-generated themes, the quotes were not directly from participants but were instead summarized and streamlined to be more closely connected to the theme. However, since this was the AI-then-human-generated thematic analysis, the researchers identified and replaced any false quotes and also developed new themes to fill in gaps.

3.2. Thematic Analysis Grading

After the thematic analysis was complete, the first author (N.L.S.) blinded each set of themes and sent each group the thematic reports generated by the other groups with accompanying rubrics to evaluate the set of themes quality and representation of the data (Table 2).

We present each of the coauthors' final grades and the associated rank for the different thematic analysis strategies and overall team averages in Table 3. Figure 2 presents a heat map illustrating the average criterion-level scores assigned by all graders across seven dimensions of thematic quality for each analytic workflow.

Table 3. Grades and ranks of each thematic analysis type.

Grader (Co-Authors)	Fully Human-Generated		Human-Then-AI-Generated		Fully AI-Generated		AI-Then-Human-Generated	
	Grade (%)	Rank	Grade (%)	Rank	Grade (%)	Rank	Grade (%)	Rank
AP	93.33	1	88.89	2	42.22	3	N/A	N/A
DDLS	37.78	3	53.33	2	64.44	1	N/A	N/A
ELS	88.89	1	68.89	2	57.78	3	N/A	N/A
GYM	N/A	N/A	82.22	2	77.78	3	93.33	1
BDO	N/A	N/A	95.56	2	88.89	3	100	1
SA	N/A	N/A	64.44	2	57.78	3	86.00	1
MLD	N/A	N/A	80.00	2	75.56	3	95.56	1
AKK	95.56	2	86.67	3	73.33	4	100	1
DH	64.44	3	77.78	2	26.67	4	84.44	1
Average	76.00	2	77.53	2.11	62.72	3	93.22	1

Note: N/A indicates instances where graders were excluded from evaluating a text version that they themselves developed, in order to prevent self-assessment bias.

Average co-author ratings (0–10 or 0–5 scales) for seven dimensions of thematic quality under four analytic workflows				
	Fully human generated	Human-then-AI* generated	Fully AI* generated	AI*-then-human generated
Theme Definition (score 0-10)	7.60	8.89	8.33	9.67
Theme Saturation (score 0-10)	7.20	5.44	3.33	9.00
Contextual Understanding (score 0-5)	3.80	4.44	3.22	5.00
Theme Integration (score 0-5)	4.40	4.44	3.56	4.83
Theme Independence (score 0-5)	3.60	4.00	4.22	4.83
Thematic Depth (score 0-5)	3.60	3.56	2.22	4.50
Theme Relevance & Utility (score 0-5)	4.00	4.11	3.11	4.83
Color scale ranges from red = 0 (lowest possible score) to blue = maximum potential score (5 or 10, depending on the metric). Theme Definition and Theme Saturation were rated on a 0–10 scale; all other criteria were rated on a 0–5 scale.				
*AI=Artificial Intelligence				

Figure 2. Heat map of average criterion-level scores across analytic workflows.

The average grades were 76.00% for fully human-generated themes, 77.53% for human-then-AI-generated themes, 62.72% for fully AI-generated themes, and 93.22% for AI-then-human-generated themes. The average ranks were 2 for fully human-generated themes, 2.11 for human-then-AI-generated themes, 3 for fully AI themes, and 1 for AI-then-human-generated themes. As such, the fully AI-generated methodology for thematic analysis was subpar compared to fully human-generated themes. That said, the use of AI proves to be beneficial, as the human-then-AI-generated themes appeared to be comparable to traditional qualitative analysis methods and can be conducted in a quarter of the time of traditional methods. Further, the AI-then-human-generated themes were graded and ranked higher in quality than the traditional or other methods. However, the researchers on the AI-then-human data analysis team reported the burden to be similar to that of traditional analysis.

One evaluator (DDLS) rated AI-generated outputs higher than the other eight evaluators across multiple criteria. While we cannot determine the underlying cause of this discrepancy, it may reflect evaluator-level differences in discipline, expectations, or approaches to interpreting thematic depth. Because this divergence meaningfully influenced the distribution of scores, we include DDLS's criterion-level ratings in Supplementary S8, which can be compared directly with the average patterns presented in Figure 2.

4. Discussion

In this paper, we examined NYC residents' perceptions and lived experiences of climate change and tested the capability of AI to develop qualitative themes based on the transcripts. To do so, we first collected NYC residents' perceptions and thoughts on climate change utilizing the StreetTalk research method. Next, our research team split into isolated groups to conduct qualitative data analysis, employing varying degrees of AI integration. The sets of themes were blinded and then ranked by the research team using a standardized rubric. The results of the study indicate that the AI-then-human-generated themes were superior, while those fully generated solely by AI were deemed inferior. To further contextualize these findings, we next discuss the themes generated through the AI-then-human approach, followed by a discussion of the utility of AI in qualitative data analysis and a summary of strengths, limitations, and future directions.

4.1. NYC Residents' Perception of Climate Change Thematic Findings

Here, we will elaborate on the following nine AI-then-human-generated themes, contextualizing them within the existing literature: (1) personal responsibility and action, (2) community unity and support, (3) government and corporate responsibility, (4) concern for future generations, (5) climate change impact, (6) climate-related conspiracy theories, (7) low literacy around local climate change, (8) helplessness, (9) competing interests around climate change.

4.1.1. Personal Responsibility and Action

Personal responsibility and action underscore the accountability that individuals felt to mitigate climate change. Participants emphasized the significance of personal actions, ranging from simple gestures such as proper waste disposal to conscientious water usage practices. Individuals understood how their personal actions impact the environment. Prior research has demonstrated that those who are concerned with climate change are more likely to act, such as supporting climate change legislation and changing personal behaviors [54–56].

4.1.2. Community Unity and Support

However, participants also understood that they could not address climate change alone, exemplified by community unity and support. The NYC residents sampled stressed the importance of collective action and solidarity within their communities to effectively tackle climate change. Participants believed that collective efforts, such as community gardens and advocacy organizations, may be effective interventions to mitigate climate change on a more local level. Historically, grassroots community activism has been pivotal for promoting environmental health and societal change [57–59].

4.1.3. Government and Corporate Responsibility

While there was a general understanding of individuals' and communities' roles in addressing climate change, participants had varying opinions on government and corporate responsibility. Some participants did not believe that the government or large corporations were responsible for causing or mitigating the effects of climate change. This skepticism may stem from the documented practice of companies and governments hiring public relations firms to shape public perception and deflect responsibility for environmental issues, even when they are the leading contributors or when government oversight has allowed detrimental practices to persist [60–62]. Numerous studies have documented the use of public relations firms to employ sophisticated strategies to dissociate companies and government from culpability while presenting themselves as proactive in crisis management [60–62]. As such, companies and governments avoid blame and put the onus of climate change on individual action, even though research has consistently demonstrated their significant contribution to environmental degradation and climate disruption [55,62]. However, others recognized the substantial role corporations and governments have played in exacerbating climate change and their responsibilities to mitigate this looming threat. These individuals emphasized the crucial need to hold companies and governments accountable for their environmental impacts and many expressed skepticisms about the efficacy of their current mitigation initiatives.

4.1.4. Concern for Future Generations

Irrespective of to whom NYC residents attributed responsibility for causing and mitigating climate change, there was steadfast and uniform concern for future generations. This was specifically relevant to parents, especially mothers, who were concerned for their children's and grandchildren's futures. Becoming a parent often catalyzes a profound shift in perspective regarding the urgency of the climate crisis [63]. Parenthood prompts

a reevaluation of the world's threats, leading to a heightened sense of immediacy in addressing the climate crisis [64,65]. The concern for future generations underscores NYC residents' understanding that climate change is worsening, and future generations will suffer if it is not more aggressively mitigated.

4.1.5. Climate Change Impacts

While there was a concern for future generations, many NYC residents claimed to have already witnessed the tangible climate change impacts affecting their daily lives. Participants connected climate change to shifting weather patterns, recounting experiences such as flash floods leading to the loss of vehicles; higher electric bills to accommodate greater cooling needs during hotter summers; and alterations in gardening or urban agricultural practices. Understanding the concrete ramifications of climate change for daily life has been pinpointed as an important motivator for individual action [66,67].

4.1.6. Climate-Related Conspiracy Theories and Low Literacy Around Local Climate Change

Although there was an overall understanding of climate change impacts, some participants shared climate-related conspiracy theories and exhibited low literacy around local climate change issues. Some participants endorsed climate-related conspiracy theories, attributing climate events to governmental or extraterrestrial interference. These dangerous theories fuel misinformation and often deter people from environmentally friendly initiatives, posing challenges to combating climate change [68]. These perspectives highlight a distrust in official narratives and a tendency to seek alternative explanations for climate phenomena, indicating a gap in scientific and climate related literacy. Concurrently, participants struggled to connect broader climate change issues with local community concerns, exemplified by references to individuals littering in a park as the primary manifestation of climate change or not understanding how increases in extreme weather relates to climate change. These two themes underscore the importance of high-quality climate change education to combat misinformation and low climate literacy [69,70].

4.1.7. Helplessness

Participants expressed a profound sense of helplessness regarding the ability of individuals or governments to effectively address the climate crisis. Many believed that climate change was irreversible, and some feared that it will lead to an inevitable mass extinction. Climate change helplessness can also be concerning, as studies have suggested that it can lead to inaction and a reluctance to adopt environmentally friendly changes [71,72].

4.1.8. Competing Interests Surrounding Climate Change

Participants also shared concerns around competing interests surrounding climate change. Particularly, they highlighted tensions between business interests, current lifestyles, and the sacrifices needed to mitigate climate change. NYC residents recognized the complexity of finding pragmatic solutions, acknowledging, for instance, the challenge of transitioning away from fossil fuels while considering economic implications and societal readiness. These perspectives illustrate the multifaceted nature of the climate change discourse, emphasizing the necessity of navigating competing interests to achieve meaningful progress towards sustainability.

4.2. The Utility of AI in Qualitative Data Analysis

While the integration of AI presents significant opportunities for streamlining qualitative research, our results underscore the necessity of human-assistance and oversight in using AI in qualitative analysis to ensure accuracy and reliability. This is evident in our control trial's results, where the fully AI-generated themes were scored the lowest and the AI-then-human-generated themes were scored the highest. Fully human and human-then-

AI themes were scored similarly, with averages falling approximately 15% below those of AI-then-human themes and 15% above fully AI-generated themes. When examined across the specific evaluation criteria, both the fully AI-generated and human-then-AI-generated approaches tended to perform the poorest on adequate coverage of all relevant themes in the data, demonstrated understanding of the context when assigning themes, depth of analysis within each theme, and relevance of themes to research questions or objectives. These shortcomings highlight areas where interpretive nuance and contextual awareness remain difficult for AI to replicate.

As such, our study underscores the critical need for sustained human involvement to ensure the accuracy and reliability of AI-generated insights, while also highlighting the enhanced robustness AI has to offer in thematic analysis. Qualitative data often contains nuances, ambiguities, and cultural contexts that may challenge AI algorithms' comprehension and interpretation [73]. Human analysts bring contextual understanding and cultural sensitivity to the analytic process, allowing for nuanced judgments that are not suitable for AI [74,75]. Further, human involvement provides an additional layer of quality assurance to the analytic process. Humans can critically evaluate the validity and reliability of AI-generated insights, identify errors or inaccuracies, and ensure that the analysis aligns with the research objectives and theoretical framework [75,76]. Qualitative data analysis that leverages both AI and human expertise through a co-creation of themes allows for more robust and higher quality results. Despite the more robust findings, the group that conducted the AI-then-human thematic analysis shared that it was an iterative process and the time burden appeared to be comparable to fully human thematic analysis. As such, this study suggests that when used appropriately with proper human supervision, AI may serve as a valuable tool for co-producing thematic analysis to enhance quality and rigor without necessarily reducing time.

The team encountered some difficulties in utilizing TeamGPT for qualitative analysis. These included TeamGPT's text limit, as well as the fabrication of quotes. The generation of fabricated quotes is particularly concerning, as it could have drastically altered the study's findings if not identified and corrected. This highlights the critical need for thorough human oversight and validation when using AI tools in qualitative analysis, as failing to detect such errors would result in inaccurate or misleading conclusions. We hope that this article encourages computer scientists and software engineers to develop AI systems as user-friendly as TeamGPT, but with special specifications for qualitative analysis. For instance, existing qualitative data analysis software, such as NVivo and ATLAS.ti, may consider integrating AI or platforms, such as TeamGPT, can develop features to upload and store transcripts and specification of theoretical approach to qualitative analysis.

4.3. Strengths, Limitations, and Next Steps

This study has several strengths, both in the utilization of the new StreetTalk methodology to explore new dimensions of the public's perception of climate change and in the creative control trial designed to examine the efficacy of AI data analysis for qualitative research. The StreetTalk methodology allows for rapid data collection and dissemination of findings, facilitating timely insights into NYC residents' experiences, knowledge, and perceptions of climate change. Additionally, it enables the distribution of information that is easily accessible to the public, bridging the gap between academia and the wider community [48]. Further, the use of AI for thematic analysis presents innovative opportunities to streamline data processing and enhance efficiency in identifying key themes.

However, there are also limitations to consider with this study. The reliance on the StreetTalk methodology may introduce selection bias, favoring respondents comfortable with appearing on social media and excluding homebound or privacy-conscious individu-

als. Despite efforts to mitigate this bias, such as using techniques to protect participants' identities, the results may not fully represent the diversity of NYC residents. Demographic data (e.g., age, sex, and education level) were not collected to preserve participant comfort during spontaneous public interviews. While this approach supported open participation, it limits the ability to interpret findings across demographic subgroups. Moreover, since the study was conducted in the context of NYC and based on the perspectives of 22 participants, the findings should not be generalized beyond this sample.

The StreetTalk interviews are intentionally focused and brief, potentially limiting the depth of responses compared to traditional qualitative research methods. Consequently, the insights obtained may not fully capture the nuances of participants' experiences and perspectives. Future research should evaluate AI-assisted thematic analysis across longer or more complex qualitative inputs, such as focus groups or in-depth interviews. Doing so will help clarify how AI models—which often improve with increased input but can also become less precise, redundant, or prone to fabrication depending on data volume and structure—perform across different qualitative contexts.

Future examination of the StreetTalk street-intercept and social media-based methodology is warranted to better understand how public settings shape participation and disclosure. Although participants were compensated, provided with clear explanations of the study purpose, and signed IRB-approved consent and media release forms, the public and visible nature of the StreetTalk methodology may influence how comfortable individuals feel sharing sensitive opinions or experiences. At the same time, this format reflects how many people now express perspectives in social and digital spaces and may reduce the hierarchical dynamics of traditional research interviews by fostering more informal, peer-like exchanges. Continued refinement of this approach could help bridge participatory research and science communication, offering a model for engaging diverse publics in environmental discourse.

5. Conclusions

We employed the StreetTalk methodology to rapidly capture and disseminate public perceptions of climate change among NYC residents, alongside an innovative exploration of AI's role in qualitative data analysis. We conducted a four-armed control trial to evaluate AI's capabilities for qualitative theme development of New York City residents' perceptions and lived experiences with climate change. This trial involved varied degrees of AI integration in qualitative data analysis. The resulting themes were graded and ranked by the research team, ultimately identifying the AI-then-human-generated themes as the most effective method. In this hybrid approach, AI produced initial thematic categories that were then refined, corrected, and contextualized by human researchers, a process that improved coherence but did not reduce analytical workload. These findings represent an initial step toward establishing best practices for integrating AI into qualitative data analysis, emphasizing that its effectiveness depends on active human supervision, critical interpretation, and iterative refinement rather than full automation.

The resulting themes encompassed personal responsibility and action, community unity and support, government and corporate responsibility, concern for future generations, climate change impact, climate-related conspiracy theories, low literacy around local climate change, helplessness, and competing interests around climate change. Taken together, the themes identified in this study have direct implications for local action and intervention design. The recurring difficulty participants had in connecting climate change to NYC-specific problems (e.g., flash floods that damaged vehicles, higher cooling costs, degraded air quality) suggests that policymakers and community organizations could prioritize hyperlocal climate education that explains “what climate change looks like in

this neighborhood.” Similarly, the strong concern for future generations indicates that parent- and school-focused engagement efforts may be particularly effective avenues for climate communication and interventions that emphasize intergenerational responsibility and action. Finally, the theme of community unity and support highlights the potential of community gardens, mutual-aid-style preparedness efforts, and block-level initiatives as culturally resonant entry points for climate mitigation and adaptation. Together, these findings point toward a multi-level strategy for climate engagement and resilience—one that empowers local collaboration while requiring coordinated action and accountability from governmental and corporate institutions—to create more just, sustainable, and climate-literate urban communities.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su172310459/s1>.

Author Contributions: Conceptualization, N.L.S., E.L.S. and D.H.; Methodology, N.L.S., E.L.S. and D.H.; Software, N.L.S. and D.H.; Validation, N.L.S. and D.H.; Formal analysis, N.L.S., G.Y.M., M.L.D., D.D.L.S., D.B.O., A.K.K., A.P., S.A. and E.L.S.; Investigation, N.L.S., G.Y.M., M.L.D., D.D.L.S., D.B.O., A.K.K., A.P., S.A., E.L.S. and D.H.; Resources, N.L.S. and D.H.; Data curation, N.L.S., D.D.L.S. and D.H.; Writing—original draft, N.L.S.; Writing—review & editing, N.L.S., G.Y.M., D.B.O., A.K.K., A.P., S.A., C.C.E., E.L.S. and D.H.; Visualization, N.L.S. and D.H.; Supervision, N.L.S., G.Y.M. and D.H.; Project administration, N.L.S., G.Y.M., M.L.D. and D.H.; Funding acquisition, D.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Alfred P. Sloan Foundation and the JPB Foundation. This work was also supported, in part, by the National Institutes of Health (P30ES019776). The content is solely the responsibility of the authors and does not necessarily represent the official views of NIH.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by Columbia University IRB Exp of IRB-AAAU3071 on 1 July 2025.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interests.

References

1. Handmer, J.; Honda, Y.; Kundzewicz, Z.W.; Arnell, N.; Benito, G.; Hatfield, J.; Mohamed, I.F.; Peduzzi, P.; Wu, S.; Sherstyukov, B. Changes in impacts of climate extremes: Human systems and ecosystems. In *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation Special Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK, 2012; pp. 231–290.
2. Turner, M.G.; Calder, W.J.; Cumming, G.S.; Hughes, T.P.; Jentsch, A.; LaDeau, S.L.; Lenton, T.M.; Shuman, B.N.; Turetsky, M.R.; Ratajczak, Z. Climate change, ecosystems and abrupt change: Science priorities. *Philos. Trans. R Soc. B* **2020**, *375*, 20190105. [[CrossRef](#)] [[PubMed](#)]
3. Sprague, N.L.; Uong, S.P.; Zonneville, H.; Chatterjee, T.; Hernández, D.; Rundle, A.G.; Ekenga, C.C. The CHANGE (Climate Health ANalysis Grading Evaluation) tool for weight of evidence reviews on climate change and health research. *Environ. Health* **2024**, *23*, 7. [[CrossRef](#)] [[PubMed](#)]
4. Khan, O.; Parvez, M.; Kumari, P.; Parvez, S.; Ahmad, S. The future of pharmacy: How AI is revolutionizing the industry. *Intell. Pharm.* **2023**, *1*, 32–40. [[CrossRef](#)]
5. Davenport, T.H. *The AI Advantage: How to Put the Artificial Intelligence Revolution to Work*; MIT Press: Cambridge, MA, USA, 2018.
6. Ligozat, A.-L.; Lefevre, J.; Bugeau, A.; Combaz, J. Unraveling the Hidden Environmental Impacts of AI Solutions for Environment Life Cycle Assessment of AI Solutions. *Sustainability* **2022**, *14*, 5172. [[CrossRef](#)]
7. Wu, C.-J.; Raghavendra, R.; Gupta, U.; Acun, B.; Ardalani, N.; Maeng, K.; Chang, G.; Aga, F.; Huang, J.; Bai, C. Sustainable ai: Environmental implications, challenges and opportunities. *Proc. Mach. Learn. Syst.* **2022**, *4*, 795–813.

8. Goel, S.; Guha, A.; Tripathy, B. The Inevitable Artificial Intelligence Revolution in Healthcare. In *Data-Driven Analytics for Healthcare*; Apple Academic Press: New York, NY, USA, 2025; pp. 35–54.
9. Lewis, J.I.; Toney, A.; Shi, X. Climate change and artificial intelligence: Assessing the global research landscape. *Discov. Artif. Intell.* **2024**, *4*, 64. [\[CrossRef\]](#)
10. Kumar, V.; Ranjan, D.; Verma, K. 9—Global climate change: The loop between cause and impact. In *Global Climate Change*; Singh, S., Singh, P., Rangabhashiyam, S., Srivastava, K.K., Eds.; Elsevier: Amsterdam, The Netherlands, 2021; pp. 187–211.
11. Ellwanger, J.H.; Kulmann-Leal, B.; Kaminski, V.L.; Valverde-Villegas, J.; Veiga, A.B.G.; Spilki, F.R.; Fearnside, P.M.; Caesar, L.; Giatti, L.L.; Wallau, G.L. Beyond diversity loss and climate change: Impacts of Amazon deforestation on infectious diseases and public health. *An. Acad. Bras. Ciências* **2020**, *92*, e20191375. [\[CrossRef\]](#)
12. Sprague, N.L.; Uong, S.P.; Jacobowitz, A.L.; Packard, S.E.; Quinn, J.W.; Keyes, K.M.; Rundle, A.G. Examining racial and ethnic heat exposure disparities in NYC (NYC) across different spatial and political scales through geographic effect measure modification. *Environ. Res.* **2024**, *250*, 118521. [\[CrossRef\]](#)
13. Masson-Delmotte, V.; Zhai, P.; Pirani, A.; Connors, S.L.; Péan, C.; Berger, S.; Caud, N.; Chen, Y.; Goldfarb, L.; Gomis, M. *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK, 2021; Volume 2, p. 2391.
14. Parmesan, C.; Morecroft, M.D.; Trisurat, Y. *Climate Change 2022: Impacts, Adaptation and Vulnerability*; GIEC: Paris, France, 2022.
15. Sprague, N.L.; Uong, S.P.; Kelsall, N.C.; Jacobowitz, A.L.; Quinn, J.W.; Keyes, K.M.; Rundle, A.G. Using geographic effect measure modification to examine socioeconomic-related surface temperature disparities in New York City. *J. Expo. Sci. Environ. Epidemiol.* **2024**, *35*, 792–801. [\[CrossRef\]](#)
16. Drummond, C.; Fischhoff, B. Individuals with greater science literacy and education have more polarized beliefs on controversial science topics. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 9587–9592. [\[CrossRef\]](#)
17. Kleinberg, S.; Toomey, A.H. The use of qualitative research to better understand public opinions on climate change. *J. Environ. Stud. Sci.* **2023**, *13*, 367–375. [\[CrossRef\]](#)
18. Adger, W.N.; Barnett, J.; Brown, K.; Marshall, N.; O'Brien, K. Cultural dimensions of climate change impacts and adaptation. *Nat. Clim. Change* **2013**, *3*, 112–117. [\[CrossRef\]](#)
19. Saylor, K.M. *Artificial Intelligence and National Security*; Congressional Research Service: Washington, DC, USA, 2020; p. 4 5178.
20. Milosevic, T.; Verma, K.; Carter, M.; Vigil, S.; Laffan, D.; Davis, B.; O'Higgins Norman, J. Effectiveness of Artificial Intelligence-Based Cyberbullying Interventions From Youth Perspective. *Soc. Media + Soc.* **2023**, *9*, 20563051221147325. [\[CrossRef\]](#)
21. Chen, X.; Liu, Z.; Wei, L.; Yan, J.; Hao, T.; Ding, R. A comparative quantitative study of utilizing artificial intelligence on electronic health records in the USA and China during 2008–2017. *BMC Med. Inform. Decis. Mak.* **2018**, *18*, 55–69. [\[CrossRef\]](#)
22. Dunn, S. Identity manipulation: Responding to advances in artificial intelligence and robotics. In Proceedings of the WeRobot 2020, Virtual, 22–25 September 2020.
23. Floridi, L.; Cows, J. A Unified Framework of Five Principles for AI in Society. In *Machine Learning and the City*; John Wiley & Sons: Hoboken, NJ, USA, 2022; pp. 535–545.
24. Ranschaert, E.; Topff, L.; Panykh, O. Optimization of radiology workflow with artificial intelligence. *Radiol. Clin.* **2021**, *59*, 955–966. [\[CrossRef\]](#)
25. De Vries, A. The growing energy footprint of artificial intelligence. *Joule* **2023**, *7*, 2191–2194. [\[CrossRef\]](#)
26. Spalević, Ž.; Marković, F.; Marković, S. Artificial Intelligence: The New Inevitability of Contemporary Society. *Kult. Polisa* **2023**, *20*, 88–106. [\[CrossRef\]](#)
27. Tabbakh, A.; Al Amin, L.; Islam, M.; Mahmud, G.I.; Chowdhury, I.K.; Mukta, M.S.H. Towards sustainable AI: A comprehensive framework for Green AI. *Discov. Sustain.* **2024**, *5*, 408. [\[CrossRef\]](#)
28. Schwartz, R.; Dodge, J.; Smith, N.A.; Etzioni, O. Green ai. *Commun. ACM* **2020**, *63*, 54–63. [\[CrossRef\]](#)
29. Zhao, T.; Wang, S.; Ouyang, C.; Chen, M.; Liu, C.; Zhang, J.; Yu, L.; Wang, F.; Xie, Y.; Li, J. Artificial intelligence for geoscience: Progress, challenges and perspectives. *Innovation* **2024**, *5*, 100691. [\[CrossRef\]](#) [\[PubMed\]](#)
30. Sun, W.; Bocchini, P.; Davison, B.D. Applications of artificial intelligence for disaster management. *Nat. Hazards* **2020**, *103*, 2631–2689. [\[CrossRef\]](#)
31. Chen, C.-f.; Napolitano, R.; Hu, Y.; Kar, B.; Yao, B. Addressing machine learning bias to foster energy justice. *Energy Res. Soc. Sci.* **2024**, *116*, 103653. [\[CrossRef\]](#)
32. Cows, J.; Tsamados, A.; Taddeo, M.; Floridi, L. The AI gambit: Leveraging artificial intelligence to combat climate change—Opportunities, challenges, and recommendations. *AI Soc.* **2023**, *38*, 283–307. [\[CrossRef\]](#) [\[PubMed\]](#)
33. Alzoubi, Y.I.; Mishra, A. Green artificial intelligence initiatives: Potentials and challenges. *J. Clean. Prod.* **2024**, *468*, 143090. [\[CrossRef\]](#)
34. Surya, L. An exploratory study of AI and Big Data, and it's future in the United States. *Int. J. Creat. Res. Thoughts (IJCRT)* **2015**, *3*, 2320–2882.

35. Pencheva, I.; Esteve, M.; Mikhaylov, S.J. Big Data and AI—A transformational shift for government: So, what next for research? *Public Policy Adm.* **2020**, *35*, 24–44. [\[CrossRef\]](#)
36. Carrell, D.S.; Halgrim, S.; Tran, D.-T.; Buist, D.S.; Chubak, J.; Chapman, W.W.; Savova, G. Using natural language processing to improve efficiency of manual chart abstraction in research: The case of breast cancer recurrence. *Am. J. Epidemiol.* **2014**, *179*, 749–758. [\[CrossRef\]](#) [\[PubMed\]](#)
37. Bernert, R.A.; Hilberg, A.M.; Melia, R.; Kim, J.P.; Shah, N.H.; Abnoui, F. Artificial intelligence and suicide prevention: A systematic review of machine learning investigations. *Int. J. Environ. Res. Public Health* **2020**, *17*, 5929. [\[CrossRef\]](#)
38. Jiang, J.A.; Wade, K.; Fiesler, C.; Brubaker, J.R. Supporting serendipity: Opportunities and challenges for Human-AI Collaboration in qualitative analysis. *Proc. ACM Hum.-Comput. Interact.* **2021**, *5*, 1–23. [\[CrossRef\]](#)
39. Creswell, J.W.; Poth, C.N. *Qualitative Inquiry and Research Design: Choosing Among Five Approaches*; Sage publications: Thousand Oaks, CA, USA, 2016.
40. Abram, M.D.; Mancini, K.T.; Parker, R.D. Methods to integrate natural language processing into qualitative research. *Int. J. Qual. Methods* **2020**, *19*, 1609406920984608. [\[CrossRef\]](#)
41. Kalpokaite, N.; Radivojevic, I.; Best Practice Article: Auto-Coding and Smart Coding in ATLAS.ti Cloud. 2018. Available online: <https://atlasti.com/guides/qualitative-research-guide-part-2/auto-coding-smart-coding> (accessed on 6 October 2025).
42. Rietz, T.; Maedche, A. Cody: An AI-based system to semi-automate coding for qualitative research. In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems, Tokohama, Japan, 8–13 May 2021; pp. 1–14.
43. Mason, J.L.; Johnston, E.; Berndt, S.; Segal, K.; Lei, M.; Wiest, J.S. Labor and skills gap analysis of the biomedical research workforce. *FASEB J.* **2016**, *30*, 2673. [\[CrossRef\]](#) [\[PubMed\]](#)
44. Benhayoun, L.; Lang, D. Does higher education properly prepare graduates for the growing artificial intelligence market? Gaps' identification using text mining. *Hum. Syst. Manag.* **2021**, *40*, 639–651. [\[CrossRef\]](#)
45. Martin-Kerry, J.M.; Graham, H.M.; Lampard, P. 'I don't really associate climate change with actual people's health': A qualitative study in England of perceptions of climate change and its impacts on health. *Public Health* **2023**, *219*, 85–90. [\[CrossRef\]](#)
46. Toan, D.T.T.; Kien, V.D.; Giang, K.B.; Minh, H.V.; Wright, P. Perceptions of climate change and its impact on human health: An integrated quantitative and qualitative approach. *Glob. Health Action* **2014**, *7*, 23025. [\[CrossRef\]](#)
47. Mahl, D.; Guenther, L.; Schäfer, M.S.; Meyer, C.; Siegen, D. "We are a Bit Blind About it": A Qualitative Analysis of Climate Change-Related Perceptions and Communication Across South African Communities. *Environ. Commun.* **2020**, *14*, 802–815. [\[CrossRef\]](#)
48. Sprague, N.L.; Fan, I.B.; Dandeneau, M.; Hernandez Perez, J.F.; Birmingham, J.; De Los Santos, D.; Riddick, M.I.; Meltzer, G.Y.; Siegel, E.L.; Hernández, D. StreetTalk: Exploring energy insecurity in New York City using a novel street intercept interview and social media dissemination method. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 1109. [\[CrossRef\]](#)
49. Goldkuhl, G. Pragmatism vs interpretivism in qualitative information systems research. *Eur. J. Inf. Syst.* **2012**, *21*, 135–146. [\[CrossRef\]](#)
50. Braun, V.; Clarke, V. Toward good practice in thematic analysis: Avoiding common problems and be(com)ing a knowing researcher. *Int. J. Transgender Health* **2023**, *24*, 1–6. [\[CrossRef\]](#)
51. Castleberry, A.; Nolen, A. Thematic analysis of qualitative research data: Is it as easy as it sounds? *Curr. Pharm. Teach. Learn.* **2018**, *10*, 807–815. [\[CrossRef\]](#)
52. Vaismoradi, M.; Jones, J.; Turunen, H.; Snelgrove, S. Theme development in qualitative content analysis and thematic analysis. *J. Nurs. Educ. Pract.* **2016**, *6*, 100–110. [\[CrossRef\]](#)
53. Sebele-Mpofu, F.Y. Saturation controversy in qualitative research: Complexities and underlying assumptions. A literature review. *Cogent Soc. Sci.* **2020**, *6*, 1838706. [\[CrossRef\]](#)
54. Bouman, T.; Verschoor, M.; Albers, C.J.; Böhm, G.; Fisher, S.D.; Poortinga, W.; Whitmarsh, L.; Steg, L. When worry about climate change leads to climate action: How values, worry and personal responsibility relate to various climate actions. *Glob. Environ. Change* **2020**, *62*, 102061. [\[CrossRef\]](#)
55. Boto-García, D.; Buccioli, A. Climate change: Personal responsibility and energy saving. *Ecol. Econ.* **2020**, *169*, 106530. [\[CrossRef\]](#)
56. Sprague, N.L.; Zonneville, H.M.; Jackson Hall, L.; Williams, R.; Dains, H.; Liang, D.; Ekenga, C.C. Environmental health perceptions of urban youth from low-income communities: A qualitative photovoice study and framework. *Health Expect.* **2023**, *26*, 1832–1842. [\[CrossRef\]](#)
57. Bullard, R.D. *Dumping in Dixie: Race, Class, and Environmental Quality*; Routledge: New, York, NY, USA, 2018.
58. Shepard, P.M. Advancing environmental justice through community-based participatory research. *Environ. Health Perspect.* **2002**, *110* (Suppl. S2), 139. [\[CrossRef\]](#)
59. Middlemiss, L.; Parrish, B.D. Building capacity for low-carbon communities: The role of grassroots initiatives. *Energy Policy* **2010**, *38*, 7559–7566. [\[CrossRef\]](#)
60. Schultz, F.; Kleinnijenhuis, J.; Oegema, D.; Utz, S.; van Atteveldt, W. Strategic framing in the BP crisis: A semantic network analysis of associative frames. *Public Relat. Rev.* **2012**, *38*, 97–107. [\[CrossRef\]](#)

61. Hansen, A. *Environment, Media and Communication*; Routledge: New, York, NY, USA, 2018.
62. Brulle, R.J.; Werthman, C. The role of public relations firms in climate change politics. *Clim. Change* **2021**, *169*, 8. [CrossRef]
63. Benoit, L.; Thomas, I.; Martin, A. Review: Ecological awareness, anxiety, and actions among youth and their parents—A qualitative study of newspaper narratives. *Child Adolesc. Ment. Health* **2022**, *27*, 47–58. [CrossRef]
64. Gibson, C.; How climate experts think about raising children who will inherit a planet in crisis. *The Washington Post*, 14 February 2020. Available online: https://www.washingtonpost.com/lifestyle/on-parenting/how-climate-experts-think-about-raising-children-who-will-inherit-a-planet-in-crisis/2020/02/14/b4f3405a-4e69-11ea-b721-9f4cdc90bc1c_story.html (accessed on 6 October 2025).
65. Lawson, D.F.; Stevenson, K.T.; Peterson, M.N.; Carrier, S.J.; L Strnad, R.; Seekamp, E. Children can foster climate change concern among their parents. *Nat. Clim. Change* **2019**, *9*, 458–462. [CrossRef]
66. Crease, A.; Singhasaneh, N. Climate Change Conversations with Children: Making Sustainability Meaningful, Tangible, and Actionable. Master’s Thesis, Massachusetts Institute of Technology, Cambridge, MA, USA, 2023.
67. Lorenzoni, I.; Nicholson-Cole, S.; Whitmarsh, L. Barriers perceived to engaging with climate change among the UK public and their policy implications. *Glob. Environ. Change* **2007**, *17*, 445–459. [CrossRef]
68. Douglas, K.M.; Sutton, R.M. Climate change: Why the conspiracy theories are dangerous. *Bull. At. Sci.* **2015**, *71*, 98–106. [CrossRef]
69. Bangay, C.; Blum, N. Education responses to climate change and quality: Two parts of the same agenda? *Int. J. Educ. Dev.* **2010**, *30*, 359–368. [CrossRef]
70. Elshof, L. Can education overcome climate change inactivism. *J. Act. Sci. Technol. Educ.* **2011**, *3*, 15–51.
71. Salomon, E.; Preston, J.L.; Tannenbaum, M.B. Climate change helplessness and the (de)moralization of individual energy behavior. *J. Exp. Psychol. Appl.* **2017**, *23*, 15–28. [CrossRef]
72. Gunderson, R. Powerless, stupefied, and repressed actors cannot challenge climate change: Real helplessness as a barrier between environmental concern and action. *J. Theory Soc. Behav.* **2023**, *53*, 271–295. [CrossRef]
73. Bano, M.; Zowghi, D.; Whittle, J. Exploring Qualitative Research Using LLMs. *arXiv* **2023**, arXiv:2306.13298. [CrossRef]
74. Dwivedi, Y.K.; Hughes, L.; Ismagilova, E.; Aarts, G.; Coombs, C.; Crick, T.; Duan, Y.; Dwivedi, R.; Edwards, J.; Eirug, A. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *Int. J. Inf. Manag.* **2021**, *57*, 101994. [CrossRef]
75. Morgan, D.L. Exploring the use of artificial intelligence for qualitative data analysis: The case of ChatGPT. *Int. J. Qual. Methods* **2023**, *22*, 16094069231211248. [CrossRef]
76. Kaartemo, V.; Helkkula, A. A systematic review of artificial intelligence and robots in value co-creation: Current status and future research avenues. *J. Creat. Value* **2018**, *4*, 211–228. [CrossRef]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.