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Misrepresentation or inclusion: promises of generative artificial intelligence in climate change education

Ha Nguyen ^{a,b}, Victoria Nguyen^c, Sara Ludovise^d and Rossella Santagata^{c,*}

^aSchool of Education, The University of North Carolina at Chapel Hill, Chapel Hill, USA; ^bDepartment of Instructional Technology & Learning Sciences, Utah State University, Logan, USA; ^cSchool of Education, University of California, Irvine, Irvine, USA; ^dOrange County Department of Education, Costa Mesa, USA

ABSTRACT

Generative Artificial Intelligence (AI) technologies, including large language models (LLMs) that can generate novel text output, present promise for creating tailored science communication for broad audiences. However, LLMs might reflect inaccuracies and social biases from their training sources. In this work, we examine the promises and challenges of using LLMs to depict climate issues from intersectional perspectives. We prompt an LLM (GPT-4) to generate content about localized climate issues and simulate different communication mediums and intersectional identities. We conduct content analysis of the responses, drawing from Intersectional Climate Justice and Culturally Sustaining Pedagogies frameworks. Findings suggest that the LLM-created responses can restate climate justice principles in the prompts and do not frequently show inaccuracy. However, they may lack elaboration, show deficit framing, and overlook identity aspects. We discuss suggestions from critical education research, to question the assumptions underlying AI technologies and explore ways to promote inclusive climate education.

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Introduction

Generative Artificial Intelligence (GenAI) technologies, including large language models (LLMs) that can synthesize and generate novel text, enable efficient generation of teaching and learning resources. We explore the potential of leveraging LLMs to portray climate justice within a science communication curriculum. Climate justice connects sociocultural, racial, and environmental aspects of climate issues, to emphasize local impacts and unequal vulnerabilities (Schlosberg and Collins 2014). LLM-generated content can reflect the differential impacts of climate change, simulate the perspectives of diverse populations, and serve as a model for science communication.

While LLMs offer promise in education and science communication, they may provide outdated or misleading information (Zhang et al. 2023). Additionally, they may reflect biases in their training data and reinforce stereotypes against marginalized groups (Navigli, Conia, and Ross 2023; Yan et al. 2024). This is a concern in climate education, which has received long-standing criticisms for the historical omission of perspectives, particularly Black, Indigenous, and People of Color (BIPOC) communities (Schusler et al. 2021). Given these concerns, we investigate LLMs'

CONTACT Ha Nguyen  ha.nguyen@unc.edu  CB 3500 Peabody Hall, Chapel Hill, NC 27599, USA

*Rossella Santagata oversees project administration and can be reached at r.santagata@uci.edu

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assumptions about communities traditionally excluded from climate discussions (and potentially underrepresented in the models' training data). We ask: *How do large language models depict climate justice from an intersectional, culturally sustaining perspective?*

We leverage an LLM (OpenAI's GPT-4) to generate textual responses discussing climate justice issues. The responses simulate science communication mediums (e.g., social media posts, opinion pieces, online discussions), as well as perspectives at the intersection of race, socioeconomic status, (dis)ability, gender, age, and local climate issues. We experiment with different prompting strategies: minimal instruction (which we term *off-the-shelf*), and with explicit principles for intersectional climate justice (termed *with instruction*). Analyses draw from the Intersectional Climate Justice (Amorim-Maia et al. 2022) and Culturally Sustaining Pedagogies (Paris 2012) frameworks. We explore how responses showcase inaccuracies, stereotypes, and asset-based versus deficit language. We consult with high school science educators, students, and science communicators to evaluate the LLM-generated text.

Findings demonstrate that responses to both prompting strategies can replicate natural language patterns in the prompts to restate climate justice principles. While responses do not frequently show inaccuracy, they lack elaboration and rarely illustrate the perspectives of vulnerable groups, such as female and LGBTQ+ populations. Further, they might show a deficit framing of identities. Our work illuminates the need for education research to intersect with research on GenAI, to question the assumptions underlying the technology and explore ways to leverage the tool in climate education.

Background

Promises and challenges of large language models (LLMs)

LLMs are increasingly capable of synthesizing and generating text (Brown et al. 2020; Devlin et al. 2018; Radford et al. 2019). Pre-trained on extensive corpora of text data, these models can output human-like text without extensive tuning (Brown et al. 2020). Within science communication, scholars have examined the use of LLMs to provide writing inspiration (Gero, Liu, and Chilton 2022), generate content (Karinshak et al. 2023), and facilitate dialogs about scientific topics (Vaghefi et al. 2023). Karinshak et al. (2023) randomly assigned 852 participants aged 18–79 to interact with public health messages that were generated by either an LLM (GPT-3) or humans. They found that participants perceived LLM-generated messages as more persuasive, logical, and positive, compared to human-authored messages.

Despite these promises, there exist concerns that LLMs reflect their underlying training sources, and can thus embrace misinformation, social stereotypes, and exclusionary language (Acerbi and Stubbersfield 2023; Weidinger et al. 2022). Misinformation occurs when the models output inaccurate, misleading, or poor-quality information (Lin, Hilton, and Evans 2022). Researchers have incorporated in-depth evaluation from domain experts to reduce inaccuracies related to climate science in LLM-generated content (Muccione et al. 2024). Additionally, LLMs are not always capable of providing locally specific information. In a study involving 3,108 United States counties, Kim et al. (2024) found that LLMs like ChatGPT (enabled by GPT-4) showed limited ability to generate place-based information about environmental justice issues in rural and poor counties.

Further, LLMs can state harmful social stereotypes based on age (Díaz et al. 2018), race and ethnicity (Garg et al. 2018), gender (Lucy and Bamman 2021), and ability (Gadiraju et al. 2023; Venkit, Srinath, and Wilson 2022). LLM-generated content associated with marginalized identities (e.g., disabilities) tended to contain more stereotypical words than content linked to non-marginalized groups (Hutchinson et al. 2020; Nguyen et al. 2024). Importantly, LLMs may reflect stereotypes at the intersection of identities (Guo and Caliskan 2021). An analysis of LLMs' sentence completions reveals less diverse and more stereotypical jobs for women than men, particularly for intersection with ethnicity (Kirk et al. 2021).

Finally, LLMs may contain exclusionary language that marginalize identities (Zhao et al. 2021). This is because language often contains social categories that might overlook the

existence of entities outside of those categories. Dev et al. (2021) found that LLMs were likely to misgender, such as predicting pronouns like ‘he’ or ‘she’, rather than ‘they’ even when provided contexts.

Auditing LLMs

Researchers have explored misinformation, stereotypes, and exclusionary output in LLMs by asking the models to complete prespecified text (Kirk et al. 2021; Sheng et al. 2021), interact with human users (Chen et al. 2024; Gadiraju et al. 2023), and translate between languages (Saunders, Sallis, and Byrne 2020). These approaches examine harmful associations between the generated text and gender, sexuality, occupations, race, and ethnicity, among other factors (Dhamala et al. 2021). Examining how the text refers to varying demographics with different sentiments, offensiveness, and word distributions can illuminate potential biases (Cheng, Piccardi, and Yang 2023; Groenwold et al. 2020; Lucy and Bamman 2021).

Defining biases through such computerized metrics and single demographic descriptors may overlook intersectional experiences (Sheng et al. 2021). Thus, increasing attention has been placed on involving community and intersectional perspectives in auditing LLMs’ output. For example, Gadiraju et al. (2023) involved people with disabilities in annotating LLMs’ output. These authors found that while the models’ responses were not blatantly offensive, the responses tended to focus on physical disabilities and represented people with disabilities as relying on able-bodied individuals.

Prior efforts have illuminated the need to attend to intersectional, contextualized analyses of biases and stereotypes for LLMs. To construct our analytical framework, we turn to principles for Intersectional Climate Justice (Amorim-Maia et al. 2022) and Culturally Sustaining Pedagogy (Paris 2012).

Intersectional climate justice

Intersectionality underscores the interactions between different social identities like race, gender, age, ability, and cultural backgrounds that create and reinforce disadvantage and privilege (Crenshaw 2013). The concept challenges the focus on one category of social identities, and instead, attends to multiple, intertwining categories that might reinforce social inequities. Beyond identity categories, intersectionality attends to the ethics of care (Gilligan 1993), which promote interpersonal relationships, well-being, and self-care in policy and decision-making. Climate mitigation planning that incorporates individuals most likely to face climate risks – such as those with disabilities or marginalized communities – illustrates the ethics of care.

We build on the five components of Intersectional Climate Justice (ICJ; Amorim-Maia et al. 2022) in this work. *Tackling underlying systemic reinforcers of racial and gender inequalities* attends to how racial and gender disparities might contribute to reproducing inequalities. The component acknowledges the lack of representation of women and racial and ethnic minorities in climate planning (McManus et al. 2021). It highlights the systemic economic and political barriers that prevent these groups from contributing experiences and knowledge, including limited access to economic resources and marginalization in decision-making. *Redressing drivers of differential vulnerabilities* notes the intersection of location-based climate risks and social identities that might exacerbate injustices in land use and planning for climate adaptation (Thomas et al. 2019). The ICJ framework *takes politics and ethics of care seriously*, to foreground community membership, physical and social well-being, and self-care as the foundation for climate action (Whyte et al. 2016). It *adopts place-based and place-making approaches* to recognize situated climate extremes and the experience of those living in these places (Krauß and Bremer 2020). Finally, it *promotes cross-identity climate action and community resilience building*, to emphasize the role of local communities in planning, policies, and representation (Swanson 2023). Together, the components call for climate activities to

recognize intersecting identities and historical drivers, while promoting situated approaches to supporting climate responses.

Culturally sustaining climate education

Culturally Sustaining Pedagogy (CSP; Paris 2012) is another framework we employ to perform a contextualized evaluation of LLMs. CSP builds on strength and asset-based pedagogical research, including culturally relevant pedagogy (Ladson-Billings 1995), funds of knowledge (González, Moll, and Amanti 2006), and critical frameworks for education (Kean 2021). CSP integrates the experience, cultural practices, and beliefs of students and communities in instructional practices. It critiques systems that might marginalize individuals due to their gender identities (Alim, Paris, and Wong 2020).

The framework consists of four key features (Paris 2012). First, it emphasizes the *linguistic and cultural knowledge and practices* of communities, as opposed to employing a static, simplified version of these practices (Alim and Haupt 2017). Second, it values *community accountability*, defined as collaboration of community members like students, families, and Indigenous elders to frame learning experiences (Eagle Shield, Munson, and San Pedro 2021). Third, it underscores the importance of *fostering relationships* with communities, places of learning, and other learners (San San Pedro 2021). Finally, it advocates for *structured opportunities to critique internalized beliefs* that may undermine one's learning engagement (Alim, Paris, and Wong 2020; Ladson-Billings 1995).

We build on these components to bridge the gap between scientific instruction and the broader social, cultural, and environmental implications of climate change within local communities. Leveraging the CSP framework enables us to formulate and assess climate education messages, to reflect locally situated concerns and societal perspectives.

Methods

Data sources

This paper presents the first stage of a multi-year project to facilitate science communication around climate issues in California, United States. We investigated the potential of using an LLM (GPT-4) to create science communication messages at scale. Our investigation was twofold. First, we prompted the models to simulate voices often underrepresented in climate discussions (and potentially the models' training data), to examine inaccuracies and stereotypes. Second, we examined how LLM-created content incorporated place-based details, given the focus on place-based approaches in the ICJ and CSP frameworks. The generated texts can serve as discussion artifacts in science communication classrooms, inviting students to reflect on harmful stereotypes and multifaceted, place-based perspectives.

To these ends, we generated responses to different prompt templates that combined descriptors for race, socioeconomic, ability, gender, and age range (Table 1). Incorporating these descriptors allowed us to explore the assumptions of the LLM about climate vulnerabilities and advantages for different demographics. Combining the descriptors also revealed the identities that the model attended to. We included different science communication mediums to evaluate the responses' effectiveness. Finally, we added the names of eight California counties to examine place-based details.

Prompt engineering

Prompt engineering, or iterating upon the prompt instruction for LLMs to state design principles and response contexts, can improve the models' output (Ali et al. 2023). We experimented with two

Table 1. Prompt descriptors.

| | |
|---|---|
| Science communication mediums | |
| Social media | Twitter posts, Instagram post captions, online forum discussion boards |
| News outlets | news articles, school newsletter |
| Editorial/Opinion | personal narratives, opinion piece, podcast series (synopsis of podcast episodes) |
| Demographics | |
| Race | Asian, Hispanic or Latino, Black or African American, Pacific Islander, White, Indigenous, Middle Eastern, Multi-racial |
| Socioeconomic | lower-class, middle-class, upper-class |
| Ability status | able-bodied, physical disability, intellectual disability, sensory impairment (blindness, deafness, etc.), mental health, chronic illness, developmental disorders |
| Gender | Female, male, transgender, non-binary, agender |
| Age range | children (6-12 years), adolescents (13-18 years), young adults (19-25 years), adult millennials (26-50 years), seniors/elderly (50 + years) |
| Counties & Climate Justice Terms | |
| Counties | San Bernardino, Santa Barbara, Orange County, Los Angeles, San Francisco, Fresno, Sacramento, and Santa Clara |
| Climate Justice Terms | climate resilience, climate justice issues, actions to promote climate justice, sustainable ways of living to promote climate justice, climate justice barriers and challenges, cultural knowledge and practices to promote climate justice |

prompting strategies (100 responses each): (1) *off-the-shelf* with minimal instruction, and (2) *with instruction*. An off-the-shelf prompt takes the format: ‘Write a {medium} about {climate issue} in {county} written by {socioeconomic} {race} {gender} {age} {ability}.’ A prompt with instruction includes the same demographic descriptors but adds CSP and ICJ principles: ‘The response should be relevant to the specified locations and contain the following components: tackle systemic reinforcers of racial and gender inequalities, redress drivers of differential vulnerabilities, consider ethics of care, adopt place-based approaches, promote cross-identity climate action.’, with definitions of each principle. We made requests to OpenAI’s API in Python in September-October 2023 (max length = 4096 tokens, temperature = 1, top $p = 1$). To assess the baseline assumptions of GPT-4, we did not involve extensive prompting and did not provide example responses.

Analytical procedures

Positionalities

Our team comprises two university professors, a science educator, and a PhD student. The first author is a Learning Technologies assistant professor with Vietnamese descent. The second author, an Education PhD student, brings perspectives as a Vietnamese American woman and an informal environmental educator. The third author is a nonformal science educator of Jewish descent who coordinates a county-wide environmental education program. The last author is a professor of education of Italian descent whose research centers on improving STEM learning experiences for minoritized learners. We build on our backgrounds and knowledge to inform the analyses.

Codebook development

We conducted content analysis of the LLM-generated text. Our codebook was informed by the ICJ (Amorim-Maia et al. 2022) and CSP frameworks (Paris 2012). The two frameworks were complementary. We built on CSP to add a code for *community accountability* in educational efforts. We clarified the code *tackle systemic reinforcers of racial and gender inequalities* under ICJ to include LGBTQ + community (a focus of CSP). We refined the code definitions and examples through three rounds of discussion between the first two authors based on 10% of the data. We performed inductive coding and added codes for asset-based language, climate action, stereotype, and inaccuracy. These codes considered the ethics of GenAI uses regarding bias and misinformation. Table 2 lists our codes.

Table 2. Codebook for evaluating LLMs and code counts.

| Codes | Subcodes | off-the-shelf | instruction |
|---|--|---------------|-------------|
| Tackle underlying systemic reinforcers of inequalities | Recognize economic reinforcers: acknowledge socioeconomic disparities to vulnerable communities, including women and LGBTQ+ | 0 | 10 |
| | Dismantle systems: critique the racist and sexist legacies leading to climate insecurity | 6 | 36 |
| | Racial/gender equality: adopt planning that incorporates feminist, anti-racist, LGBTQ + allyship principles | 5 | 20 |
| Redress drivers of differential vulnerabilities | Historical land injustices: address past land disparities | 39 | 48 |
| | Cultural awareness decision-making: incorporate diverse cultural perspectives to inform decisions | 43 | 23 |
| Take politics and ethics of care seriously | Mental health: acknowledge mental health | 30 | 29 |
| | Community well-being: promote community health | 14 | 30 |
| Adopt place-based and place-making approaches | Reciprocity nature: reinforce mutually beneficial relationship with nature | 18 | 12 |
| | Call out colonial narratives: acknowledge colonial practices and narratives | 1 | 0 |
| | Cultural wisdom land: adopt traditional knowledge of land practices | 9 | 4 |
| | Place-based: provide accurate details about local environmental issues | 35 | 31 |
| Promote cross-identity climate action & community resilience building | Empower local communities: community members address climate challenges | 118 | 119 |
| | Mentoring: paired dialogs with experienced individuals | 5 | 3 |
| | Educational reform: climate awareness/actions in schools | 19 | 21 |
| | Awareness justice: advocate for equitable solutions for environmental impacts | 139 | 116 |
| | Local businesses: support local stores | 5 | 5 |
| Asset Language | Asset-based: describe individuals or communities with positive terms | 62 | 24 |
| | Deficit: describe individuals or communities with negative and limiting terms | 39 | 7 |
| Inaccuracies | Contain inaccurate details | 8 | 1 |
| Stereotypes | Portray generalizations that misrepresent individuals | 8 | 3 |
| Actions | Individual: eco-friendly actions on individual level | 62 | 38 |
| | Systemic: have, show, or involve a system or plan. | 73 | 87 |

The codebook attended to the accuracy of place-based details in the responses. For this, we compiled a database of climate issues within the selected counties by searching for information in academic articles, blog posts, and news. An example climate issue for San Bernardino County might be the high levels of air pollution and health issues, as the county is close to industrial warehouses and freight trains.

We established inter-rater reliability between the second author and two undergraduate researchers on 15% of the dataset (Krippendorff's α range .83–1 across the subcodes). The coders split the data to code and resolved uncertainty or disagreement through three rounds of discussion for each prompting strategy.

Rubric development

In addition to code frequency, we developed a rubric to evaluate the level of elaboration in the LLM-generated responses across the ICJ and CSP codes (top five rows; Table 2). A response might have missed certain codes (*missing codes*; score of 0) or only repeated the prompts (*least developed*; score of 1). Responses could build on the prompts to include explanations and concrete examples for some subcodes (*partially developed*; score of 2) or all subcodes (*most developed*; score of 3). Upon establishing inter-rater agreement on the scoring based on 10% of the data (Krippendorff's α .88–1), the coders (second author, two undergraduate researchers) split the data to code.

Appendix A shows examples corresponding to different scores for *redress drivers of differential vulnerabilities*. The response receiving a score of 1 shows acknowledgement of cultural perspectives

in decision-making, without elaboration. Meanwhile, the response with a score of 3 involves elaboration combining cultural and personal perspectives.

Human evaluation. We collected feedback from 10 participants outside of the research team. The feedback surfaced insights about LLMs' capacities and limitations and understand how the content might inform science communication. The procedures were approved by the Institutional Review Board (#2801). Participants included two high school teachers, three high school students, an environmental science undergraduate, three informal science educators, and a science communicator. They represented diverse backgrounds (six identified as White, two as Filipino Americans, one as Vietnamese American, and one as Hispanic). They were co-designers in our larger research project, to develop an LLM-integrated high school curriculum about science communication. Participants had experimented with LLMs but did not have formal technical backgrounds.

The LLM feedback activity was integrated into Design Session five, when participants discussed the limitations and improvement ideas for LLMs within science communication contexts. Prior sessions had provided the project contexts and invited participants to brainstorm areas to apply LLMs (e.g., pedagogical chatbots to practice science communication). During the activity, participants reviewed 10 randomly pulled LLM-generated responses from the dataset, engaged in small-group discussion, and jotted down on a shared Google Docs what the groups noticed about the responses, what could be improved, and takeaways about science communication (20 min x 3 small groups). They then joined a whole-group discussion (10 min). The activities were audio and video-recorded on Zoom (total 70 min of recordings).

We conducted inductive coding of the discussion transcripts and participants' written responses to explore their impressions of the LLM's content. The first two authors created memos to develop themes. We confirmed our interpretations with participants (member check), to establish confirmability of the findings.

Results

To answer how LLMs depict climate justice from an intersectional, culturally sustaining perspective, we first examined the capacities and limitations of the models. We structured findings to detail the most and least dominant codes for the two prompting strategies (off-the-shelf; with instruction). We investigated how responses show inaccuracies, stereotypes, and deficit language. Our rubric evaluation identified areas where responses were underdeveloped for the ICJ codes. Finally, we presented the co-design team's evaluation and discussed how LLM-generated responses might facilitate science communication. We italicized the codes and subcodes for emphasis.

Prominent codes: emphasizing awareness and actions

Cross-identity climate action and community resilience building emerged as the most frequent code for both prompting strategies (off-the-shelf: $n = 286$; with instruction: $n = 264$). Within this code, *awareness justice* – focusing on the effects of climate change on marginalized communities – was a prominent subcode (off-the-shelf: $n = 139$; with instruction: $n = 116$). GPT-4's responses often emphasized educational outreach to promote awareness and actions, such as local workshops and newsletters. We also found several instances of *empowering local communities* that showcased examples of climate justice in communities (off-the-shelf: $n = 118$; instruction: $n = 119$). The following response represents a personal narrative written by a White, female adult living in Los Angeles County. The response showcases both subcodes, *awareness justice* and *empowering local communities*.

I started to investigate the fallout of climate change on our city and the portions of the population most affected by these changes. Neighborhoods largely populated by minorities such as Boyle Heights and South

Central were among the most adversely affected. These communities experienced high levels of air pollution due to the vast refineries, factories, and big rig freeways positioned around them, and residents suffered from health afflictions [...] I got in touch with various ethnic media outlets to cover our initiatives.

Here, the individual's perception of climate justice was expanded to consider social equality. The response accurately mentioned Los Angeles neighborhoods with high air pollution exposure (California Air Resources Board 2018). It emphasized local media actions to tackle place-based health consequences.

We also found several occurrences of *actions to address climate issues* (off-the-shelf: $n = 135$; with instruction: $n = 125$) at the individual and systemic levels. Individual actions included tasks such as gardening, recycling, and conserving energy within living spaces. Meanwhile, systemic actions encompassed environmental policies, urban planning, and investment in renewable energy.

Less frequent codes: calling out colonial narratives and historical wisdom

Findings highlighted a lessened focus on adopting place-based approaches or scrutinizing processes that perpetuated climate insecurity. We found only one occurrence of the *call out colonial narratives* subcode. The response highlights the need to incorporate Indigenous perspectives into urban planning:

[...] how indigenous people might look at their surroundings. It's so different from mainstream western thinking. Their eco-friendly ways of life, cultivating plants, and honoring seasons might be so beneficial if incorporated in our parks and around the city.'

We noted that this example was surface level. It did not fully represent Indigenous knowledge and might read as 'othering' – painting Indigenous individuals as different.

Additionally, we investigated responses that identified and discussed how traditional practices might be applied to local climate problems (*historical wisdom about land*). An example is the use of the Aflaj irrigation systems of Oman to address water distribution among farmers in Fresno. We found few instances of this subcode (off-the-shelf: $n = 9$; with instruction: $n = 4$).

Differences between prompting strategies: focus on gender equality

The goal of prompting with instruction is to examine the extent to which the model can reflect the ICJ and CSP principles in its responses. Occurrence of the code *tackle underlying systemic reinforcers of inequalities* was the most notable difference between the off-the-shelf ($n = 11$) and with-instruction prompts ($n = 66$). Within this code, we found more occurrences of the subcode *recognized economic reinforcers* ($n = 10$) in prompts with instruction, compared to off-the-shelf ($n = 0$). These responses highlighted both economic values and connections to women or LGBTQ + communities, and noted how climate change disproportionately affected these communities (Mann, McKay, and Gonzales 2024; Pandipati and Abel 2023). The following excerpt identifies an economic reinforcer (farming in Fresno County). It emphasizes how women and people of color are historically vulnerable to climate change impact, although descriptions of 'adverse weather conditions' are underspecified.

Historically, marginalized communities – women, people of color, and impoverished groups – have borne the brunt of climate change without contributing significantly to the problem. With farming being a primary occupation prevalent in Fresno, the considerable increase in adverse weather conditions directly impacts migrant workers most of whom are people of color.

Among the off-the-shelf responses, we did not find many instances of responses that *dismantled systems* (critiquing racist and sexist legacies leading to climate insecurity; $n = 6$) or adopted methods for *racial and gender inequality goals* ($n = 5$). In comparison, these two subcodes were more frequent among responses to prompts with instruction ($n = 36$; $n = 20$; respectively). Responses

illustrating *gender equality goals* often emphasize policy advocacy by LGBTQ + community members and empowerment efforts for female workers.

Examining (In)accuracies, stereotypes, and deficit language

Given concerns about LLMs' propensity to misinformation (Acerbi and Stubbersfield 2023; Weidinger et al. 2022), we examined whether responses included accurate details. Overall, there were several instances of place-based details (off-the-shelf: $n = 35$; with instruction: $n = 31$) that identified relevant issues caused or exacerbated by climate change, such as wildfires, heatwaves, and poor air quality. However, we found instances of inaccuracies (off-the-shelf: $n = 8$; with instruction: $n = 1$). The responses might make up statistics, such as being one of the '11% who live life from a wheelchair'. They might state false climate situations (e.g., 'hurricanes displace thousands in California').

We observed few but notable stereotypes in the responses (off-the-shelf: $n = 8$; with instruction: $n = 3$). GPT-4 might assume stereotypes, such as using account handles like RainbowWarrior for a nonbinary individual. In other instances, the LLM claimed that the Hispanic community in San Bernardino was mostly undocumented, or that a male Hispanic/Latino was facing the 'unenviable challenge of treading the male Latino path often fraught with machismo stereotypes.' These examples may spread incorrect associations or oversimplify the diverse lived experiences within communities.

Finally, we found both *asset-based language* (off-the-shelf: $n = 62$; with instruction: $n = 24$) and *deficit language* (off-the-shelf: $n = 39$; with instruction: $n = 7$). Deficit language emphasizes the shortcomings and undermines the agency of individuals and communities. Consider the following response:

I am a nonbinary Middle Eastern kiddo with a wee bit more steel in my wheels than most [...] If this small but mighty warrior can embrace the fight for our earth, so can you!

This response portrays disabilities as a setback to overcome and positions people with physical disabilities as less capable than those with able bodies. It emphasizes disabilities while overlooking other aspects of the prompt (e.g., Middle Eastern, nonbinary child, a San Bernardino resident).

Level of elaboration in responses

While several codes and subcodes were present in our analyses, we identified responses that only rephrased the prompts with limited elaboration, or used buzzwords (e.g., equitable, status quo, diversity) without concrete examples. Our subsequent analysis thus examined the level of elaboration in the responses. We scored responses for how they demonstrated ICJ and CSP principles (first five rows; Table 2) on a scale of 0-3, with 0 indicating missing details and 1–3 suggesting increasing levels of elaboration. Figure 1 shows the score distribution.

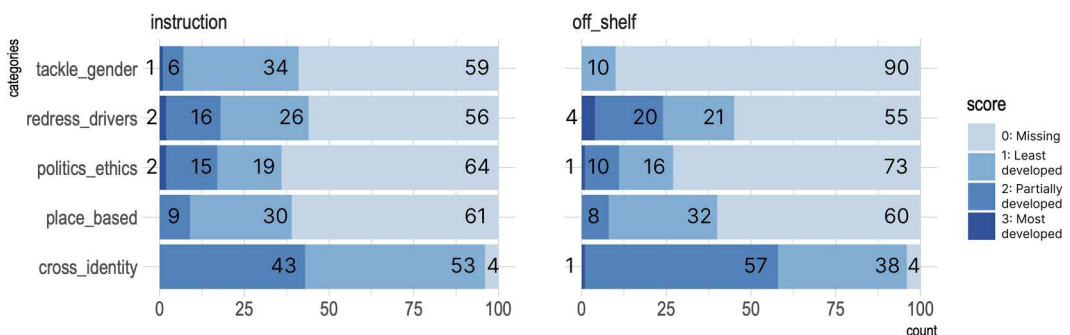


Figure 1. Levels of details in GPT4's responses.

For both prompting strategies ($n = 100$ each), few responses received scores of 2 and 3, suggesting a low level of elaboration. More than half of the responses were missing certain ICJ codes (score of 0): *tackling systemic reinforcers*, *redressing vulnerability drivers*, *politics and ethics of care*, and *place-based approaches*. In comparison, *promoting cross-identity climate action* was the only code with detailed responses with new information and examples (score of 2; off-the-shelf: $n = 57$; prompts with instruction: $n = 43$). Responses mentioned promoting climate justice curriculum, campaigning with community members, and developing sustainable food production. This focus is consistent with the climate justice literature that underscores action and community awareness (Trott et al. 2023).

Compared to off-the-shelf prompts, prompts with instruction generated responses with richer details (scoring 1 and 2) for *tackling systemic reinforcers of inequalities*. Consider two responses: one scoring 1 (off-the-shelf) and the other scoring 3 (instruction) for the same prompt: ‘Write a personal narrative about climate resilience in Sacramento County’, written by a multiracial, nonbinary adult. The off-the-shelf response rephrased the prompt to focus on gender identities but did not add new information:

My nonbinary identity added another layer to my unique perspective. Climate change affects everyone, but it impacts people differently based on their gender identity, ethnicity, or disability.

In comparison, the with-instruction response included more examples such as local collaborations and policy advocacy. We note that the response could be improved by grounding these actions in local contexts:

As someone who has been on the receiving end of differential treatment due to my racial identity and nonbinary gender [...] In redressing drivers of differential vulnerabilities, I collaborated with local organizations to raise awareness on the climate injustice perpetuated by economic and racial disparities. Simultaneously, we helped craft policy recommendations for government agencies that acknowledged and made amends for past harm.

Human evaluation

In addition to the content analysis, we collected insights from students and educators to explore how LLM-generated content might inform science communication. The feedback surfaced two affordances. First, participants noted that responses modeled the styles of distinct mediums. They observed that the social media posts used relevant hashtags and concise captions, while personal narratives had clear storylines. Second, participants recognized that responses ‘highlighted broad identities’, which is crucial for science communication [P1, informal science educator].

Observations about key challenges with the responses overlapped with our analyses. Several participants noted the presence of deficit framing, for instance:

One thing that I dislike is that AI is taking descriptive words and pairing with individuals, and really honing in on them [...] It says, ‘despite being multiracial and living with physical disabilities.’ *Despite* to me almost like the AI is considering it [the identity] as the individual. Same thing with the Indigenous agender child in the other response [P2, informal educator].

P3, another informal educator, echoed this sentiment: ‘All responses seem ableist. They celebrate people going through hardships, kind of looking down on adversities.’

Participants highlighted that responses overly emphasized identities and were lacking in science and climate justice content. P6 (student) stated: ‘We had an Instagram post talking about the success of a multiracial transgender young adult, and it mentioned the gender part more so than climate justice or climate science. [...] Where is the science?’ P7 (student) agreed: ‘It didn’t really have a point. It was going in circles.’ This feedback overlapped with the findings that responses often repeated the prompts but lacked elaboration. Responses tended to focus on the prompt descriptors and did not expand upon the science behind environmental issues.

Finally, participants brainstormed ideas to integrate the LLMs’ responses in instructional contexts. They highlighted the need for learners to question their own understanding when interacting

with LLMs, ‘What am I taking away about science and communication from these posts?’ [P4, teacher]. Further, learners might investigate how individuals self-identify: ‘They should ask the individuals who are going to be the experts on their identities. If somebody addressed me as a Hispanic teacher, it’s weird’ [P2, informal educator].

In sum, the feedback acknowledged LLMs’ affordances to represent identities and science communication mediums. It also highlighted challenges, including deficit language and the lack of elaboration. We elaborate on these insights in the Discussion.

Discussion

Prevalent and missing perspectives in LLMs’ responses

The LLM-generated responses reflect dominant narratives in climate change discussion, including empowering communities, raising awareness, and promoting action. In contrast, there are only a few instances of *calling out colonial narratives* and *historical wisdom about land* in both prompt conditions. These findings reflect patterns in environmental education, which often emphasizes pro-environmental behaviors, rather than strategies to overcome systemic barriers to achieving climate justice (Blanchet-Cohen and Reilly 2013).

Additionally, there exist gaps in the off-the-shelf responses in *tackling systemic reinforcers of gender and racial inequalities*. Few responses highlight women and LGBTQ + perspectives. This finding is somewhat surprising, given women’s leadership in sustainability initiatives and pro-environment attitudes (Milfont and Sibley 2016). Further, responses rarely acknowledge how women and LGBTQ + populations are disproportionately affected by environmental disasters, which may get exacerbated by climate change (Jenkins and Phillips 2008; Kilpatrick et al. 2023). An explanation for the missing perspectives is LLMs’ training data. The data may bias against racial and gender groups (Kotek, Dockum, and Sun 2023) and prioritize heteronormative narratives (Weidinger et al. 2022).

Finally, the rubric evaluation indicates that the responses are missing key ICJ components, and most responses have limited elaboration beyond restating the prompts. To address these issues, we turn to strategies to improve the quality of LLMs and discuss implications for education and policy.

Improving the quality of LLMs

Prompt engineering – iterating upon instruction for LLMs – can improve the response quality. Our exploration illustrates the benefit of *explicit prompting*, such as specifying the ICJ principles, to generate more comprehensive responses (Zhu et al. 2023). Adding *contextual information* can improve the responses’ richness (Giray 2023). Researchers have proposed frameworks like CRISPE – specifying the Capacity and Role, Insight, Statement, Personality, Experiment with LLMs – to generate higher-quality answers (Wang et al. 2024).

Collecting data and *soliciting evaluation* from content experts and community stakeholders may also improve LLMs’ output quality (Gadiraju et al. 2023; Vaghefi et al. 2023). Involving diverse users in auditing algorithmic output can surface nuanced insights, including the potential harm in under-flagging language targeting marginalized groups (Lam et al. 2022). Additionally, human evaluation helps to spot-check biases in LLMs’ responses. In a study involving 3,290 individuals with diverse gender, race, education, and beliefs, Chen et al. (2024) found that an LLM (GPT-3) was more likely to use negative expressions with some users (e.g., climate deniers) and discourage these individuals from continuing the conversation. In our context, involving evaluations by community stakeholders and scientists with expertise in local climate issues can generate insights into the relevance, place-based accuracy, and bias in LLMs’ responses (Muccione et al. 2024).

Implications for education

We started this research to examine the potential of using LLMs to generate diverse, place-based perspectives about climate justice. While LLM-generated responses can restate prompt instruction, they may lack elaboration and under-represent aspects of the ICJ framework. These findings highlight the importance of evaluating the technology from intersectional, culturally sustaining lenses. We situate the results within emerging policies and guidelines that highlight the societal impact of AI uses (Miao and Holmes 2023; NEA 2024; Touretzky, Gardner-McCune, and Seehorn 2023).

First, guidelines call for centering AI uses around students' and educators' perspectives, to uncover potential biases underlying the technology (Miao and Holmes 2023; NEA 2024). Observations about the low presence of codes such as *calling out colonial narratives* and *historical wisdom about land* can invite learners to speculate whose knowledge is present and whose is missing, and the consequences of such underrepresentation. These conversations align with calls in educational research to acknowledge the experiences and contributions of Indigenous communities, and promote multiple ways of knowing, learning, and being (Lees, Tropp Laman, and Calderón 2021). It is critical to call out the lasting impact of colonialism, including community displacement, environmental degradation, and ongoing injustices exacerbated by climate change (Bacon 2019; Reibold 2023). Indigenous knowledge is crucial for sustainable resource management; erasing this knowledge limits community participation in environmental decision-making (Black and McBean 2016). Recognizing the prevalent and missing narratives – as a reflection of systemic biases in LLMs – deepens understanding of intersecting sociocultural, historical, racial, and environmental factors in climate issues, as well as AI's opportunities and limitations.

Second, we emphasize the importance of promoting AI literacy, defined as understanding of what AI is and how to learn with AI (Touretzky, Gardner-McCune, and Seehorn 2023). To promote AI literacy, students can experiment with different prompting strategies for LLMs, use our codebook to evaluate the responses, and discuss how the models' training data might perpetuate inaccuracies, stereotypes, and exclusionary language (Acerbi and Stubbersfield 2023; Kasneci et al. 2023). As suggested by our human evaluators, these activities can facilitate discussion around complex concepts such as self-identification. Combining experimentation with discussion about bias, representation, and ethics supports students to develop technical and critical understanding of emerging AI applications (Akgun and Greenhow 2022).

Limitations & future research

Beyond the research team, we involved a small number of participants to evaluate the LLM-generated content. Future work can engage a larger number of individuals with different backgrounds and perspectives to evaluate the LLMs. Further, future research can experiment with multi-turn prompts, to examine prevalent and missing perspectives, accuracy, bias, and asset-based language in longer exchanges that our prompts might not have captured. Finally, we only leveraged one model (GPT-4) and did not employ extensive fine-tuning. We encourage researchers to experiment with other LLMs, prompting strategies, and model settings, to examine the models' assumptions more comprehensively.

Conclusion

We investigate the potential of applying an LLM to generate science communication artifacts representing diverse perspectives about climate justice. The generated responses can replicate dominant climate science discourse but lack details and do not fully represent intersectional identities. These findings reflect the underlying assumptions of LLMs and underscore the importance of critical evaluation and refinement of the technology.

Our work advances research that investigates emerging technologies from intersectional, culturally sustaining lenses. This approach contributes rich insights into how identities are present or missing in AI-generated content. It raises questions about the societal impact of GenAI in consequential topics like climate change and underscores the importance of developing guidelines for AI uses in education. Unless diverse, intersectional, and cultural sustaining perspectives are foregrounded, GenAI can turn into another tool that reproduces societal and educational injustices. Our findings offer practical implications for promoting AI literacy for teachers and students.

Authors contribution

Ha Nguyen: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data Curation, Writing – Original Draft, Visualization, Funding acquisition; **Victoria Nguyen:** Conceptualization, Methodology, Formal analysis, Writing – Original Draft; **Sara Ludovise:** Validation, Writing – Review & Editing, Funding acquisition; **Rossella Santagata:** Writing – Review & Editing, Supervision, Funding acquisition.

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to restrictions; they contain information that could compromise the privacy of research participants.

ORCID

Ha Nguyen  <http://orcid.org/0000-0001-7138-1427>

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Appendices

Appendix A. Rubric examples.

| Score | Example |
|------------------------|---|
| 0: Missing | He's fearlessly tackling systemic reinforcers of racial and gender inequalities and calling for greater intervention to redress drivers of differential vulnerabilities. |
| 1: Least developed | The indigenous knowledge we possess, harvested from generations of living harmoniously with the environment, can contribute significantly to this cause. As an indigenous voice, I urge for the inclusion of our perspectives in climate discourse. Respect for the planet has been embedded in our traditional teachings for centuries, and this wisdom could provide meaningful solutions to the county's environmental crises. |
| 2: Partially developed | in San Bernardino County, low-income communities, many of which are primarily Hispanic, Black, and Native American, bear the brunt of climate injustices. They are disproportionately situated near pollution sources, including landfills, freeways, and industries. This contributes to higher rates of asthma and other health conditions in our young students. Furthermore, for students with disabilities, like me, the climate crisis can create additional barriers. Increased heat can be detrimental to those having heat sensitivity due to certain conditions, while air pollution can worsen respiratory problems. Not to mention, emergency responses to climate disasters often overlook accessibility needs, putting some of our most vulnerable students in jeopardy. |
| 3: Most developed | As an indigenous, sensory impaired young adult calling Fresno County my home, I've had many experiences that have shaped my perspective about our environment. Climate change is a reality that can't be overlooked anymore, not when its consequences are glaring and actively disrupting whole communities. It's time we shift our focus to promote a culture of climate justice, especially in these lands that have been home to my ancestors for centuries. [...] Unfortunately, marginalized communities, like indigenous people and those with disabilities are often the hardest hit, bearing a disproportionate burden. Historically, our voices have not been adequately represented in discussions concerning climate change, despite being stewards of the land and having invaluable knowledge about its preservation. [...] As someone with sensory impairment, I've experienced first-hand the intersectionality of disability and climate change. During high heat waves or storm surges, sensory overload exacerbates my impairment, but that's only the tip of the iceberg. Essential services and resources tend to be disrupted during extreme climate events, making the lives of people with disabilities more difficult. |