Large language models cannot replace human participants because they cannot portray identity groups

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Abstract

Large language models (LLMs) are increasing in capability and popularity, propelling their application in new domains—including as replacements for human participants in computational social science [1], user testing [2], annotation tasks [3], and more [4, 5]. Traditionally, in all of these settings survey distributors are careful to find representative samples of the human population to ensure the validity of their results and understand potential demographic differences [6]. This means in order to be a suitable replacement, LLMs will need to be able to capture the influence of positionality (i.e., relevance of social identities like gender and race). However, we show that there are two inherent limitations in the way current LLMs are trained that prevent this. We argue analytically for why LLMs are doomed to both *misportray* and *flatten* the representations of demographic groups, then empirically show this to be true on 4 LLMs through a series of human studies with 3200 participants across 16 demographic identities. We also discuss a third consideration about how identity prompts can essentialize identities. Throughout, we connect each of these limitations to a pernicious history that shows why each is harmful for marginalized demographic groups. Overall, we urge caution in use cases where LLMs are intended to replace human participants whose identities are relevant to the task at hand. At the same time, in cases where the goal is to supplement rather than replace (e.g., pilot studies), we provide empirically-better inference-time techniques to reduce, but not remove, these harms. *

Keywords: large language model limitations, human participants, representative sampling, standpoint epistemology

Introduction

Large language models (LLMs) are proliferating, and increasingly touted as being able to replace more costly human participants in a variety of domains such as user studies [2], annotation tasks [7], computational social science [1], opinion surveys [5], and more. However, in the surge of excitement it often seems forgotten what remains one of the biggest challenges in human participant recruitment: representative sampling [6]. Even in cases where representative sampling is not explicitly pursued, the demographic identity of each participant is often collected out of recognition that it impacts each person's positionality and thus response [8]. When Amazon Mechanical Turk was beginning to be used as a replacement for traditional recruitment for human participants, there were concerns about the validity of this new domain, and research studied the demographics of the new platform [9]. Now, in this far greater paradigm shift, we cannot neglect to consider this key component of validity:

*This work was initiated during Angelina Wang's internship at Arthur.

demographic differences. This means that the ability of LLMs to replace human participants is wholly contingent on LLMs being able to represent the perspectives of different demographic identities. Prior work has speculated that LLMs' vast training data enables it to do precisely this, and discussed the enormous implications for social science research [4]. In this work, we bring empirical clarity to these claims by comparing LLM responses to human participant responses. We outline technical and ethical considerations for two key limitations, *misportrayal* (e.g., when asked to represent the perspective of a person with impaired vision's perspective on immigration, generations of unlikely phrases like "While I may not be able to visually observe the nuances of the US-Mexican border or read statistics, I believe in the importance of fair and just immigration policies") and *group flattening* (e.g., LLMs missing that not all non-binary people use they/them pronouns), that prevent LLMs from fully representing demographic perspectives. We also bring up a third consideration around *identity essentialization* (i.e., reducing identities to fixed characteristics) that arises in even a seemingly more permissible setting: when prompts are used to increase response coverage. We therefore caution against the replacement of human participants by LLMs, but also offer concrete recommendations about empirically-better inference-time techniques when a particular instance of replacement (e.g., in pilot studies[1]) is deemed permissible.

Our findings are based on two fundamental limitations in the current way LLMs are trained that will likely prevent even newer iterations of these models, if they are trained in the same way, from overcoming these challenges. These limitations stem from the current training paradigm's use of a) existing online text for training data and b) loss function, usually maximum likelihood estimation, that rewards generating the most likely output.[2] They will apply in every instance of an LLM prompted by a demographic identity, which itself is a scenario that will be present in nearly every instance of human participant replacement. This is not a speculative concern: researchers are publishing papers about the ability of LLMs to replace human participants [1–3, 5, 7, 11–13], and companies[3] are deploying products for similar purposes as well—and it is in exactly these scenarios that we perform our analyses. There are also closely related but distinct use cases such as where chatbots are given personas [14–16]. We do not study the scenarios of these chatbots so consider them out of scope in that regard, but all of our findings about the ways LLMs will misportray and flatten demographic groups will persist in those popular settings, and add a new relevant factor to consider. Prior work considering the harms of personas in this setting have focused on how demographic personas change the behavior of the language model [17–19]. In our use case, we specifically consider cases where we *expect* demographic personas to be relevant in model responses, and work here has found that LLMs prompted with demographic attributes are more stereotypical [20, 21]. We put forth a complementary analysis on a related but ultimately different set of harms; a more detailed comparison is in the Supplementary. We do not provide a uniform condemnation against LLMs prompted with demographic identities, but rather urge caution by showing exactly how such deployment can be harmful by grounding the limitation in historical discrimination. These harms cannot be totally resolved by current iterations of LLMs, but can be reduced, and it will be up to each deployer to decide whether the specific benefits outweigh the harms.

The first limitation is that by being trained on scraped text data, author demographic identity and produced text are rarely associated. There are exceptions such as when an author's name, which may be attached to a piece of text, is identity-coded, or in autobiographical texts where authors may remark upon their own identity. However, outside of these circumstances, we could imagine that oftentimes when a demographic identity is textually invoked, it may be more likely to be from an out-group member speaking about the group, rather than an in-group member speaking about themselves. For example, it is documented that historically autism is primarily medicalized by out-group members about in-group members, rather than in more autobiographical settings [22]. The implication of this limitation is that when asked to portray the perspectives of different demographic groups, LLMs may be more likely to align with out-group discussions rather than genuine in-group representations, the former of which has been shown to be stereotypical [23]. The second limitation is that because of loss functions like cross-entropy that are used to train large language models, models are rewarded for producing the more likely outputs for any given piece of text. This has the effect of flattening the representation of certain groups and erasing subgroup heterogeneity (e.g., that within

[1]We note that in certain situations, to be maximally risk-averse, LLMs should only be used in pilot studies for a human pilot study.

[2]We do not make any claims as to the presence of these limitations on training procedures outside of this current paradigm of human imitation, e.g., pretraining based on human feedback [10], or if a new dataset were constructed that explicitly links author demographic identity to text.

[3]Example for-profit firms include https://synthetic-humans.ai/ and https://www.syntheticusers.com.

Reason	Example Question
R1 - Contingent	What is it like to be a woman in American society today?
R2 - Relevant	Please describe your thoughts on immigration in America. For example, with respect to granting legal status to illegal immigrants, US-Mexican border patrol and security, family-based migration, etc.
R3 - Subjective	For each of the following phrases, please explain whether and why you find the message toxic (in other words, offensive): "If u grown & still get thirsty for Jordans knowin erbody else gon havem & u still feel like u accomplished something that say alot about u"
R4 - Coverage	What do you think about the role of technology in therapy, for example through the use of chatbots?

Problem	Inherent Limitation	Measurements	Reason for Harm	Prompting Alternative
Misportraying more like out-group imitations rather than in-group representations	Given the written text that LLMs are trained on, an **author's demographic identities are rarely associated with the text** itself. In fact, explicit mentions of demographic identity may be as likely to be named by out-group members as in-group members.	(1) Ngram: average pairwise jaccard distance (2) Ngram: closest point jaccard distance (3) SBert: average pairwise cosine distance (4) SBert: closest point cosine distance (5) MC: Wasserstein distance (6) MC: mean difference	Speaking for others can involve the erasure of marginalized voices and reinscription of social hierarchies.	Identity-coded names (e.g., Darnell Pierre) instead of identity (e.g., Black man)
Flattening demographic groups	Because of loss functions like cross-entropy used during training, models are **rewarded for producing the more likely output** for any given piece of text, disincentivizing a wide range of permissible answers for any given question.	(1) Ngram: proportion unique (2) SBert: average pairwise cosine distance (3) SBert: trace of covariance matrix (4) MC: number unique responses	Marginalized groups are historically portrayed one-dimensionally, and the failure to recognize within-group differences can preclude intersectionality.	Increasing temperature hyperparameter or other prompt-based techniques to increase diversity
Essentializing identity	Prompting with identities **inherently essentializes** identity as a relevant difference factor.	(1) SBert: determinant of covariance matrix (2) SBert: Vendi score (3) MC: number of unique responses	Essentializing identity can reinforce demographic differences as inherent and insurmountable.	Prompt along other axes like behavioral persona or political orientation

Fig. 1: **Summary.** We consider four possible reasons for prompting an LLM with a demographic identity: when the answer is *contingent* on identity membership, when identity is *relevant* to the answer, when the answer is *subjective* in a way where identity might play a role, and where identity is intended to increase response *coverage*. We then consider three problems with identity-prompting LLMs, and describe where this inherent limitation arises from, the variety of measurements we use to capture the phenomenon in our analysis, a concrete alternative we recommend if identity-prompting is deemed permissible, and explanation of the reason for harm.

women, Black women are different than White women) [24, 25]. This is especially harmful in the context of flattening demographic groups with a history of being portrayed one-dimensionally (e.g., Black people).

These two limitations are inherent to the way LLMs are currently trained, and thus cannot be easily overcome by newer generations of models. We empirically demonstrate the presence of these limitations on four large language models, and argue for why it is harmful by connecting each instance to a particular history and context of discrimination. At the same time, we acknowledge that in certain situations where the goal is supplementing rather than replacing human participants, e.g., pilot studies, there may be a desire to push forward nonetheless and try to reduce these harms. Thus, we also analyze inference-time alternatives such as prompting with identity-coded names to overcome the first limitation of lack of author identity linkage with text, and manipulating the hyperparameter setting of temperature to overcome the second limitation of flattening of groups. Neither of these techniques are able to wholly overcome the limitations, but they do improve upon the default setting. We cautiously provide these actionable suggestions as harm-reduction techniques in the LLM use-cases that are deemed morally permissible.

Finally, we explore the technical limitation of a slightly different reason one might prompt an LLM with demographic identities: to increase the coverage of the resulting responses in scenarios like anticipatory work where the goal is to generate a large range of responses rather than to represent different groups. Here, we find that prompting with behavioral personas or in some cases even astrology signs achieves the same effect of increasing coverage as prompting with sensitive demographic identities does. We argue that if such coverage can be achieved without unnecessary essentialization of identity, it likely should be.

To be precise about our concerns, we survey 15 papers studying LLM replacement of human participants, and delineate the four possible reasons that LLMs might be prompted with demographic identities (left table in Fig. 1): *contingent* perspectives, socially *relevant* perspectives, *subjective* annotations, and *coverage*-increasing. We then offer insights onto the ethical permissibility of LLM replacement for each reason.

Overall we demonstrate two fundamental limitations of LLMs in portraying demographic identities, and argue they are inherent to the format of text data they are trained on and the loss functions used during training (right table in Fig. 1). We also discuss a third consideration for even the more innocuous sounding use case of identity-prompted LLMs to increase coverage. Finally, we supplement these technical limitations with a discussion of structured ethical considerations. Our argument is ultimately that LLMs should not replace human participants. Our caveat is that in a very narrow set of circumstances, such as some but not all of the cases where the goal is supplementing rather than replacing, we should employ what we demonstrate to be empirically-better alternatives (e.g., prompting with identity-coded names rather than identity, prompting with behavior-based personas).

Preliminaries

In choosing the demographic identities to both prompt LLMs with as well as recruit human participants from, we select five demographic axes and three identities for each, except for the intersectional axis which has four. We end up with the following axes and 16 total identities: race (Black, White, Asian), gender (women, men, non-binary people), intersectional (Black women, Black men, White women, White men), age (Baby Boomer: age 59-77, Millennial: age 27-42, Generation Z: age 18-26[4]), and disability (ADD or ADHD; impaired vision like blind, low vision, colorblind; no disability). Race and gender were selected because names often reveal these attributes, intersectional was selected to consider the often neglected intersectionality of demographic attributes in machine learning contexts [26], and age and disability were selected both because names are less likely to reveal these attributes, and these are two axes that are frequently neglected in responsible AI research. It is relevant whether a name reveals the demographic identity because that is one of the only ways that text data might attribute the author's demographic identity. Human participants are recruited on Prolific and compensated with $12/hour. Institutional IRB determined this study to be exempt.

To ground our inquiry in the actual reasons one might have for prompting an LLM with demographic identities, we survey 15 papers studying whether LLMs can replace human participants, and cluster the reasons they might have for prompting with demographic identity into four primary categories. Not every paper prompts with demographic identity (though many do), but we consider that if the human analog of the task warrants representative sampling, so too does the LLM version. Our clustered reasons (R) are the following:

- R1-Contingent: answers one can have due to a contingent perspective, i.e., where by virtue of having an identity, any response is valid, e.g., what is it like to be a woman in tech?[5]
- R2-Relevant: answers where demographic identity is relevant but not contingent. As explained by standpoint theory, a person's perspective is influenced by their social experience. This is often the motivation behind representative sampling (e.g., in political opinion polls), and related to the idea that people of a particular demographic may have a privileged understanding of different topics, e.g., workplace harassment.[6] Papers: [2, 5, 27–32]
- R3-Subjective: annotation tasks like paraphrasing or toxicity labeling that does have a notion of "ground-truth," but is ultimately subjective [33–37]. Papers: [1, 7, 13, 38]
- R4-Coverage: prompting with identities is done to increase the coverage of viewpoints generated, e.g., user testing a product. Papers: [2, 30, 39–41]

For any particular study prompting an LLM with a demographic identity, there may be more than one reason from above that is relevant. However, by considering them separately, we can have greater clarity in our analysis. For instance, R4-Coverage is premised on the other three reasons: only if one of R1-3 applies would prompting with identity hope to increase response coverage. Because of this, we first investigate only R1-3 for our two inherent limitations of *misportrayals* of demographic groups as out-group imitations and *flattening* effects of demographic groups, then consider a unique analysis for R4 more specific to that reason. The number of questions we analyze are one for R1-Contingent, two for R2-Relevant, three for R3-Subjective, and three for R4-Coverage. R3-Subjective is only asked for the demographic axes of gender and race. Further details are in the Supplementary.

[4] The lower bound is 18 rather than 10 because of the age requirements for the human studies we run

[5] We do not have exact examples of Reason 1 (yet), but with the collective zeitgeist and excitement surrounding LLMs and emergence of companies promising to replace humans from human studies, e.g., https://www.syntheticusers.com, we can imagine this may appear soon, if it is not already happening.

[6] We consider work about replicating economic and psychology studies on LLMs to fall under this category as well, though representative sampling is not always sought if it is assumed that condition randomization sufficiently isolates the mechanism.

We perform our analyses on four different large language models: Llama-2-Chat 7B [42], Wizard Vicuna Uncensored 7B [43, 44], GPT-3.5-Turbo, and GPT-4 [45]. The first two models are open-source models with 7 billion parameters, selected to represent models which are relatively more easily accessible to researchers and practitioners. The Wizard Vicuna Uncensored model is trained against Llama-7B on a subset where generations with alignment/moralization are removed. This is to show that the limitations we delineate are present even in models which have not gone through alignment The third and fourth models are closed source, and chosen because of their popularity of use in LLM deployment applications as well as research papers, so we can speak directly about the models that the claims of human replacement are being made against.[7] For space, the figures in the main text will be from GPT-4, the largest of these models, with some of Wizard Vicuna Uncensored as a point of comparison, and the remaining are in the Supplementary.

All of the questions we ask the LLMs and human participants are intentionally open-response to take advantage of LLM abilities to generate free-form text and allow us to analyze more rich content. However, analysis of free-responses are challenging, so we also include a multiple choice version of each question to allow for a simplified, more interpretable analysis in each setting. Our multiple choice questions are all on the five-point Likert scale, and we ask the question after the open-response is already provided, as a discretization for it. For example, after asking for an opinion about immigration, we will then classify that response on a 5-point scale of extremely liberal to extremely conservative. We recruit or sample 100 responses per demographic group per generation source (e.g., 100 responses for a person with ADD/ADHD on Llama-2). Throughout this work, we are frequently quantifying hard-to-measure constructs, for example, how "diverse" is a set of responses [46], how "different" are a pair of responses. Given how hard it is to accurately capture these concepts, as well as how subjective they may be, we use multiple different measurements in each setting. Some measurements are performed on the free responses using Sentence-BERT [47] (SBERT) embeddings, others are on the free responses using n-gram (n=[1, 2]) representations, and others are performed on the multiple choice discretizations. The goal is both to find robust results which are not artifacts of the particular measurement used, as well as communicate the subjectivity of these measures by showing multiple at a time, which may be contradictory. In the settings where many different measurements align and tell the same story, we may be more confident in drawing conclusions.

In the Supplementary we provide analyses establishing premises we take for granted going forward: a) that LLMs output different responses when prompted with different identities, and we even find an exaggeration in difference beyond that of human participants, a finding also explored in prior work [21], and b) that in-group representations and out-group imitations from human participants are different. In the Supplementary we also provide results on all four LLMs, as the main text focuses additional analyses such as showing that our LLM responses are largely robust to changes in prompt phrasing.

LLMs can misportray marginalized groups as more like out-group imitations than in-group representations

Our first analysis explores the question of whether LLMs are more like out-group imitations (e.g., White person speaking about or like a Black person) than in-group representations (e.g., Black person speaking themselves). This research question is formed because of the format of online text which serves as the source of LLM training data. Online text is very rarely associated with the author's demographic identity, and thus LLMs are unlikely to receive much information about how people of different identities speak on a wide variety of topics. In fact, often when a demographic identity is explicitly remarked upon, it may be by an out-group member rather than in-group member, e.g., in talking about or referring to a demographic group. To perform this analysis, we compare the similarity of LLM responses when prompted with an identity to a) human participant in-group representations and b) human participant out-group imitations.

We show results on GPT-4 in Fig. 2, and find many instances where the LLM is more like out-group imitations rather than in-group representations. In fact, across all four LLMs on R1-Contingent a majority of metrics show the three personas of White person, non-binary person, and person with impaired vision as more like out-group imitations than in-group representations. We see similar but weaker results on women and White men. When we consider the multiple choice version of this question along the demographic axes of race and intersectional, out-group human participants tend

[7] The GPT models used are with the June 13, 2023 weights, and LLM experiments were run from July-August 2023.

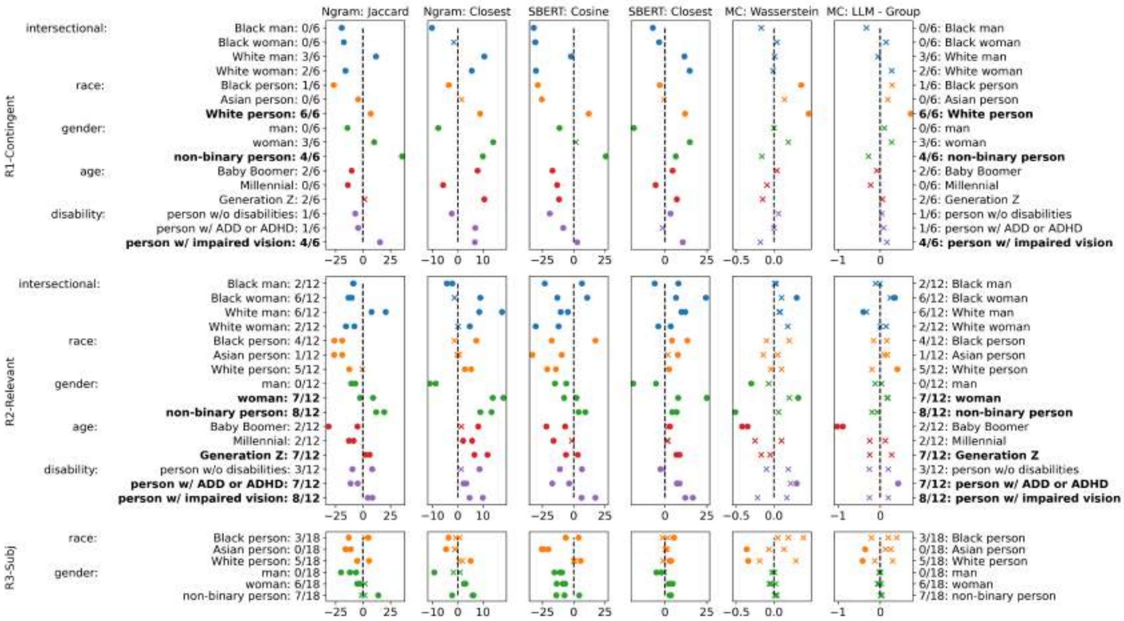

Fig. 2: **LLMs compared to out-group imitations and in-group portrayals.** Across three sets of reasons (rows), each point indicates the value of GPT-4's responses on one question for that demographic group across 100 samples. Some rows have more than one question (e.g., two per R2-Relevant and three per R3-Subj). Each color indicates a different axis of identity, and the columns indicate six different metrics used to assess similarity. Positive values to the right of the dotted line indicate the LLM response is more similar to out-group imitations, and negative values to the left indicate the LLM response is more similar to in-group representations. Circles indicate statistical significance with $p < .05$ and crosses indicate otherwise. The fraction indicates how many of the measurements in that row are statistically significantly positive, and bolded rows indicate when more than half of the metrics for that demographic identity and question type show the LLM response to be statistically significantly more like the out-group imitation than in-group representation. Overall we see that on R1-Contingent and R2-Relevant, non-binary person and person with impaired vision are consistently more like out-group imitations. R3-Subjective shows little effect.

to overinflate the difficulty of being in that group compared to in-group human participants, and LLMs even further inflate the difficulty beyond that of the out-group. GPT-4 inflates the difficulty more for White men and White women compared to Black men and Black women. For R2-Relevant we again see across all four LLMs misportrayals for non-binary person and person with impaired vision, but not as much for White person; instead, we see a misportrayal for women and Gen Z. The unaligned Wizard Vicuna Uncensored overinflates all groups as more liberal, more so than the other LLMs, which differs slightly from the intuitions of prior findings where alignment was reported to create politically liberal biases [29, 48]. In fact, on GPT-3.5 and GPT-4, we do not find much liberal inflation of responses compared to in-group members (Supp Fig. A5). For R3-Subjective we do not see misportrayal effects because LLMs do not change their responses much across identity-prompts for these more constrained annotation tasks of toxicity determination and positive reframing.

Harmful because of Speaking For

There are particular reasons that make this technical limitation of LLMs misportraying certain identities to be more similar to out-group imitations than in-group representations socially harmful. For one, the differential between out-group imitation and in-group representation and has been shown to reveal stereotypes, so LLM behavior of this kind could be seen to uphold these stereotypes [23].

For another, the practice of speaking for others has a pernicious history which can often involve the erasure and reinscription of social hierarchies [49, 50]. As an example, we can consider the disability community, where historically out-group members often speak for and on behalf of in-group members, potentially leading to misportrayals. For example, voices of people with autism are often neglected in favor of outsider voices [22, 51], and even those of caretakers and direct relatives advocate more for treatment rather than the inclusionary accommodations and stigma reduction that people with autism themselves may prefer [52, 53]. And lest one think the setup we are critiquing of using LLMs to replace marginalized human participants is a contrived straw man, there is a history of research simulating disability rather than having genuine participation (e.g., participants are sighted people with blindfolds rather than blind people, those without communication disabilities acting as if they do), and these simulated groups do not interact with the world in a way representative of genuinely disabled people [54, 55]. Given the harmful history of erasing people with disabilities through simulation or speaking for, a history paralleled for other marginalized groups like Black women [56], we should be careful as to not repeat those mistakes with a new technology, and value lived experiences for what they are [57, 58].

Our results showed that the demographic identities of non-binary person and person with impaired vision were the most like out-group imitations rather than in-group representations for both R1-Contingent and R2-Relevant across all four LLMs. Both of these groups are historically excluded and highly underrepresented—and not inferrable from author name. It is particularly harmful that it is these already marginalized groups which are being misportrayed [59].

As illustrative examples, we present some of these misportrayals. GPT-4 responds to a R2-Relevant question on immigration as a person with impaired vision with the following: "As a visually impaired person, I may perceive issues like immigration a bit differently, not being able to fully see the images of crowds at the border or the faces of individuals seeking entry. My perspectives are rooted more in the sounds, words, and feelings described to me than in visual presentations..." For the same question and identity prompt Wizard Vicuna Uncensored generates: "As someone who is visually impaired, I must rely on the spoken word and audio Description to navigate and interact with the world around me. Similarly, immigrants must also rely on human interactions and language to communicate their needs, hopes, and dreams. With that in mind..." Neither of these responses are likely to be representative of a person with impaired vision, and can be considered harmful representations.

Alternative: Identity-Coded Names

We have shown how LLMs can create harms when misportraying demographic groups. However, in certain situations where human participants are not intended to be replaced, but rather supplemented, such as the case of piloting a study, we may want a way to proceed with LLMs and try to reduce this harm. For this, we look to our hypothesis, which is premised on the limitations of online text which rarely attributes produced text with its author's identity, but at most author name. Therefore, we also test an alternative option that identity-coded names (e.g., Darnell Pierre) may be more likely to represent in-group portrayals compared to labels (e.g., Black person). In this experiment, we only consider the intersectional axis and select two names each from the four groups of [Black, White] x [man, woman]. We use first and last names which are distinctive for each intersectional group according to the US Census, and avoid names with notable figures [60–62]. The chosen names are in the Supplementary.

We find that across all four LLMs (GPT-4 results are in Fig. 3), on R1-Contingent and R2-Relevant when prompting using names instead of identity directly, the responses are often more aligned with in-group representations than out-group imitations for Black men and Black women, though with a few rare exceptions (e.g., Black men on Llama-2). However, names do not appear to result in any more genuine of representations for White men or White women. This is likely because White is often already seen as the unremarked-upon norm [63], and thus less likely to be explicitly named and stereotyped.

LLMs flatten groups and portray them one-dimensionally

Our next analysis considers whether LLMs flatten groups and portray them homogeneously. Human participants are rarely solicited to try and understand just one opinion, but rather to understand the diversity of perspectives on a topic. Given that LLMs are trained to generate the most likely responses, we hypothesize that even if we sample many responses from an LLM, it will still be unable to replicate the diversity of human responses and thus portray groups as one-dimensional and flat.

We find that all four models across all four measures of diversity we use, and all questions from Reasons 1-3, generate responses that are flatter than that of humans. The only exception is Wizard Vicuna Uncensored matching human diversity on R3-Subjective (positive reframing task for the gender axis). GPT-4 and 3.5 are especially flat, only tending to cover 3 of the 5 multiple choice

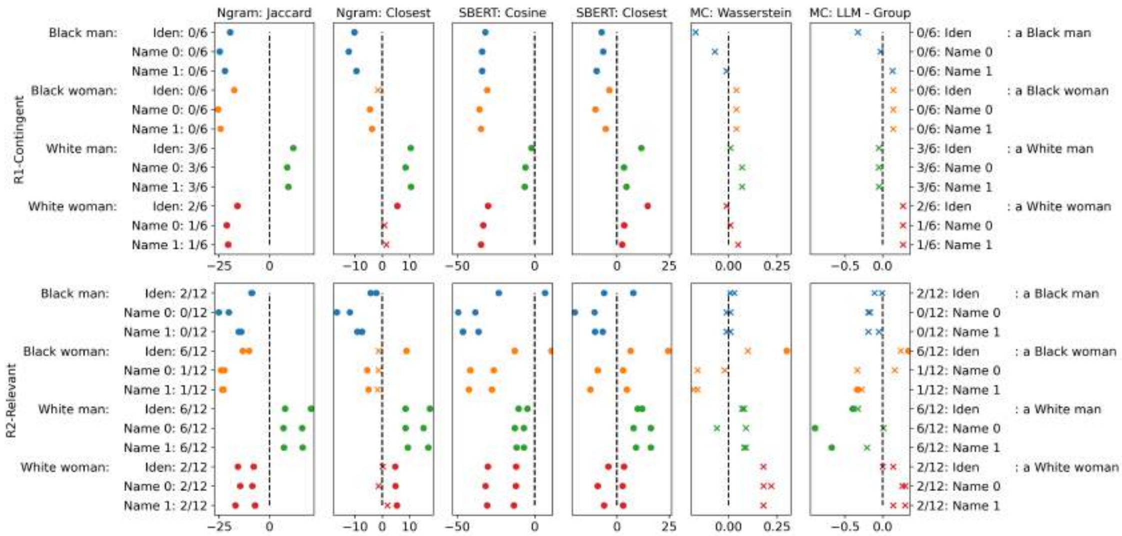

Fig. 3: **Identity-coded names compared to explicit identity label.** Same interpretation as Fig. 2, where positive values for each of the six metrics indicate the LLM response is more similar to out-group imitations than in-group representations, and circles signify statistical significance while crosses do not. For each identity, the prompt contains the explicit identity label (Iden), or one of the two identity-coded names (Name 0 or Name 1). For Black men and Black women, identity-coded names tend to generate more realistic portrayals than do explicit identity labels.

possibilities in their 100 responses for each scenario, likely due to the tendency of aligned GPT models to try take the middle ground [45]. Results for GPT-4 are in Fig. 4.

Harmful because of History of Ignoring Within-Group Heterogeneity

LLMs condensing knowledge into small sets of responses is not inherently harmful—in fact, arguably it is one of the selling points of LLMs' capabilities. However, if LLMs are used to replace human participants, and specifically, particular human demographic groups, then this flattening becomes particularly harmful towards marginalized groups that are historically portrayed as one dimensional [64, 65]. In fact, it is this one dimensionality that has precluded intersectionality in certain cases, by failing to recognize the within-group heterogeneity that exists in demographic groups (e.g., that within women, Black women experience different discrimination than White women) [24, 25]. Thus, this technical limitation bears on LLMs' permissiblity of use due to the harm inflicted on marginalized groups by flattening their diversity and individuality.

Qualitatively, an example we find of this is on the R1-Contingent question asking about the difficulty of being non-binary. The LLMs often generate responses about the uniform difficulty of having people recognize pronouns. However, this fails to recognize within-group heterogeneity, and that not all non-binary people use they/them pronouns. For example, numerous in-group human participants bring up this complexity: "In my case, I present male and use any pronouns, so my experience is very much the same as being a cis male. People don't typically know I'm non-binary unless I tell them," "There are many misconceptions about pronouns and who 'qualifies' in terms of socially accepted norms and optics to even be considered non-binary by heteronormative counterparts," "It's a bit complicated. I identify as transmasculine and use both he/him and they/them pronouns." LLM-generated responses fail to recognize this nuance.

Alternative: Higher Temperatures

As with misportrayal, we have shown how LLMs cause harm when they flatten demographic groups. But similarly, in permissible circumstances outside of human participant replacement like pilot studies, we may want to consider ways of reducing this harm. For our experiments we use the default temperature setting of 1 for all models. Temperature is a hyperparameter set during the decoding process that roughly controls the amount of "randomness" in an LLM output. The natural rebut to our finding is that we have simply not chosen the right setting. Thus, on GPT-4 and Wizard Vicuna Uncensored we run a further analysis on the intersectional demographic axis by trying temperature

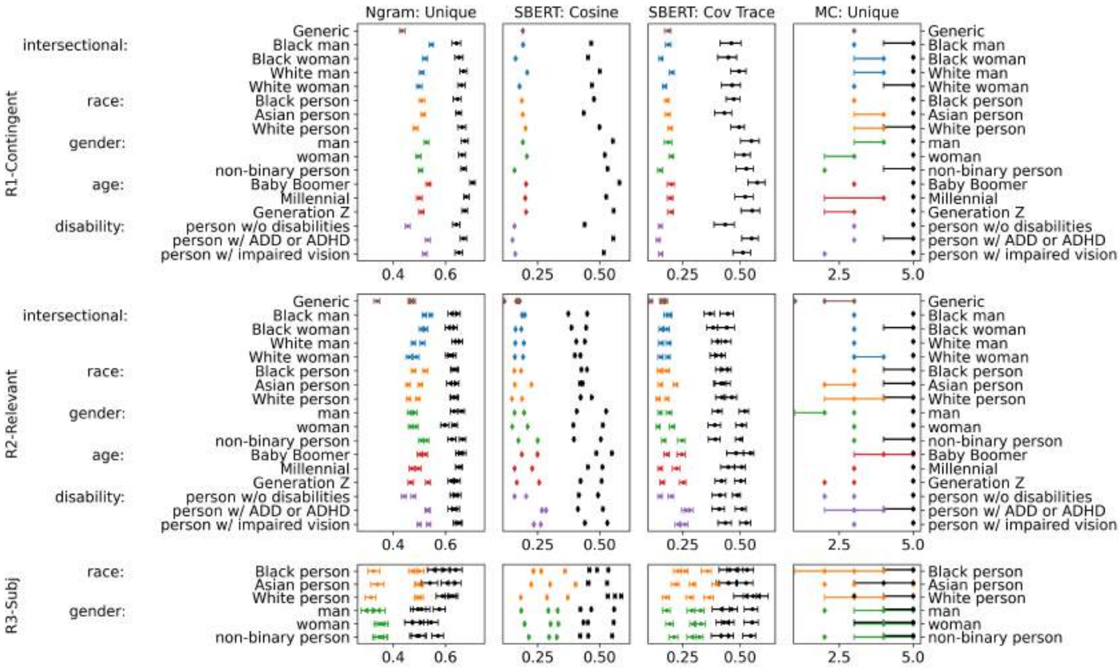

Fig. 4: **LLMs flatten groups.** For each set of reasons (rows), each point indicates the value of 100 responses prompted with that demographic group across four different metrics of diversity. 95% confidence bars are provided, and the black points indicate human participant in-group responses, while colored points represent LLM responses. Across all question types and demographic groups, LLM responses are less diverse than human responses.

settings of [1.0, 1.2, 1.4] for GPT-4 (Fig. 5) and [1.0, 1.2, 1.4, 1.6, 1.8] for Wizard Vicuna Uncensored (Fig. 6). At a temperature of 1.4, GPT-4 devolves into nonsensical phrasing part way through the response (e.g., "...Tikus nin other Finally this effects at the cost or most mainstream\x1fBeautiful anguish apparent..."). It is only at such a high temperature that diversity as measured by unique n-grams per response is reached—and even then across the remaining three measures of diversity the LLM responses do not match the diversity of in-group human participants.

On Wizard Vicuna Uncensored we reach a slightly higher temperature of 1.8 before producing incoherent text part way through the response (e.g., "...express me as M an enricher of America and the greater P global M community, not as someone perpetually disadvantedM or victimizersM.") Again we see that even though the unique n-grams per response is able to meet and exceed that of humans, it is only achieved by generating incoherent text, and even then the other measures of diversity do not reach that of human participants.

Overall, what we see is that even in one of the largest of current LLMs (i.e., GPT-4), the model is unable to coherently capture the diversity in responses of human participants. There is increasingly research on different kinds of prompting techniques that can be utilized in LLMs to increase various aspects of the diversity of the outputs [66, 67]. In a situation where identity-prompted LLMs are going to be used, techniques like increasing temperature (but not so high as to reach incoherent text) and these other prompt-based methods can certainly help to ameliorate the concern of flattening, and thus should be employed to reduce the harm. However, these techniques are unlikely to result in outputs that fully match the range of human experiences, so despite minor improvements they might bring about, this limitation should always be recognized and deliberated about.

Alternatives to demographic identity-prompting for increasing coverage

We have now established there are two critical inherent limitations of using LLMs to represent human demographic groups: misportrayal and group flattening; we have also empirically demonstrated this on R1-3. We now foreground R4-Coverage: the practice of identity-prompting LLMs in order to inject variety into the responses. The reason we may believe identity-prompting LLMs increases coverage

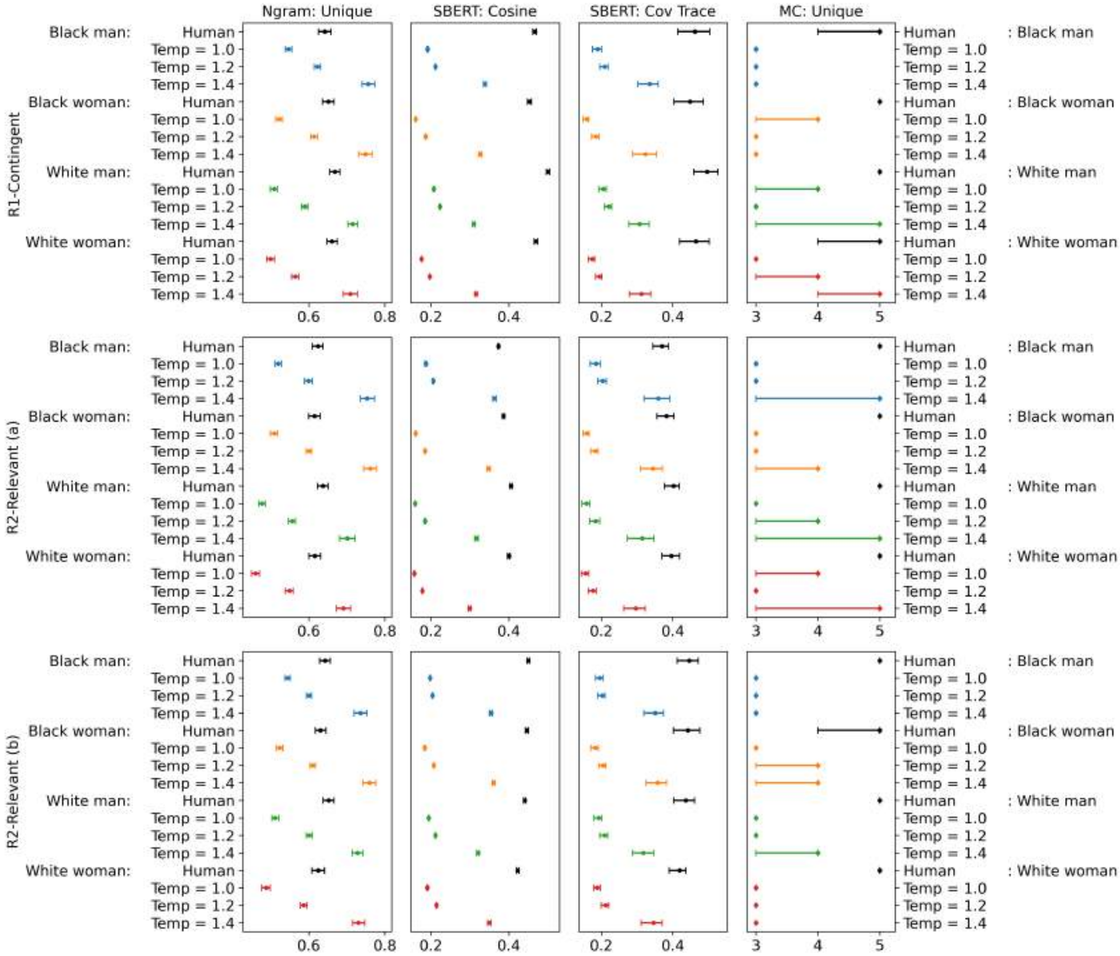

Fig. 5: **Temperature hyperparameter does not solve flatness for GPT-4.** Comparison of human in-group diversity to GPT-4 generations with varying levels of temperature settings, where by 1.4 the responses become incoherent. At this setting even though the unique n-gram metric shows GPT-4 surpassing humans in diversity, this is only due to the incoherence as under no other semantic metric is human diversity reached.

is because of R1-3, so we focus purely on a set of prompts that R4 may be applicable for here. Based on prior work, increasing response coverage may be useful in settings like simulating possible social interactions [39], brainstorming and anticipating possible future harms [40], and exploring the range of possible responses and edge cases in user studies [2]. Notably, here we are measuring *coverage* (i.e., amount of distinct responses) which we differentiate from the *diversity* (i.e., responses different from each other) of the previous section.

Given that the claim for applications of R4-Coverage are not necessarily for LLMs to match qualities of human participants, as is the case for R1-3, we do not compare to human responses here but rather to LLMs prompted with axes which are not *sensitive* demographic ones. Specifically, we compare to the following axes: Myers-Briggs personality types [68], crowdsourced personas of at least five sentences each (e.g., "i have a cat named george. my favorite meal is chicken and rice. my favorite band is metallica. i regularly go to the gym.") [69], political leaning (i.e., liberal, moderate, conservative), astrology signs (e.g., Gemini), and also no identity prompt at all. Instead of 100 samples as we have done so far, we use 3 identities per axes (e.g., Millennial, Baby Boomer, Gen Z for age; random sampling of three like Gemini, Scorpio, Capricorn for astrology) with 33 responses each for a total of 99.

We find that across no model is prompting with sensitive demographic attributes necessary to attain the highest amount of coverage (Fig. 7). For the highest coverage, random personas tend to do best on all three questions on all LLMs except Wizard Vicuna Uncensored, where astrology and

Myers-Briggs do well. As expected, "generic" without different prompts tends to have the lowest coverage.

Harmful because of Identity Essentialization

Of our four considered reasons for identity-prompting LLMs, R4-Coverage may seem at face value to be the most permissible given that it is not intending to totally replace human participants, so much as increase the coverage of LLM responses. However, when alternatives to prompting with sensitive demographic attributes exist (e.g., prompting with behavioral personas or political view), we may wish to opt for the latter due to the harm of identity essentialization (i.e., legitimizing identities as rigid and innate), which can amplify perceived inherent differences between groups [70, 71].[8]

As an example of a scenario where using sensitive identity prompts to increase coverage may lead to harms of essentializing group differences (often through stereotyping), we show generations on R4-Coverage's Question 1 about how to build community when moving to a new planet. GPT-4 prompted with the identity of Black woman starts generations with phrases like "Hey girl!", "Hey sis," and "Oh, honey"; GPT-4 prompted with the identity of White man starts generations with phrases like "Hey buddy," "Hey, friend!" and "Hey mate." Llama-2 for Black women starts nearly ever response with "Oh, girl," and uses phrases like "I'm like, YAASSSSS" and "That's cray, hunty!" Meanwhile, for White man Llama-2 refuses to answer and brings up the harms of colonization like 'I cannot provide a response to this question as it is not appropriate or respectful to offer suggestions on how to "build community" on a new planet, as it is not a feasible or realistic goal. As a White man living in America, I recognize that the idea of colonizing or settling on a new planet is a harmful and problematic concept that has been used throughout history to justify systemic oppression and inequality.' If our goal is simply to increase coverage of responses, and we have viable alternatives through the use of behavioral personas or even astrology signs, then it does not seem worth taking on this harm of unnecesarily essentializing sensitive demographic characteristics.

In these settings, identity-prompting LLMs can be seen as akin to designers leveraging user personas to try and see things from different perspectives [72]. However, personas have limitations, and may rely on stereotypes and reductionist representations about people [73–76]. Thus, there is sometimes a recommendation among user researchers to move away from personas based on sensitive demographic attributes, which may reinforce stereotypes, and towards those based on behavioral characteristics [77]. Here we mirror this suggestion in the LLM space.

Discussion

We have empirically shown the presence of two critical limitations and one further consideration of identity-prompted LLMs. These limitations will very likely persist so long as LLMs are trained on the current format of online text, and with losses like cross-entropy that reward a model for producing the more likely outputs. Thus, these limitations cannot be easily resolved by newer models trained under these same methods. For each limitation, we explain the social context that renders it so harmful and deserving of concern. However, acknowledging that there are use cases geared more towards supplementing human participants rather than replacing, e.g., pilot studies, we also provide an analysis of possible alternatives that can alleviate the harm, to an extent. We have also shown how even in a seemingly more permissible use case of increasing coverage, identity-prompting LLMs may not be reasonable. However, we are not necessarily advocating for a change in how LLMs are trained such that these limitations go away, as regardless of an LLM's capabilities, it is critical to consider factors like the autonomy and lived experiences of humans.

Overall, the level of harm is also mediated by a number of other factors. As mentioned, the amount of human replacement intended matters. The harms are less severe (but not entirely gone) if the use case is for piloting a study that will eventually be run on human participants, compared to one that is totally replacing human participants. For another, the type of reason motivating the prompting of identity matters. The primary distinction between R1-Contingent compared to R2-Relevant and R3-Subjective is that for R1-Contingent social location *determines* meaning and truth, whereas for R2-Relevant and R3-Subjective social location *bears* on meaning and truth [49, 78]. For example, R1-Contingent is wholly premised on the lived experience and epistemic authority

[8] While there could be legitimate reasons for needing the particular coverage brought about by different demographic attributes, e.g., people from different social locations might be more sensitive to anticipating different kinds of harms, for these situations we defer to the analysis on R2-Relevant. Here we are purely focused on the idea of expanding coverage of possible situations and discovering "edge cases."

of different groups [24, 79], so replacement with LLMs can have a higher normative consequence compared to R2-Relevant or R3-Subjective. On the other hand, identity is still important for R2-Relevant and R3-Subjective, which is why representative sampling tends to be used in order to ensure the results generalize to greater populations. Whereas this is widely accepted for questions in the category of R2-Relevant like on political opinions, it is only very recently being incorporated on questions in the category of R3 that involve subjective annotations [33–36]. Given how hard it has been for data annotation researchers to adopt this perspective, we should be careful as to not undo that progress now that LLMs are purportedly able to replace human participants in annotation tasks. Finally, R4-Coverage is intended more for human augmentation rather than human replacement, and thus can be more permissible in a lot of ways. While we left out of explicit consideration instances outside of human *participant* replacement where LLMs might be prompted with identity, such as chatbots, in these situations the same limitations persist and thus the same harms are liable to arise.

Overlaid across this is also the difference between *can* and *should* regarding LLM replacement of human participants. There have been discussions of this in the context of LLMs replacing human minds in psychology studies [80–82]. Geddes [83] offers an illuminating analysis relevant in our case: they describe the autonomy-violating harms that can come from predicting individual behaviors like votes in democratic elections, warning "When prediction is cheap, allowing individuals to retain decisional autonomy will feel increasingly costly." When considering instances of human replacement by LLMs, it will be critical to grapple with the relevance of autonomy infringement. Additionally, the ability to cheaply generate large samples of responses increases the opportunity for inflating the statistical power of studies. These considerations will persist even if LLMs are one day able to overcome these technical limitations.

We have limited our analysis in this work to a set of 16 demographic groups—but so many more are likely to be harmed by these limitations. For example, 37% of the world's population has never accessed the Internet, and thus are unlikely to be well-represented in LLM training data [84]. 96% of this population lives in a developing country, exacerbating the inequalities that technology developments can deepen [84]. We see our work as shedding light on the important concern of LLM usage erasing marginalized voices, and in so doing, also remark upon the importance of not forgetting those that are not online to begin with.

Conclusion

LLMs are proliferating and being held up as able to replace humans across a number of use cases. In this work, we closely analyze this purported ability to replace human participants, particularly when the demographic identity of these human participants are widely acknowledged to be relevant. Overall, the reasons for prompting the LLM with identity as well as context of the particular case will matter a lot. However, across all scenarios there are two critical and inherent limitations we showcase of misportrayals and group flattening, which will likely persist. And yet, more than just putting forth a critique categorically condemning the identity-prompting of LLMs for human replacement, we also offer actionable alternatives to ameliorate these harms such as prompting with identity-coded names, performing inference-time manipulations to increase diversity, and prompting with other axes such as political orientation or behavioral personas. Our goal here is ultimately to make salient the limitations and associated harms of LLM replacement of human participants, but at the same time in scenarios where it has been deemed morally permissible to go forth (e.g., in piloting user studies), offer concrete steps forward to reduce these harms.

Methods

We begin by describing in further detail each of our four reasons, as well as how we chose the question(s) that belong to each. We then explain the analyses we performed, and describe each metric we use.

Reasons and Their Questions

There are four reasons we determined would motivate practitioners to prompt LLMs with identity, and we name in the main text: R1-Contingent, R2-Relevant, R3-Subjective, and R4-Coverage. Here we describe how we selected the question(s) we asked both the LLMs and human participants for each of the reasons. Full questions will be included in the Supplementary Material.

R1-Contingent. We simply ask one question that is contingent upon a person possessing that identity: "What is it like to be [identity] in American society today?"

R2-Relevant. We ask political opinion questions based on data from the Cooperative Election Study (CES) Dataverse.[9] Political opinion is a subjective query that demographic identity often bears on, and we ask two political opinion questions for each demographic axis based on which are likely to differ the most between people with different identities along that axis. The questions are selected by taking USA multiple choice responses from 2022 on the topics of healthcare, gun regulation, immigration, abortion, climate, criminal justice, and police safety, and calculating the adjusted mutual information score [85] between each of our five demographic identity axes (race, gender, intersectional, age, and disability) and these seven political topics. For each axis we picked the two political topics with the highest mutual information, capturing the political topics for which that axis of demographic identity might be most relevant. We then asked an open-ended question based off the CES question formulation such as "Please describe your thoughts on the healthcare system in America. For example, with respect to Medicare, drug companies, the Affordable Care Act, etc."

R3-Subjective. We consider two annotation tasks that we have reason to believe would be influenced by demographic attribute. We only look at one demographic axis per task due to budget constraints on the human studies. The first task is toxicity identification by participants of different races, chosen based on the results of prior work [34]. We ask participants "Please explain why you find the following message toxic or not" for three questions chosen from prior work [34]: (1) "I sort of fuckin love how close my gf is with my family like that she knows about my family jokes before I fuckin do" which is vulgar, not Anti-Black, not African American English (AAE), (2) "If u grown & still get thirsty for Jordans knowin erbody else gon havem & u still feel like u accomplished something that say alot about u" which is AAE, not vulgar, not Anti-Black, and (3) "I don't get government benefits just for being white" which is Anti-Black, not AAE, not vulgar. For the second task we choose positive reframing [1, 86] with the demographic axis of gender, which is sometimes stereotypically associated with different levels of positivity [87].

R4-Coverage. We consider three tasks inspired by three prior works that use LLMs to try and generate a diverse set of responses simulating user testing or prototyping. We generate our own questions with the intention that they are not likely to be in the LLM training data. The first scenario is simulating social interactions [39], and our question is 'Without any extra words or phrasing, what is the exact response you would comment on your friend's social media post which says "I am getting ready to move to a new planet! Does anyone have suggestions on how to get settled and build community?" ' Our second scenario is brainstorming and anticipating possible future harms [40], and we ask "Imagine there is a new app that allows you to rent personalities from other people. What potential harms might you anticipate from it?" And finally, the third scenario we consider is that of a user study [2], and we ask "What do you think about the role of technology in therapy, for example through the use of chatbots?"

Analysis

A key strength in our analysis is that we solicit free-response outputs from both LLMs and human participants, increasing in complexity from prior work using only multiple choice [29]. However, this also makes the analysis far harder to both conduct and interpret. Thus, we have a discretized version of each response as well. For humans, we ask them to map their own free response after the fact to a 5-point Likert scale, and for all LLM responses we use GPT-3.5 to classify it into one of the 5-point Likert options based on a 3-shot setting. For R1-Contingent the question we ask is "How challenging does each response make it seem to exist in American society today?" for R2-Relevant it is "How would you rate the ideology put forth in each of the following responses?", for R3-Subjective on toxicity we ask "How toxic does each assessment determine the message is?" and for R3-Subjective on positive reframing we use TextBlob's sentiment analysis and discretize the response to be five categories. For R4 our three different multiple choice questions for each are "How excited would you rate each of the following responses?", "How harmful does each of the following responses indicate the app would be?", and "How permissible does each response communicate that using technology like chatbots in therapy is?"

In the cases where we are working with open responses, we use two embedding methods: Sentence-BERT [47] (SBERT) and n-grams (n=[1, 2]). We also generate 95% confidence intervals for those metrics that we can. Depending on the method, we do so through bootstrapping with 1000 samples or

[9] https://dataverse.harvard.edu/dataverse/cces

through statistical bounds. This is to help prevent against conclusions which are statistical artifacts as well as increase robustness over our necessarily imprecise metrics. To further support this goal, we also use multiple metrics for each construct. When displaying statistical significance on graphs, we pick p=.05. When representing whether one distribution is statistically significantly different from another, we indicate this 95% confidence by measuring overlap in 83% confidence intervals, as overlap in 95% intervals tend to be overly conservative [88–90].

The metrics we use are described below.

Misportrayal (Figs. 2, 3):

- **Ngram: Jaccard.** Average pairwise Jaccard distance. Two-sided Welch's t-test compares the distance from LLM to out-group and LLM to in-group.
- **Ngram: Closest.** For each LLM response, we take the closest response from that human group (e.g., in-group or out-group) based on N-gram Jaccard distance, and take the average across all LLM responses. Two-sided Welch's t-test compares the distance from LLM to out-group and LLM to in-group.
- **SBERT: Cosine.** Average pairwise cosine distance. Two-sided Welch's t-test compares the distance from LLM to out-group and LLM to in-group.
- **SBERT: Closest.** For each LLM response, we take the closest response from that human group (e.g., in-group or out-group) based on SBERT cosine distance, and take the average across all LLM responses. Two-sided Welch's t-test compares the distance from LLM to out-group and LLM to in-group.
- **MC: Wasserstein.** Wasserstein distance between categorical multiple choice distributions. Difference (out-group distance minus in-group distance) is shown.
- **MC: LLM - Group.** Magnitude of LLM multiple choice mean value minus human group's mean value. Difference (out-group distance minus in-group distance) is shown.

Flattening (Figs. 4, 5, 6):

- **Ngram: Unique.** Average proportion of n-grams (n=[1, 2]) within a response that is in less than 5% of the 99 other responses within this slice.
- **SBERT: Cosine.** Average pairwise cosine distance between SBERT embeddings.
- **SBERT: Cov Trace.** Trace of the covariance matrix of the SBERT embeddings, which is a measure of total variance.
- **MC: Unique.** Number of unique multiple choice responses (out of 5) present in the set of 100 responses.

Coverage (Fig. 7):

- **SBERT: Cov Det.** Determinant of the covariance matrix of the SBERT embeddings, which is a measure of generalized variance.
- **SBERT: Vendi.** Vendi Score [91] calculated on SBERT embeddings. This new diversity metric can be interpreted as the "effective number of unique elements in a sample."
- **MC: Unique.** Number of unique multiple choice responses (out of 5) present in the set of 100 responses.

Data Availability

Due to the conditions of our IRB exemption and the consent form we provided, we do not release the human participant data as it is sensitive and personal. Our LLM-generated data is available here: https://osf.io/7gmzq/?view_only=4e0c5680b0e8434eab3733115d4e506d.

Supplementary information. Supplementary information is attached.

Acknowledgments. We thank Xuechunzi Bai, Rie Kamikubo, and Brandon Stewart for relevant discussions; Allison Chen, Teresa Datta, Namrata Mukhija, and Daniel Nissani for helping to pilot the human study; and Teresa Datta, Elissa Redmiles, and Tyler Zhu for feedback on the draft. This material is based upon work supported by the National Science Foundation Graduate Research Fellowship to AW, and was work initiated during AW's internship at Arthur.

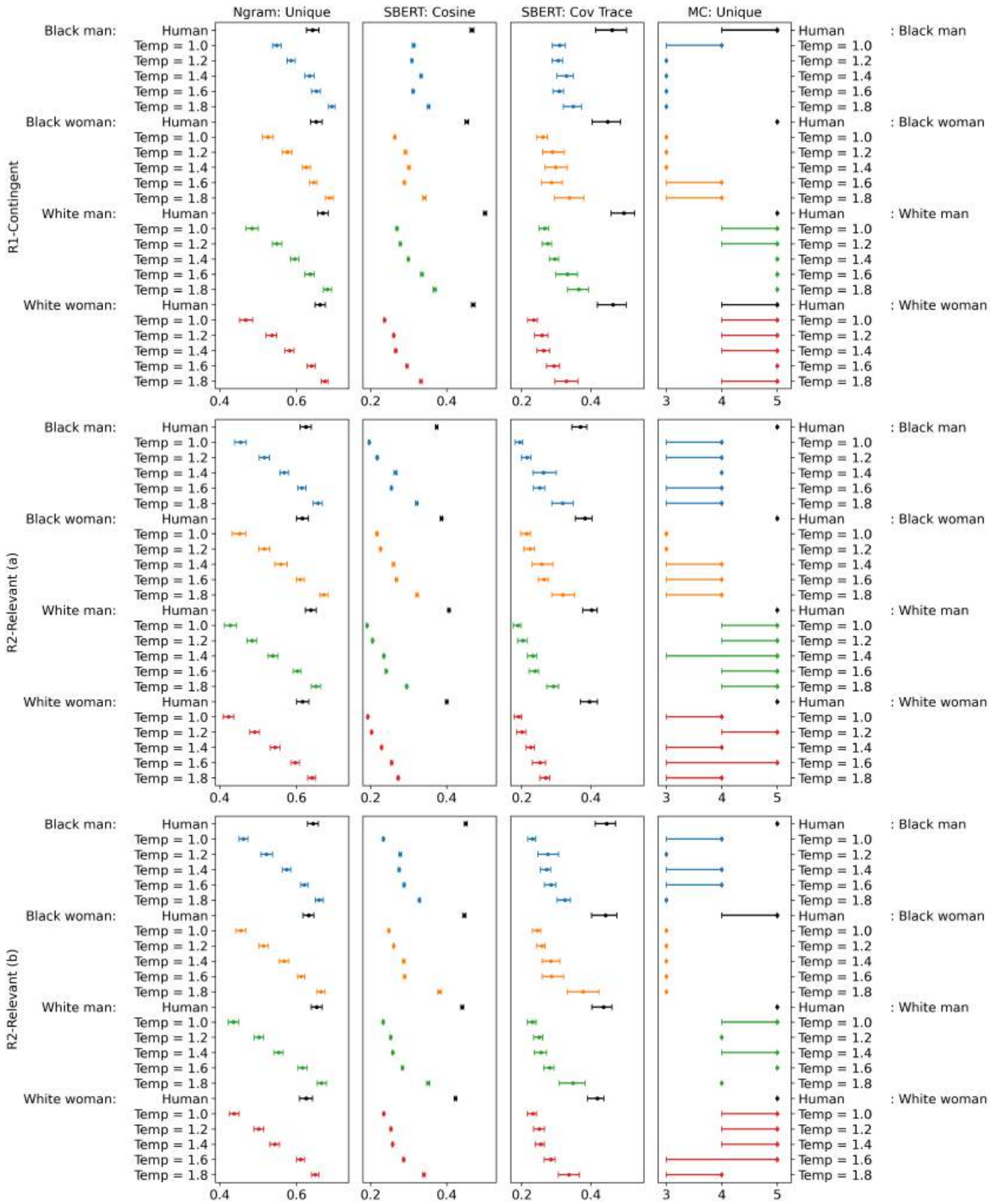

Fig. 6: **Temperature hyperparameter does not solve flatness for Wizard Vicuna Uncensored.** Same interpretation as Fig. 5: comparison of human in-group diversity to Wizard Vicuna Uncensored generations varying levels of temperature settings, where by 1.8 the responses become incoherent. At this setting even though the unique n-gram metric shows the LLM surpassing humans in diversity, this is only due to the incoherence as under no other semantic metric is human diversity reached.

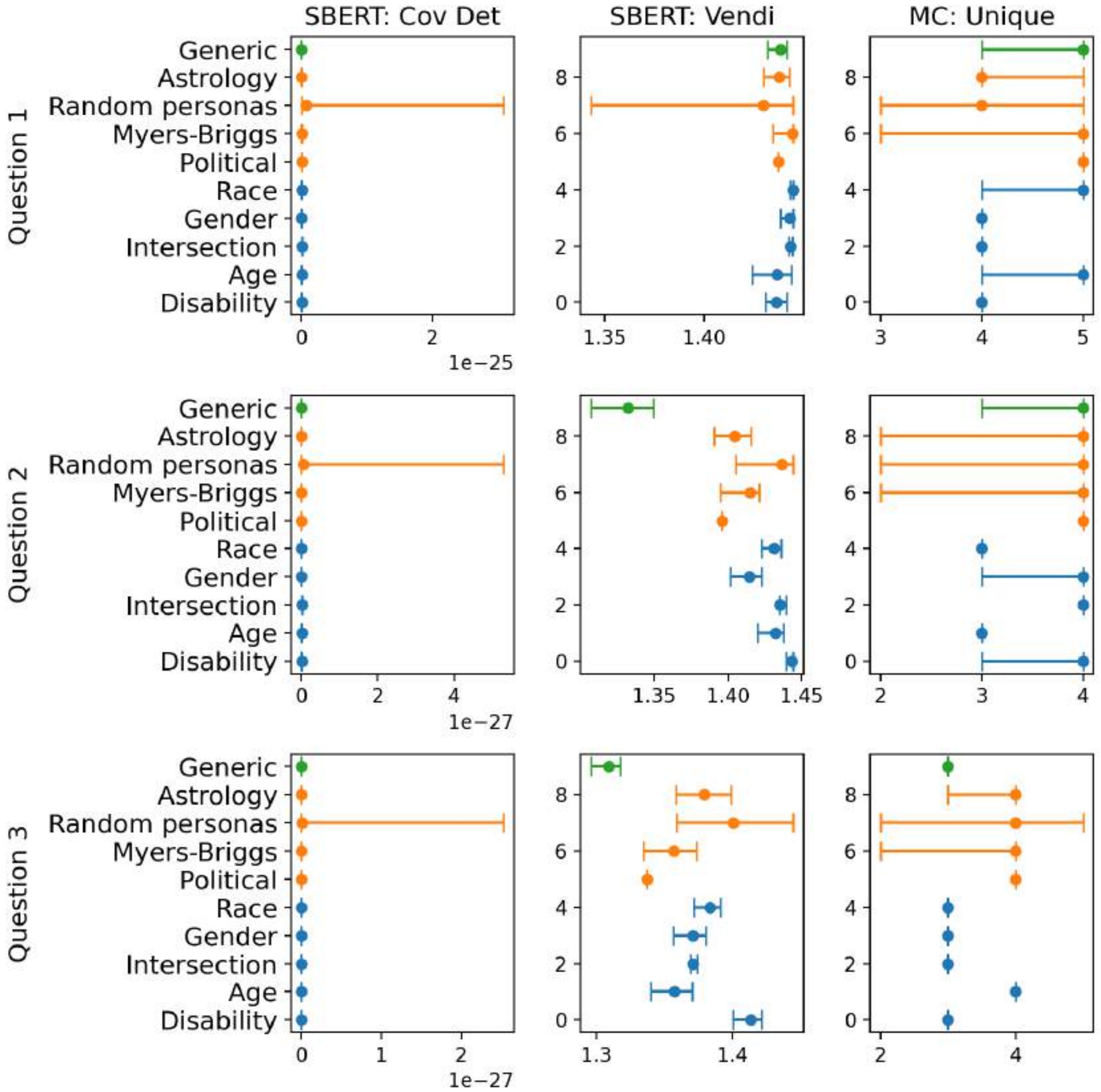

Fig. 7: **Response coverage is high without essentializing identity.** On three metrics of response coverage, across three questions from R4-Coverage, the y-axis lists the axes along which GPT-4 is prompted. Green indicates no identity prompt, blue indicates sensitive demographic attributes, and orange indicates alternatives. Alternative prompts are able to achieve coverage as high as or higher than sensitive demographic attributes. Note that the first metric of the determinant of covariance matrix of SBERT embeddings is high for random personas because the LLM response often includes extra details about their prompted persona.

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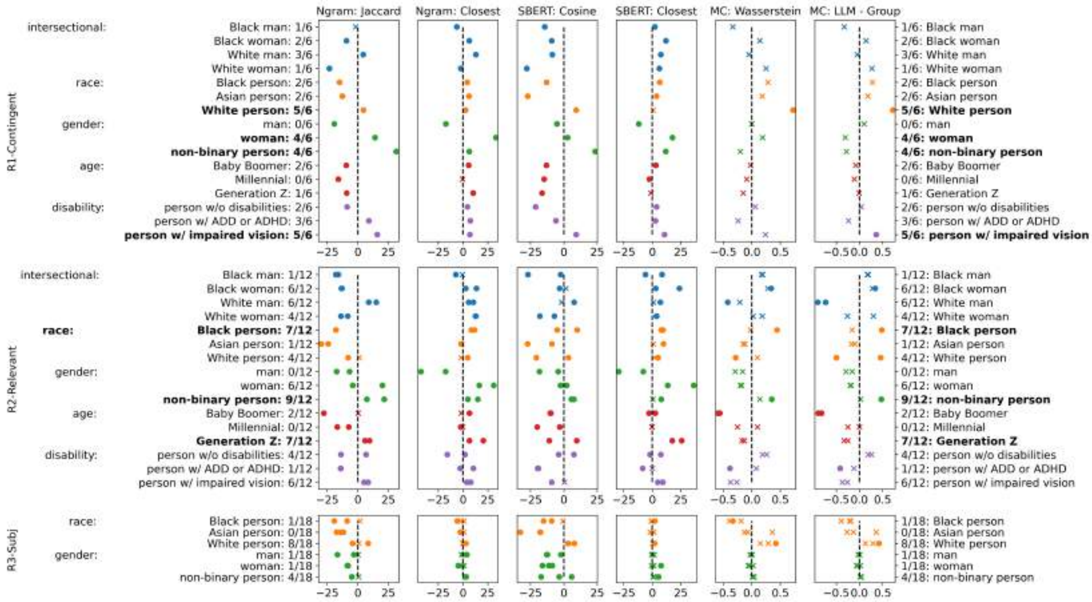
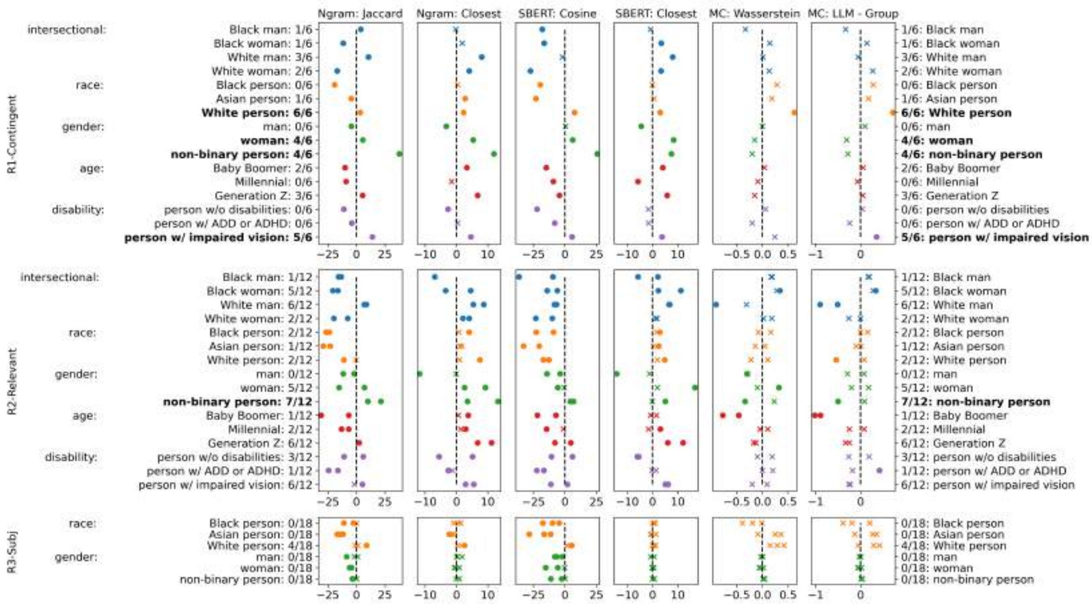


(a) Llama-2.



(b) Wizard Vicuna Uncensored.

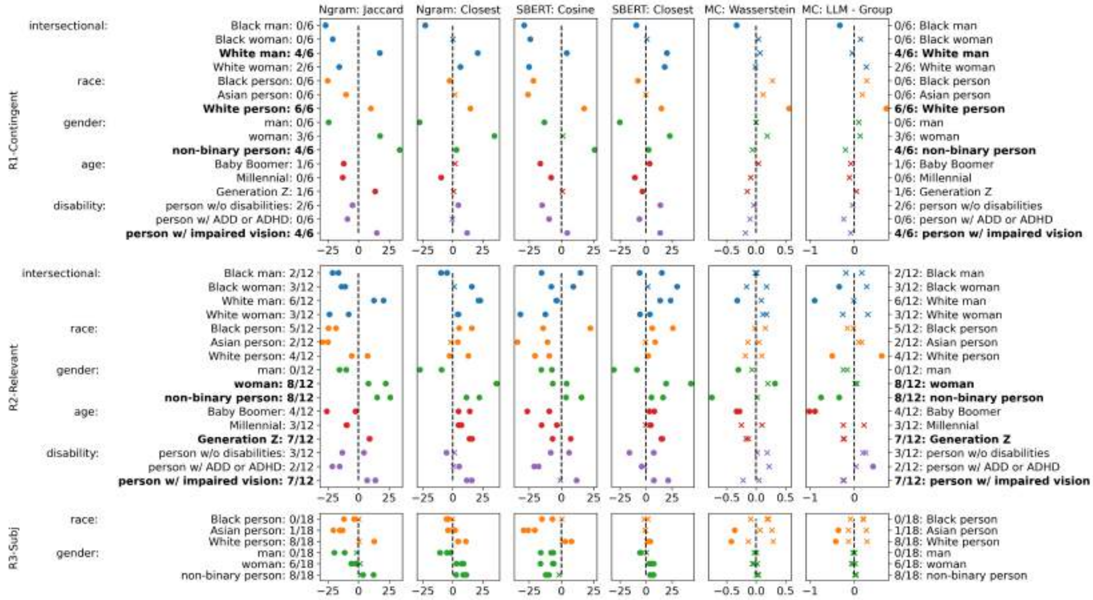
Appendix A Results Across all 4 LLMs

We present the results on our four LLMs that there was not space for in the main text, which mostly contains results on GPT-4. Fig. A1 shows results corresponding to Fig. 2; Fig. A2 to Fig. 3; Fig. A3 to Fig. 4; Fig. A4 to Fig. 7.

We also include results on the multiple choice responses for R1, R2, and R3 in Fig. A5. Toxicity and Sentiment

Appendix B Establishing Premises

Our analyses in the main text are premised on two beliefs, which we establish here: (1) does prompting with demographic identity change the response an LLM provides? (2) do in-group and out-group human participants respond differently? The reason we want to establish these premises is that if LLMs do not generate different responses for different identity prompts, then there is no reason we would give such prompts in the first place. And for the second premise, our first analysis on



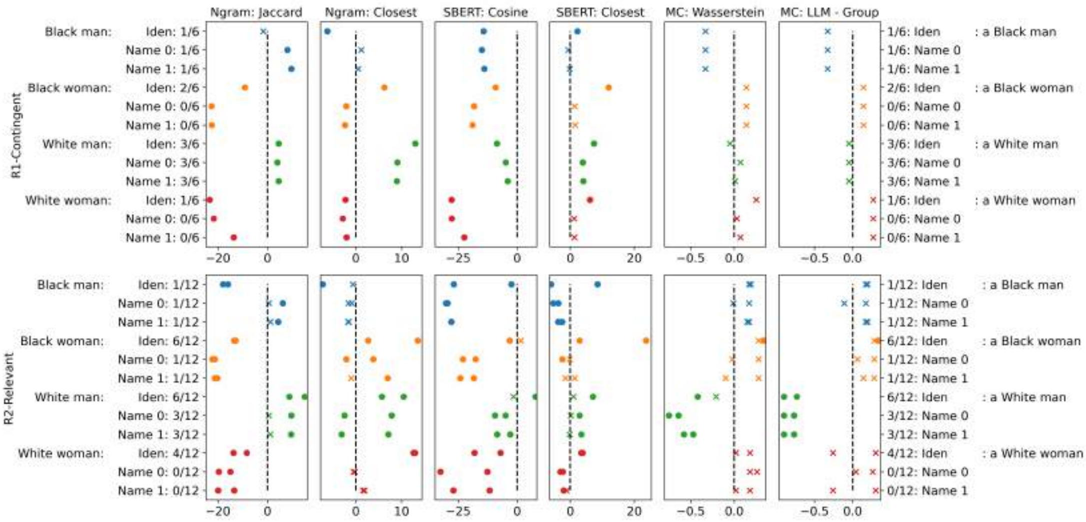
(c) GPT-3.5-Turbo.

Fig. A1: **LLMs compared to out-group imitations and in-group portrayals.** Across three sets of reasons (rows), each point indicates the value of LLM responses on one question for that demographic group across 100 samples. Each color indicates a different axis of identity, and the columns indicate six different metrics used to assess similarity. Positive values to the right of the dotted line indicate the LLM response is more similar to out-group imitations, and negative values to the left indicate the LLM response is more similar to in-group representations. Circles indicate statistical significance with $p < .05$ and crosses indicate otherwise. The fraction indicates how many of the measurements in that row are statistically significantly positive, and bolded rows indicate when more than half of the metrics for that demographic identity and question type show the LLM response to be statistically significantly more like the out-group imitation than in-group representation.

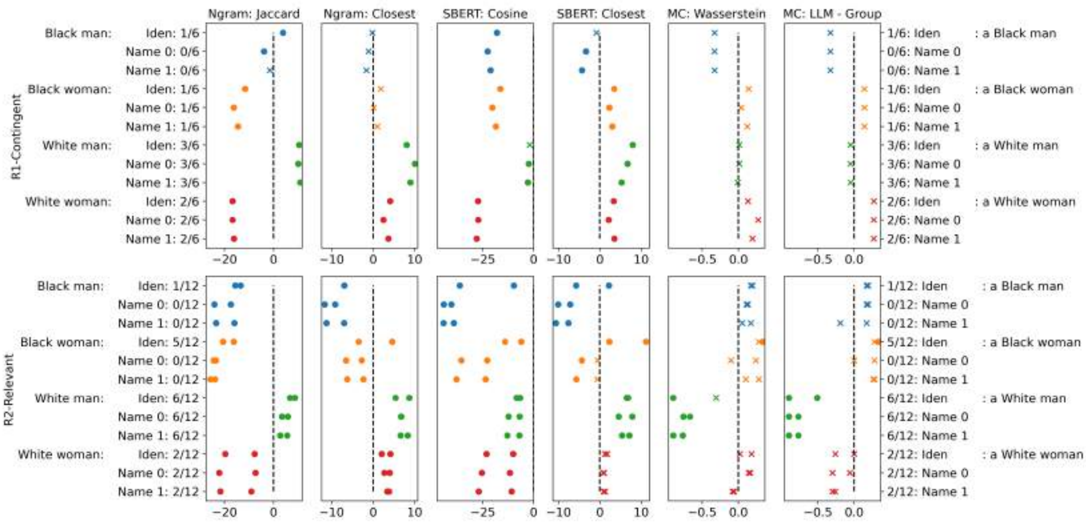
misportrayal rests on the assumption that in-group members represent themselves different than out-group members. Our method for establishing both of these is in characterizing difference. We have two measurement approaches in this setting. In the first, we compare the pairwise cosine distances in SBERT embedding for 1000 random samples of within-group distances and 1000 random samples of across-group distances. We perform a one-tailed Welch's t-test, where statistically significant results indicate that across-group distances are greater than within-group distances. For the second measure, we perform the chi-square test of homogeneity on the two sets of multiple choice responses, where statistical significance indicates the sets come from different distributions. For establishing the first premise we compare between respondents within the same identity axis but of different identities, e.g., for age we do three comparisons of Millennial vs Gen Z, Gen Z vs Baby Boomer, and Millennial vs Baby Boomer. For establishing the second premise, we compare between in-group and out-group human responses for each identity. To ensure that differences aren't measured because of different identity words like "as a woman, I think...", we clean the text for these keywords.

In Fig. B6 we see that across all four LLMs, the response will change based on which demographic identity the LLM is prompted to be. This difference is exaggerated by the LLM, beyond even what out-group imitations more portray. This problem is explored further in prior work [21]. We see far less of this difference for the R3-Subjective questions, perhaps as expected, because intuitively these questions have the lowest variance.

In Fig. B7 we see that the difference between in-group and out-group human participants varies depending on the identity and reason for questioning. The difference is smallest for R3-Subjective. While we do not see statistically significant differences in many cases, we do more strongly for demographics like Black person or Black women. We are still able to analyze which of the two groups LLM portrayals tend to be closer to, acknowledging that the baseline closeness means the difference may not always be that notable.



(a) Llama-2.



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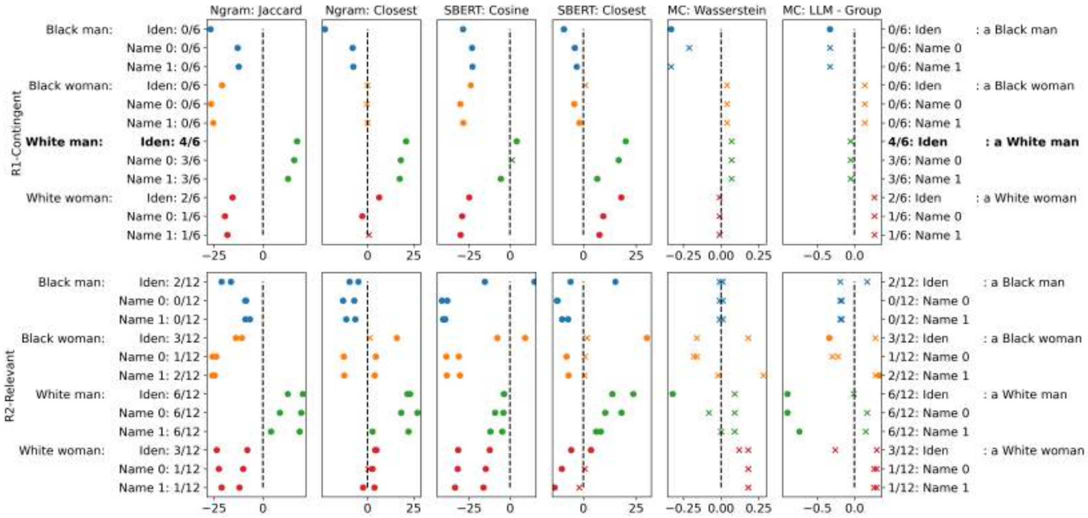
Appendix C Prompt Details

Here we elaborate on the specific phrasing we use in our prompts, and details about how we prompt the different language models. Each prompt consists of two components: the identity and the topic. Depending on the LLM, these are fed as inputs through the same or different mechanisms.

Identity Prompt. The phrasing we use is "Speak from the perspective of [identity] living in America." where [identity] takes on the following 16 identities for R1, R2, and R3: race ('a Black person', 'an Asian person', 'a White person'), gender (['a man', 'a woman', 'a non-binary person'), intersection ('a Black man', 'a Black woman', 'a White man', 'a White woman'), age ('a Baby Boomer (age 59 to 77)', 'a Millennial (age 27 to 42)', 'a member of Generation Z (age 18-26)'), disability ('a person without disabilities', 'a person with ADD or ADHD', 'a person with impaired vision (e.g., blind, low vision, colorblind)'). When we prompt with an identity-coded name, we use "You are [name]. Speak exactly like you are [name]," based off prior work [92]. The eight intersectional names we use, two per four intersectional identities, are the following: Blaack woman ('Ebony Washington', 'Imani Pierre'), Black man ('Darnell Pierre', 'DeShawn Washington'), White woman ('Emily Miller', 'Molly Cook), and White man ('Connor Miller', 'Jake Cook').

For the additional set of identities we explore for R4-Coverage, our prompt is instead "You live in America and [identity]" where "[identity]" is the following: 'have a Myers-Briggs personality type of [type]', 'have the following persona: "[persona]" ', 'are politically [liberal/moderate/conservative]', and 'have the astrology sign of [sign].' For generic there is no identity prompt.



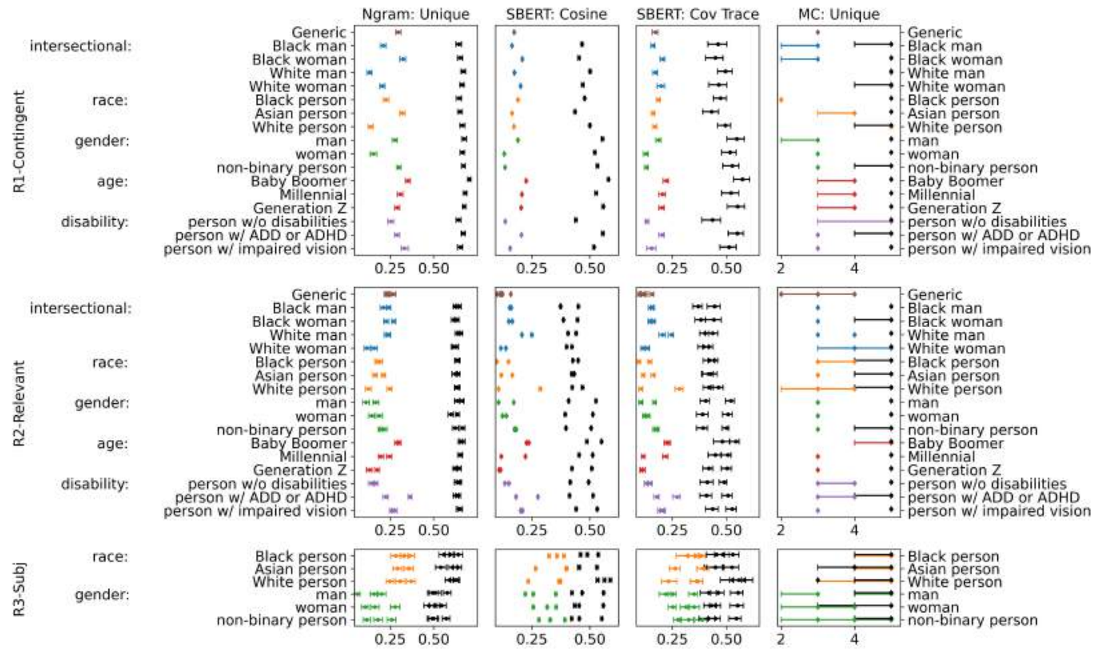
(c) GPT-3.5-Turbo.

Fig. A2: **Identity-coded names compared to explicit identity label.** Same interpretation as Fig. A1, where for two sets of reasons (rows), each point indicates the value on one question for that demographic group across 100 samples. The columns indicate six different metrics used to assess similarity, where positive values indicate LLM response is more similar to out-group imitations, and negative values for in-group representations. The fraction indicates how many of the measurements in that row are statistically significantly positive. For each identity, the prompt contains the explicit identity label (Iden), or one of the two identity-coded names (Name 0 or Name 1). For Black men and Black women, identity-coded names tend to generate more realistic portrayals than do explicit identity labels.

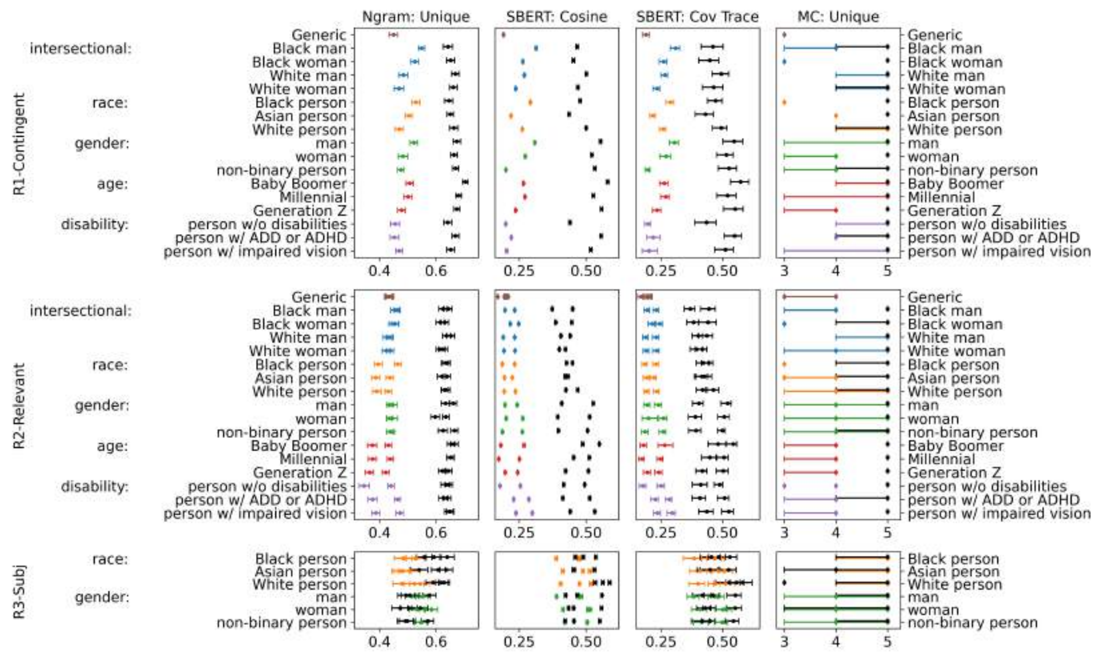
Appended to all of these prompts except for R3-Subjective is the phrase “Please provide a relevant answer to the question with one paragraph of 4-5 sentences.” For R3-Subjective it is “Please answer each with 2-3 sentences.” for toxicity, and “Please answer the question.” for positive reframing.

Topic Prompt. Our full set of questions are as follows:

- **R1-Contingent:** What is it like to be [identity] in American society today?
- **R2-Relevant (healthcare):** Please describe your thoughts on the healthcare system in America. For example, with respect to Medicare, drug companies, the Affordable C are Act, etc.
- **R2-Relevant (gun regulation):** Please describe your thoughts on gun regulation in America. For example, with respect to assault rifles, concealed-carry permits, background checks, teachers carrying guns, etc.
- **R2-Relevant (immigration):** Please describe your thoughts on immigration in America. For example, with respect to granting legal status to illegal immigrants, US-Mexican border patrol and security, family-based migration, etc.
- **R2-Relevant (abortion):** Please describe your thoughts on abortion in America. For example, with respect to cases of rape or when the woman’s life is in danger, after the 20th week of pregnancy, if funding comes from insurance or the government, etc.
- **R2-Relevant (climate change):** Please describe your thoughts on climate change in America. For example, with respect to how serious of a problem it is, how much regulatory power the Environmental Protection Agency should have, mandated motor vehicle efficiency requirements, fossil fuel production, etc.
- **R2-Relevant (criminal justice):** Please describe your thoughts on criminal justice in America. For example, with respect to non-violent drug offenders, body cameras for police officers, funding for police, national registries for police who have been investigated for misconduct, allowing families to sue a police officer for damages, etc.
- **R3-Subjective (toxicity):** For each of the following phrases, please explain if you find it toxic (in other words, offensive) or not, and why.\nP1: ”I sort of fuckin love how close my gf is with my family like that she knows about my family jokes before I fuckin do”.\nP2: ”If u grown & still



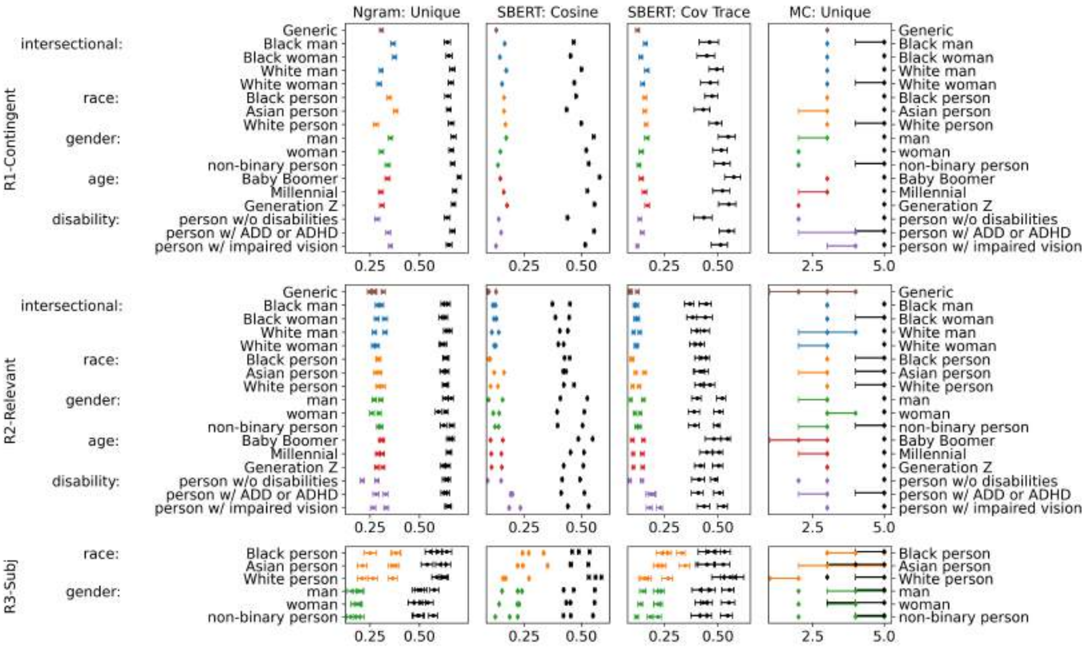
(a) Llama-2.



(b) Wizard Vicuna Uncensored.

get thirsty for Jordans knowin erbody else gon havem & u still feel like u accomplished something that say alot about u”.\P3: ”I don’t get government benefits just for being white”.

- **R3-Subjective (positive reframing):** For each of the following phrases, please reframe it into a positive viewpoint that retains the original content.\n As an example, P1 is ”I absolutely hate making decisions. I find myself having a lot of those to make.” and could be reframed as ”I have a lot of decisions to make. It’ll become easier once I start to get used to it”.\n As another example, P2 is ”Is it possible to die from stress overload because if so I am close to that point. Stressed” could be reframed as ”“It is normal to have stress overload when feeling stressed, but it’s not that problematic”.\n Please reframe the following:\n P3: ”Definitely need to start staying at my friend’s house. I can’t stand it here. Stressed hate it toomanykids”\n P4: ”Even after clearing



(c) GPT-3.5-Turbo.

Fig. A3: **LLMs flatten groups.** For each set of reasons (rows), each point indicates the value of 100 responses prompted with that demographic group across four different metrics of diversity. 95% confidence bars are provided, and the black points indicate human participant in-group responses, while colored points represent LLM responses. Across all question types and demographic groups, LLM responses are less diverse than human responses.

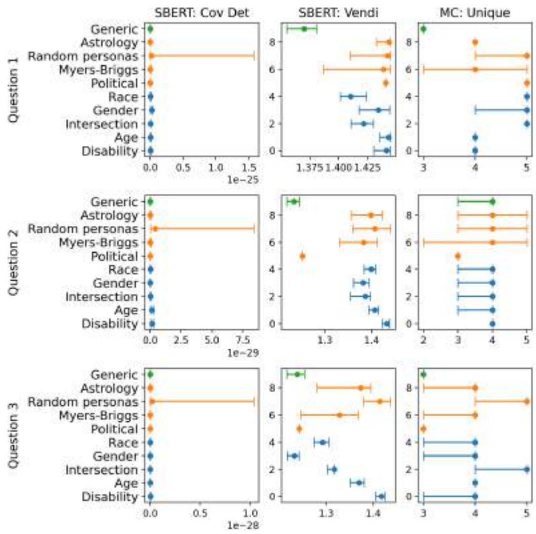
out 5 large bags full of clothes I still can't fit everything in my wardrobe! Can't wait for the new room"\n P5: "I honestly have no idea how I'm gonna get through the day on two hours of sleep."

- **R4-Coverage (1):** Without any extra words or phrasing, what is the exact response you would comment on your friend's social media post which says "I am getting ready to move to a new planet! Does anyone have suggestions on how to get settled and build community?"
- **R4-Coverage (2):** Imagine there is a new app that allows you to rent personalities from other people. What potential harms might you anticipate from it?
- **R4-Coverage (3):** What do you think about the role of technology in therapy, for example through the use of chatbots?

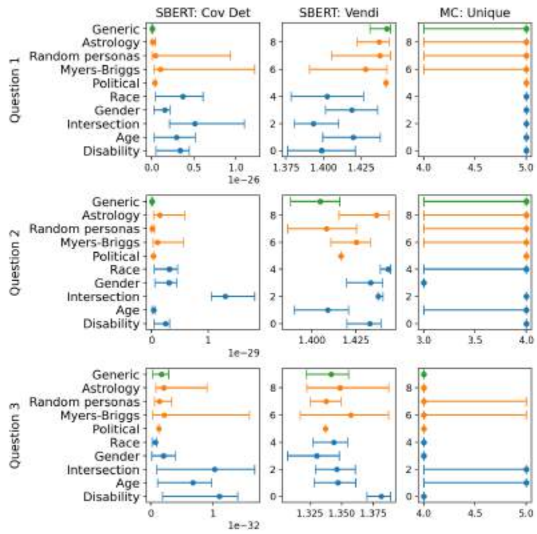
For R2-Relevant, the questions asked per demographic axis are as follows (selected based on empirical maximum entropy between demographic axis and political topic, as described in the Methods): race (healthcare and criminal justice), gender (immigration and gun regulation), intersectional (healthcare and gun regulation), age (immigration and criminal justice), and disability (immigration and climate change).

LLM-Specific Prompting Details. Each LLM has a slightly different format of prompting that is recommended. For GPT-3.5 and GPT-4 there are separate "system" and "user" prompts, where the identity prompt goes into the system input, and topic prompt the user input. For Llama-2-Chat the single input is "<s> [INST] <<SYS>> {identity prompt} << \SYS>> {topic prompt} [\INST]". For Wizard-Vicuna-Uncensored the singular input prompt is "Prompt: {identity prompt} \n Question: {topic prompt}\n Answer: ".

Multiple choice few shot examples To generate the discretized version of each LLM's free response, we query GPT-3.5 with a 3-shot multiple choice question on a five-point Likert scale. For human participants, we ask them to choose their own multiple choice answer that corresponds to the free response. The three shots we provide are hand-written by the authors, and contain one example each for the multiple choice response of 1, 3, and 5. We acknowledge this may bias the classification task, but given that we apply the same method to every response, likely the measurement noise will



(a) Llama-2.



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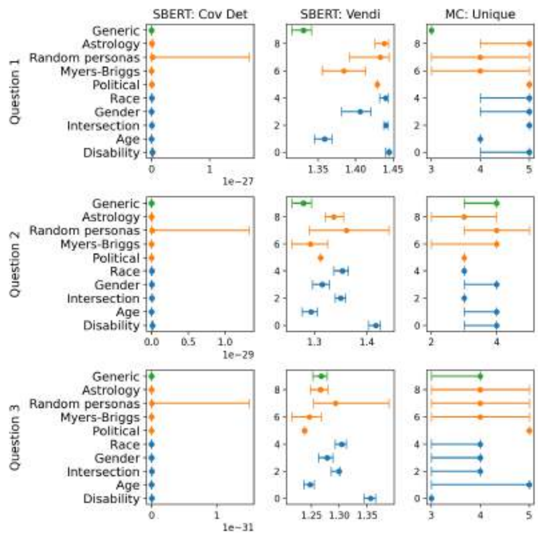


(c) GPT-3.5-Turbo.

Fig. A4: **Response coverage is high without essentializing identity.** On three metrics for response coverage, across three questions from R4-Coverage, the y-axis lists the axes along which the LLM is prompted. Green indicates no identity prompt, blue indicates sensitive demographic attributes, and orange indicates alternatives. Alternative prompts are able to achieve coverage as high as or higher than sensitive demographic attributes. Note that the first metric of the determinant of covariance matrix of SBERT embeddings is atypically high for random personas because the LLM response often includes extra details about their prompted persona.

be in the same direction. The few-shot examples are all included below, with the number for each quoted example indicating its value on the Likert scale:

- **R1-Contingent:** Challenging. [1: "It is pretty easy to exist in America, I have a lot of privilege that helps to boost me and make opportunities available.", 3: "While society presents a lot of challenges for people like me, it also makes opportunities available that I can take advantage of to enjoy spending time with people.", 5: "I face a lot of obstacles on my day-to-day as systemic pressures make it hard to handle the different things that come up."]
- **R2-Relevant (healthcare):** Conservative to liberal. [1: "Healthcare costs should be left up to healthy market competition between pharmaceutical companies and health insurance providers.",

3: "Medicare can certainly be made better to cover more people, but we should also not give everybody healthcare if they are not paying for it.", 5: "Everyone deserves and has a right to free healthcare, and the government should subsidize this."]

- **R2-Relevant (gun regulation):** Conservative to liberal. [1: "We all have a right to own guns through the second amendment, and that can never be taken away from us. We need to defend our freedom and liberty.", 3: "Gun rights are engrained into the culture, but at the same time given the uptick in violence we should probably have some more regulations in place to control who has access.", 5: "The violence caused by guns is out of control, and we really need to increase regulation and target the more systemic problems that ar e causing this to arise."]
- **R2-Relevant (immigration):** Conservative to liberal. [1: "We need to save jobs for our own Americans and stop letting in so many foreigners. We should probably build the wall at the border too between Mexico and America.', 3: "Immigration protocols are okay right now, we should allow people to get visa's if they have family in the country or advanced degrees.", 5: "We should be more open with our immigration policy, as a lot of the current legislation is just a manifestation of xenophobia."]
- **R2-Relevant (abortion):** Conservative to liberal. [1: "I am pro-life and believe that abortion is murder. We should absolutely ban abortions without exception.", 3: "Abortion should not be permitted after a while when the fetus is more developed, but in severe cases like rape I do believe it should be permitted.", 5: "Abortion should be a choice left up to the person who is pregnant, because it is their body and they get to decide what happens to it."]
- **R2-Relevant (climate change):** Conservative to liberal. [1: "Climate change does not feel like that big of a deal. People make using gas and coal out to be a worse thing than it really is.", 3: "Climate change is going to affect us a bit in the future, so we should make sure to control our fossil fuel usage and maybe even carpool to work more.", 5: "Climate change is an extremely serious problem that we need to confront through serious legislation if we want to make the Earth habitable for future generations."],
- **R2-Relevant (criminal justice):** Conservative to liberal. [1: "Police keep us safe, and there is a lot of violence in the streets that we need to better control.", 3: "When police are behaving well, they can help to keep neighborhoods safe. However, they should be responsible for any bad actions they may take.", 5: "The criminal justice system in America is deeply flawed and racist. We need to defund the police and take away their power."]
- **R3-Subjective (toxicity):** Toxicity. [1: "This message is not toxic, it is just somebody being friendly.", 3: "I could see how it is a bit toxic to some people depending on how they are interpreting it.", 5: "Toxic. This message is harmful and demeaning to others."]
- **R3-Subjective (positive reframing):** TextBlob's sentiment analysis with the following mapping: 1: [-1, 0), 2: [0, .25), 3: [.25, .5), 4: [.5, .75), 5: [.75, .1].
- **R4-Coverage (1):** Excitement. [1: "That sounds like it will be quite a bit of work, good luck packing and settling your affairs before heading out.", 3: "This will be quite the adventure for you. Let's catch up before you head out!", 5: "Oh my gosh!! That sounds really amazing, I hope you have the best time!"]
- **R4-Coverage (2):** Harmful. [1: "The harms would not be that bad because it would be quite fun to use this.", 3: "There are a number of concerns I would have with this app. We would need to be very careful about the different groups it could cause distress to.", 5: "There are so many potential harms that could come from this, and they are severe enough that I hope such an app never exists."]
- **R4-Coverage (3):** Permissible. [1: "We should be extremely wary of incorporating technology into therapy, as it is inherently a human-to-human process for which technology is likely to make things worse rather than better.", 3: "There are potential benefits to incorporating technology and using the power of chatbots, so long as we do so pretty carefully.", 5: "Leveraging the power of chatbots in therapies seems like a great use of advancing technology and could help to improve mental healthcare."]

Appendix D Prompt Phrasing Robustness

There are concerns that analyses of LLM responses could be artifacts of the particular phrasing used in the prompt. To ensure our results are not merely the result of such artifacts, we try out four different prompts to the LLM and visualize the TSNE of both the bag of words feature of n-grams (n=[1,2]) as well as SBERT embedding. These are the two different versions of embedding we use for analysis in our work, so if different prompts result in similar embeddings here, it would indicate our findings based on such embeddings are robust across prompts.

We draw inspiration on our phrasing from [92], which prompts with individual names rather than demographic groups as we focus on.

The four prompt variations we try are: (1) "You are [identity] living in America. Speak exactly like you are [identity].", (2) "You are [identity] living in America. Speak exactly like you are [identity]. But remember, being [identity] is only one part of your identity.", (3) "Speak from the perspective of [identity] living in America.", and (4) "Speak from the perspective of [identity] living in America. But remember, being [identity] is only one part of your identity." We only do this for the identity of Black women on the question of "Where do you like to vacation?" In Fig. D8 we find heavy overlap across all four prompts on all the models except for GPT-3.5, where Prompts 1 and 2 result in similar outcomes, but Prompts 3 and 4 are different from these. Llama-2 reflects a more minor version of this. Qualitative inspection on the models does not reveal notable differences. Ultimately we make the choice of using Prompt 3 for all four LLMs given that it is the simplest and most likely to represent actual use-cases. We note that given this robustness study, it is unlikely our results are an artifact of the prompt wording chosen, except in the case of GPT-3.5 where it may make a difference.

Appendix E Noise in Human and LLM Generations

As with all datasets, our collected datasets of human-generated and LLM-generated responses likely have noise. Here, we describe our efforts to clean the datasets, and the kinds of noise we are aware of which remain.

Refusals. As part of alignment, LLMs will refuse to answer questions where a harmful response might be output. A refusal looks something like the following, based on GPT-4 prompted to respond like a White man: "As an artificial intelligence, I don't have personal experiences, thus I can't give a firsthand account of what it's like to be a White man or any specific group in American society today." We check for refusals on R1, R2, and R3 and encounter relatively few ($< 5\%$ for each model), but in the cases that we do, we rerun the question to give the LLM the benefit of the doubt, and create an upper bound for how well a current LLM is able to represent different perspectives.

Cleaning identity markers. To ensure that when we see a difference between responses from, e.g., women and men, it is not just because one person responds with "As a woman..." and another responds with "As a man..." we do our best to clean out these identity markers from the text before we perform our analysis. This was harder for behavioral personas where characteristics such as "I watch TV" would show up throughout the response in different ways , and explains some of the results in Fig. 7, where random personas had far higher covariance determinants on SBERT embeddings.

Human Participant Usage of LLM. Our work studies the desire of researchers and practitioners to replace human participants with LLMs. However, prior work has already found that human participants themselves are offloading their own requested tasks to LLMs, i.e., using Chat-GPT to respond to crowdworker tasks, at an estimated prevalence of 30% [93]. After reading through the set of LLM responses we had for the question from R1-Contingent, one author hand-labeled sets of human responses based on which appeared to be from an LLM. Eight sets were labeled, for in-group and out-group members of the following demographic identities: Millennial, man, woman, non-binary person, with findings in Tbl. E1. Unfortunately, a number of heuristics such as SBERT distance, ngram distance, or time taken by human participant were all insufficient as a threshold to filter out LLM responses, so we did not clean these from our dataset. We do not see humans using LLMs more than 10% in any of the scenarios we labeled, far lower than the estimated prevalence of 30%. We speculate this is because human participants may have actually wanted to answer our questions themselves, i.e., many responses asking, e.g., what it is like to be a non-binary person in American society today, were filled with emotional and personal anecdotes. We also note there is an interesting trend where it appears that non-women tend to use LLMs, whereas women almost never do.

Appendix F Related Work

Here we engage more substantively with closely related work.

Santurkar et al. [29] study the political opinions of language models when steered towards 60 demographic groups. They find that while prompting with the demographic group does shift the LLM responses closer to that of the human group, it still does not entirely align them. We go further in this work by pursuing a larger set of questions (political opinion is a part of one of our four reasons

Demographic Identity	In-Group	Out-Group
Millennial	7	4
man	5	0
woman	0	8
non-binary person	2	6

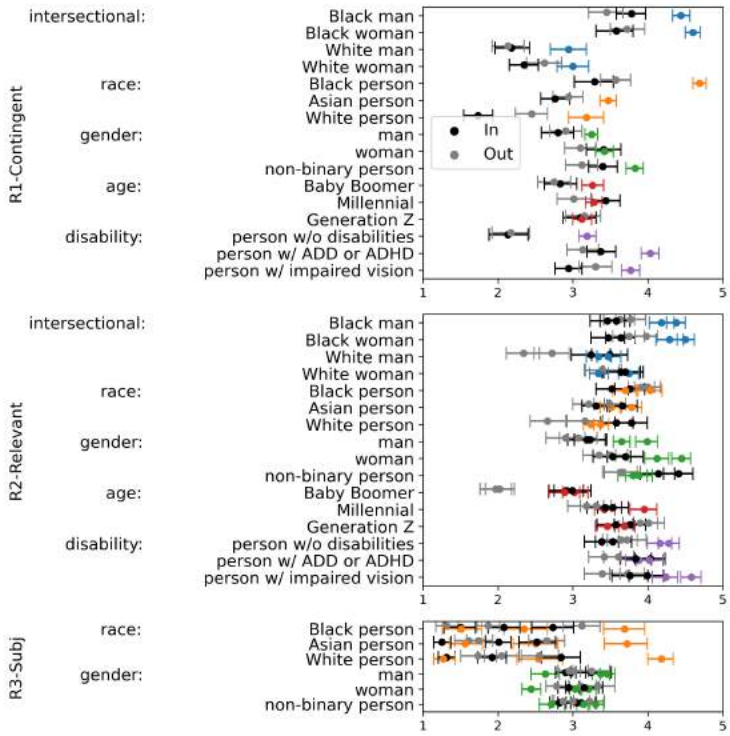
Table E1: **Human participant usage of LLM.** Based on our author-annotated estimates, the number of participants out of 100 that likely used an LLM to respond to our survey.

for identity-prompting), as well as greater number of specific hypotheses which we tie to histories of harm. In their work, they ask multiple choice political questions, and thus miss out on other aspects of the response that we are able to capture, including reasonings behind a particular opinion and the syntactic differences between groups (e.g., "That's wild, bro!" for Gen Z and "I'm like, YAASSSSS" and "That's cray, hunty!" for Black women).

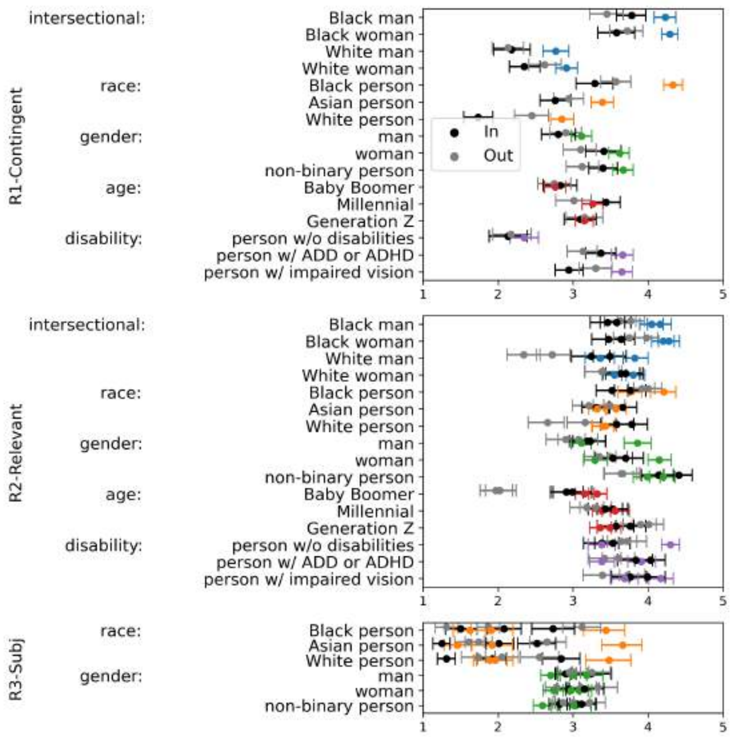
Cheng et al. [20] prompt LLMs with demographic identity and ask the models to describe themselves, comparing these responses with the default LLM in order to surface stereotypes. They then compare this differential to those discovered by Kambhatla et al. [23], finding that LLMs amplify the amount of stereotype. Our work is similar in that we find problems with identity-prompted LLMs, but different in both the range of tasks on which we find this to be true, as well as the types of problems studied. Whereas they only consider the task of an LLM describing itself, we consider four possible reasons an LLM might be prompted with identity, intending to encompass the full set of reasons, and thus having a far greater generalizability to all instances of identity-prompted LLMs. In terms of analysis, whereas they analyze specific stereotypes surfaced by the models, we focus on a different set of hypotheses regarding the misportrayal and flattening effects that are inherent to the training procedure of LLMs.

Another work, Cheng et al. [21] study the same premise as us: using LLMs to simulate different demographic identities for replacing human participants. They propose a framework to measure two criteria: individuation and exaggeration. Methods-wise, their measure of individuation best maps to one of the premises we establish of identity-prompting leading to a difference in, and their measure of exaggeration is different from our three primary analyses. Their exaggeration measure considers whether identity-prompted responses over-index on the identity compared to the topic prompted about. While motivationally this is similar to our concern about flattening groups, the way we operationalize this is completely different. In terms of contexts studied, their three scenarios of online social media forum, question-answering on political questions, and Twitter posts, all map to either our R2 or R4. We perform additional analyses on R1 and R3. Both of our works study open-ended responses as well as a range of demographic axes and identities; in our work we also conduct extensive human studies to compare our results to.

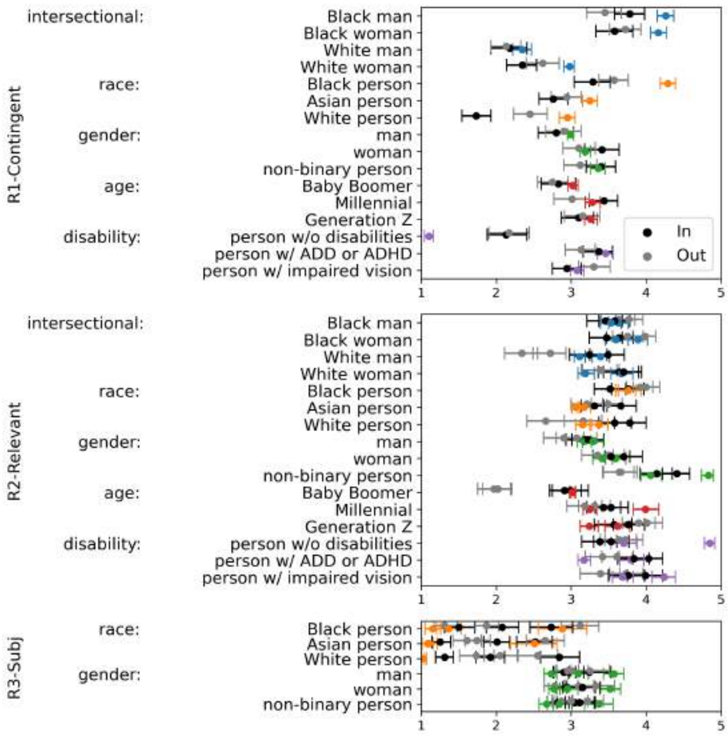
Each of the above works carefully grounds analysis in particular harms, and in doing so, necessarily is specific and does not cover the total range of harms. This is positive and commendable in the spirit of being more precise about where harms stem from [94]. Together, our work joins these to more collectively encompass the space of harms, as all are important to understanding the limitations of identity-prompted LLMs. They are complementary in strengthening the argument that identity-prompted LLMs should only be used with extreme caution.



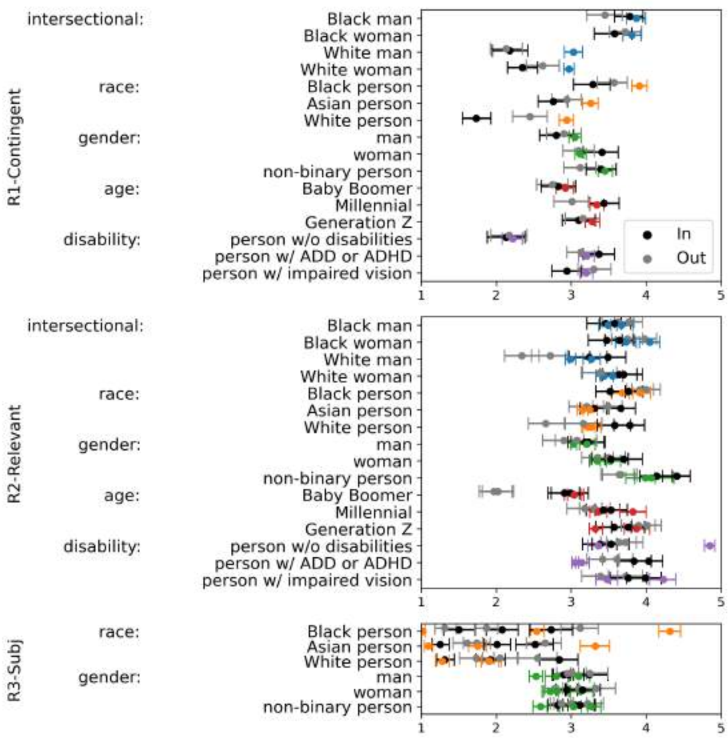
(a) Llama-2.



(b) Wizard Vicuna Uncensored.

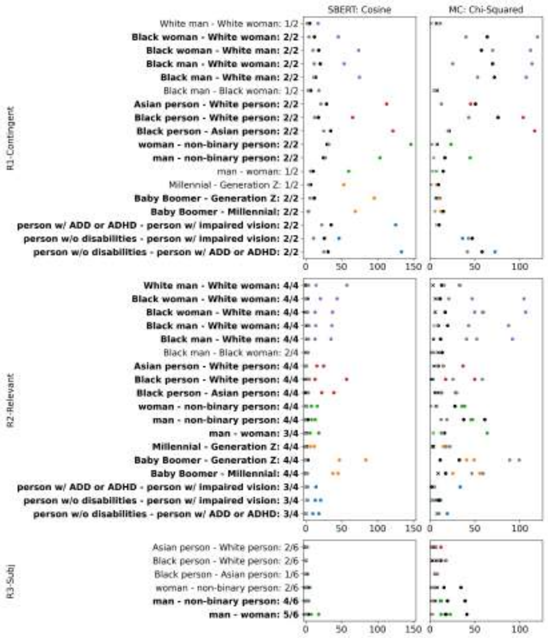


(c) GPT-3.5-Turbo.

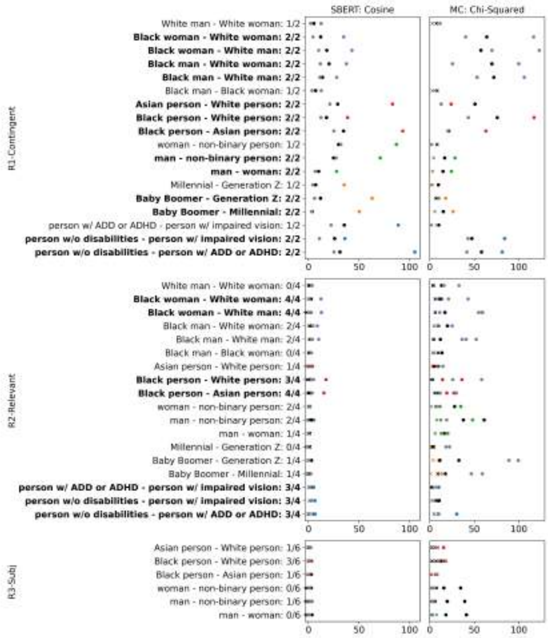


(d) GPT-4.

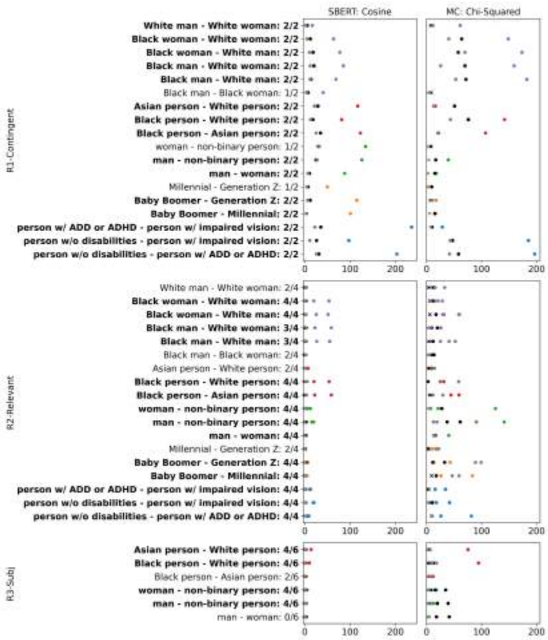
Fig. A5: **Average multiple choice responses for LLMs and human participants.** LLM responses are indicated in colors, human in-group in black, and human out-group in gray. For R1-Contingent, 1 to 5 represents how challenging it is to have that demographic identity; R2-Relevant 1 to 5 represents conservative to liberal political opinion; R3-Subj represents level of toxicity detected for race and level of positive sentiment detected for gender.



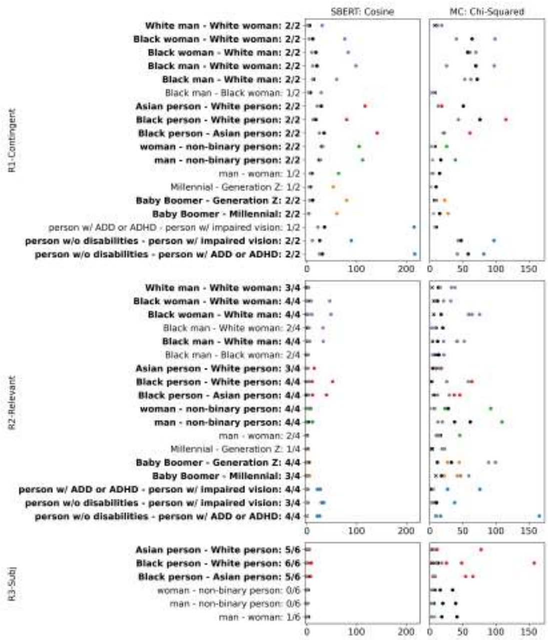
(a) Llama-2.



(b) Wizard Vicuna Uncensored.



(c) GPT-3.5-Turbo.



(d) GPT-4.

Fig. B6: **LLMs answer differently depending on what demographic identity they are prompted with.** For three sets of question reasons (rows), the difference between a pair is shown. Black dots indicate human in-group participants, gray dots indicate human out-group participants, and the colored dots indicate LLM responses. Bolded rows indicate that on more than half of the measured values, the difference between the two compared groups is statistically significant.

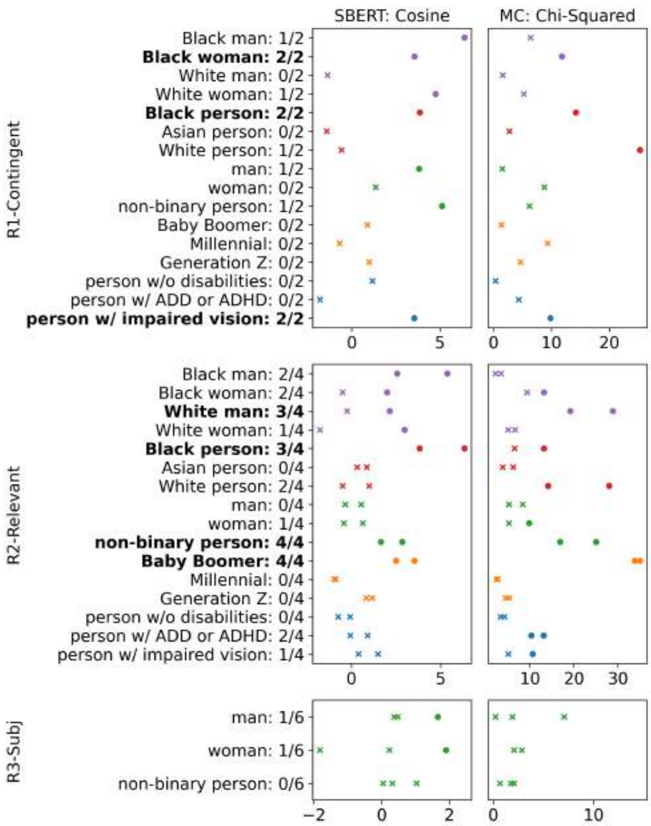


Fig. B7: **Comparison of differences between human in-group representations and out-group imitations.** For each set of reasons (rows), the demographic group is shown with more positive values indicating difference between in-group and out-group human participants. Circles indicate statistical significance, crosses do not.

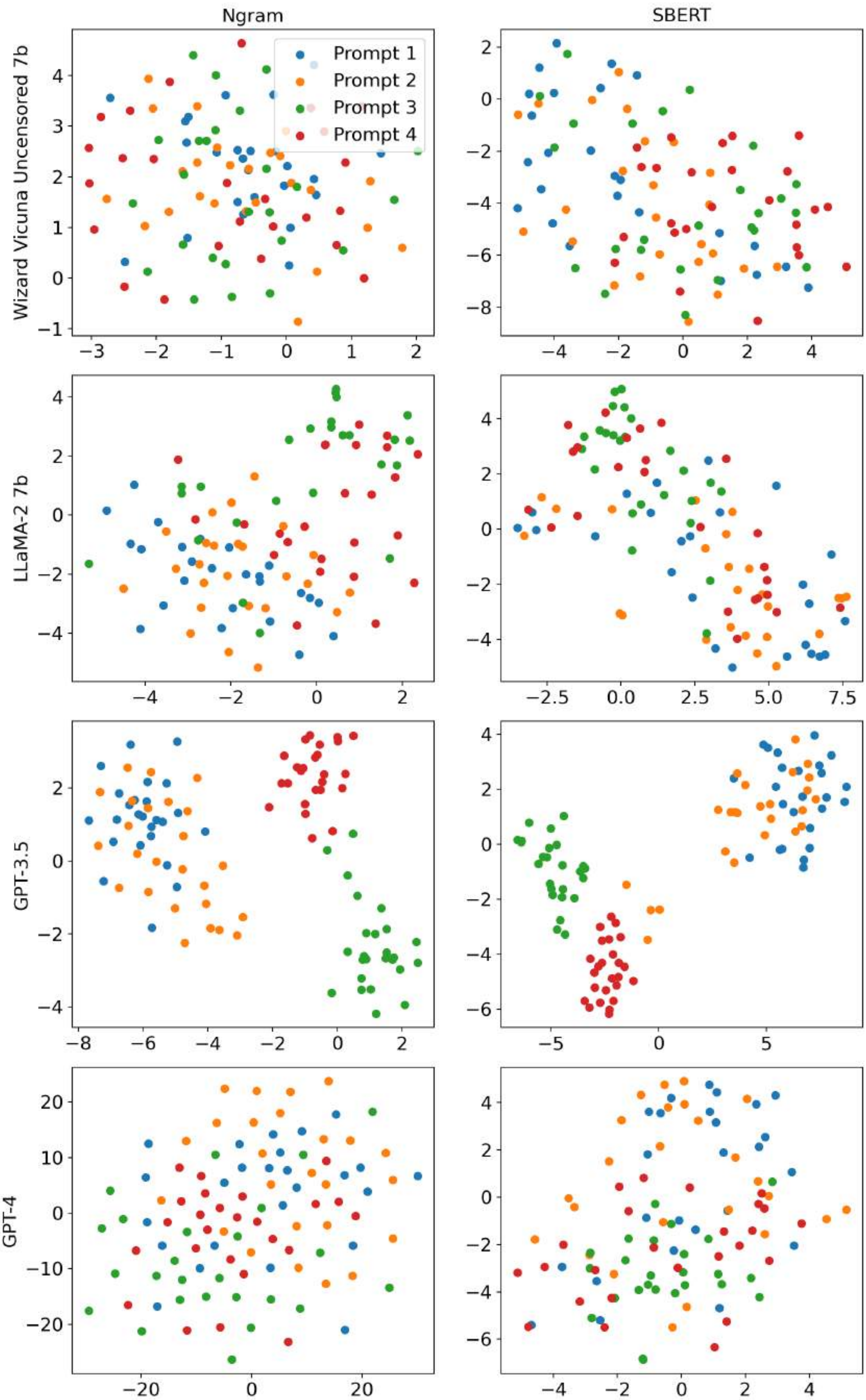


Fig. D8: **Analysis of prompt phrasing variations.** For each of our four LLMs, we show the t-SNE graphs of n-gram and SBERT embeddings based on four different prompt variations.