AI Attitudes Among Marginalized Populations in the U.S.: Nonbinary, Transgender, and Disabled Individuals Report More Negative AI Attitudes

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Abstract

As artificial intelligence (AI) technologies become increasingly pervasive, understanding public perceptions of AI is crucial for ensuring equitable adoption and impact. Attitudes toward AI, such as whether it is seen as helpful or harmful, may vary based on social identities and lived experiences. In this study, we conducted a survey (n = 742) including a representative U.S. sample and an oversample of gender minorities, racial minorities, and disabled individuals to examine how demographic factors shape AI attitudes. Our findings reveal that in the U.S. context, participants who are nonbinary, transgender, and/or women, and disabled participants, particularly those who are neurodivergent or have mental health conditions, report significantly more negative attitudes towards AI compared to majority groups. We argue that these disparities highlight a critical issue: negative AI attitudes among marginalized communities signals a continued failure to account for their needs and concerns in AI design and use. That marginalized Americans have more negative views towards AI should prompt reflection and critical examination of the prevalent rhetoric of AI's purported inevitability and its framing as a universal social good.

CCS Concepts

• **Computing methodologies** → **Artificial intelligence**; • **Social and professional topics** → **Gender**; **Race and ethnicity**; **People with disabilities**; • **Human-centered computing** → **Empirical studies in HCI**.

Keywords

AI, AI attitudes, critical AI, disability, nonbinary, transgender, LGBTQ+

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1 Introduction

As artificial intelligence (AI) is increasingly deployed in a range of domains in the United States (U.S.) [3], it is important to investigate the public's attitudes towards it [7]. Public attitude shapes AI's acceptability and trustworthiness [108, 110], and has the potential to inform AI regulation [21, 52]. Prior work found that Americans are more concerned than excited about AI, with particular concerns related to surveillance and data privacy, along with AI's impact on job availability and the "loss of the human element" in workplace contexts [28]. Further, AI attitudes may differ across deployment contexts [71, 110], personality traits (such as personal anxieties related to AI) [51], and identity characteristics [91, 108]. For instance, a number of studies have found that women have more negative AI attitudes than men [18, 30, 32, 38, 55, 74, 91].

AI's promise as a helpful tool that can improve human lives [31] is less realistic if it only applies to certain types of people. A growing body of research has shown how certain minoritized groups experience substantial harm resulting from AI and algorithmic bias [11, 17, 20, 22, 24, 35, 87]. For example, facial recognition systems often misclassify transgender[1] and nonbinary people, while at the same time surveilling them and violating their privacy, which can cause substantial harm [41, 75, 84]. Additionally, algorithmic bias in AI systems deployed by law enforcement can lead to the unwarranted arrest of Black people at disproportionately high rates [48]. AI bias also directly impacts and harms disabled people [13, 14, 82]; for example, embedded bias in algorithmic diagnostic systems can prevent disabled people from accessing necessary forms of healthcare [14]. These sorts of discrimination and biases may impact gender and racial minorities' and disabled people's attitudes towards AI. If some marginalized groups of people are more hesitant to accept and use AI than the general population [106, 112], this leads to important implications around whether and how AI should be deployed and regulated.

[1]People whose current gender is different from that assigned at birth; "trans" from here forward

We investigate the U.S. public's attitudes towards AI, and what role gender, race, and disability play in these attitudes, asking **RQ1:** How do AI attitudes differ by identity characteristics (gender, race, disability)? We conducted a survey about AI attitudes with n = 742 people living in the U.S., including a nationally representative U.S. sample along age, gender, and race (n = 297) and an oversample of people of color, trans and nonbinary people, and disabled people. We hypothesize the following:

- **H1:** Gender minorities will have more negative attitudes towards AI than cisgender people.
- **H2:** Racial minorities will have more negative attitudes towards AI than white people.
- **H3:** Disabled people will have more negative attitudes towards AI than non-disabled people.

Overall, we find strong evidence that, on average, gender minorities and people with disabilities have substantially more negative AI attitudes than those in majority groups[2]. Nonbinary participants in particular have significantly more negative attitudes towards AI than those who are not nonbinary. Trans participants also exhibited more negative AI attitudes than cisgender people, and women had lower AI attitudes than men. Disabled participants, and especially those who are neurodivergent or have mental health conditions, also have more negative AI attitudes than those without these disabilities. In contrast to our expectations, participants of color, and Black participants in particular, have significantly more positive AI attitudes than white participants.

We contribute empirical evidence about the U.S. public's attitudes towards AI, and demonstrate how race, disability, and gender shape these attitudes. We argue that more negative AI attitudes among these minoritized groups, in a world increasingly dependent on AI, serves as a critical warning: the widespread adoption of AI involves many people being required to use a technology (e.g., at work as employees) or be subjected to its use (e.g., in healthcare as patients) while they view said technology relatively negatively.

2 Related Work

2.1 Gender minorities and AI

Past work has found that AI systems demonstrate bias toward gender minorities (i.e., trans and nonbinary people), often perpetuating harm in contexts such as healthcare, employment and hiring, security, and more [3, 84, 85, 92, 94]. AI harm toward trans and nonbinary people has been demonstrated in technologies including facial recognition algorithms in law enforcement and surveillance [2, 29], algorithmic content moderation [40, 62], and stereotypical and offensive imagery of trans and nonbinary people produced by generative AI systems [101]. AI harm experienced by gender minorities can be physical, psychological, social, and economic [6], resulting in algorithmic misgendering and violations of privacy and consent [17, 34, 45, 75]. Though AI systems can be used in ways that advantage trans people (such as for gender identity exploration or to accessing trans-specific healthcare information) [23, 60], past work has found that even when AI systems provide certain benefits to trans people, they are also capable of producing biased, harmful outputs [60].

Natural language processing systems [15, 96], LLMs [27], and other AI systems attempt to categorize queer and trans identities and genders [54, 77] in ways that are incompatible with "the complexities of trans and LGBTQ+ identities and bodies" [50], creating particularly negative outcomes for nonbinary people interacting with AI systems. For example, Scheuerman et al. found that facial analysis technologies classify images in their datasets as "male" and "female," but do not classify images as "nonbinary," resulting in misclassifying images of nonbinary people 100% of the time [84]. Scheuerman et al. argue that AI systems act on "embedded [gender] binarism" [85] when drawing from datasets that do not represent nonbinary people [84, 85]. The lack of nonbinary representation in these datasets perpetuates a "cyclical erasure of and harm toward nonbinary people" [27]. However, past work has also challenged the idea that increased trans and nonbinary representation in algorithmic datasets would solve the transphobic inequities and harms produced by AI systems, or that gender minorities would necessarily want increased representation in AI systems' databases [79].

Prior research has examined cisgender people's AI attitudes, and found that women have more negative attitudes towards AI than men, potentially related to a long history of discrimination and bias towards women [18, 30, 32, 38, 55, 74, 91, 109]; however, some research has found fewer differences between cisgender women and men's attitudes toward AI [51]. Given that gender minorities also face substantial discrimination and bias, often through AI systems, we hypothesize that:

- **H1:** Gender minorities will have more negative attitudes towards AI than cisgender people.

2.2 Racial minorities and AI

Prior research has found that AI systems demonstrate racial biases, resulting in harm toward racial minorities [11, 47, 66, 70, 111]. Examples of AI systems demonstrating bias against racial minorities include image recognition algorithms disproportionately misclassifying images of darker-skinned people (particularly darker-skinned women) [20, 34, 85], and natural language processing and machine learning systems producing racially-biased output [86]. Similar to AI systems that attempt to classify and categorize gender, AI systems' racial bias, which results in harmful outcomes for racial minorities who interact with these systems, is often attributed to biased datasets that insufficiently represent racial minorities [48, 65, 85]. Racial biases in AI systems produce a wide range of negative outcomes for racial minorities, such as disproportionate surveillance and arrests of Black people subject to law enforcement agencies' biased facial recognition systems [48], negative experiences in healthcare systems that use biased AI diagnostic systems [80], and algorithmic microtargeting of "racially tailored misinformation" [73]. Past work has argued that racial bias in AI forces racial minorities to put in greater effort than others to use AI technologies while avoiding algorithmic harm [72], and that AI technologies are often designed without integrating culturally-specific considerations, resulting in usability and deployment problems in many African and other Global South nations [4]. Racial biases in

[2]Specifically, we mean that, on average, gender minorities' and disabled people's responses to Grassini's [38] validated AI attitudes scale were lower than others' responses.

AI technologies perpetuate structural racism and societal biases embedded in AI technologies themselves, resulting in the continued reproduction of existing inequities within these discriminatory systems [12, 22]. Due to these substantial biases and harms that AI systems perpetuate against racial minorities, we hypothesize that:

- **H2:** Racial minorities will have more negative attitudes towards AI than white people.

2.3 Disabled people and AI

Existing literature indicates that AI systems demonstrate ableist bias, which can harm disabled people [13, 14, 82]. Moreover, existing scholarship has described how bias toward disabled people is embedded in AI technologies, disadvantaging and harming disabled people who interact with these systems. Examples of potential harm include AI systems designed for autism diagnosis that are less likely to diagnose people who are not white and male [14], or harmful AI-generated image descriptions of disabled people [13]. Like other forms of AI bias, past work has argued that AI bias against disabled people stems from and exacerbates existing societal and systemic ableism [82, 100, 103]. Shew [90] also attributes AI bias toward disabled people to embedded "technoableism," a unique form of ableism that frames technologies as "empowering disabled people" while simultaneously "reinforcing ableist tropes about what body-minds are good to have and who counts as worthy." While some prior work has called for greater attention to disability fairness in AI development [100], other scholars have critiqued these approaches for "overemphasizing 'fairness"' [14]. Instead, they advocate for future research on AI and disability bias to center disability justice and to examine how such biases reinforce and deepen structural oppression against disabled people [14]. Given the history of AI systems demonstrating bias toward and inflicting harm on disabled people, we hypothesize that:

- **H3:** Disabled people will have more negative attitudes towards AI than non-disabled people.

2.4 Additional Sources of Variance in AI Attitudes

In addition to the aforementioned main effects of interest, existing scholarship supports the inclusion of several control variables that may contribute to the variance in AI attitudes. For example, age may have a significant impact in that younger individuals have been reported to have more positive attitudes toward AI [56] and find it more useful [5]. Similar evidence has been found along the lines of income, where individuals earning a higher income have been found to be more positive about AI [109]. Political ideology may also have an impact on general AI attitudes, as this moderated the relationship between trust in technology companies and support for the use of AI for liberal participants [107]. Further, given the differences in attitudes toward AI cited in studies conducted across the globe [83, 93], it may also be the case that time spent in the U.S. contributes to attitudes toward AI.

In addition to demographic variables, we also control for perceptions about technology more generally, as these sentiments may extend to that of AI. Previous research has found that those with positive sentiments about science and technology in general [67] and who have more experience with technology [109] express greater support for AI.

3 Methods

We conducted a survey (n = 742) to answer our research question and test our hypotheses. This study was reviewed and deemed exempt from oversight by University of Michigan's Institutional Review Board.

3.1 Data collection

We recruited survey participants through a panel survey company, Prolific. Participants were eligible for the survey if they were over the age of 18 and lived in the U.S. First, we recruited a U.S. representative sample (stratified by gender, race, and age) of n = 300. Next, because our research question focuses on gender and racial minorities and people with disabilities, we oversampled for trans and nonbinary people (n = 100), racial and ethnic minorities (n = 200), and disabled people (n = 100). We also specifically targeted trans and nonbinary people of color (n = 50). Many participants fell into several of these oversampled categories, so the total numbers of participants in each category exceed these targets. Complete participant demographic information is shown in Table 1. Our target recruitment number (n = 750) is slightly higher than our final number of participants (n = 742) because we removed some participants during data cleaning steps. Data cleaning involved removing participants who did not pass our two attention-check questions, or who completed the survey excessively quickly. We also closely monitored open-ended survey responses (not analyzed in this paper) throughout data collection to ensure data quality [3].

3.2 Survey instrument and measures

The survey questions we analyzed in this paper include seven Likert-style and two multiple choice questions about participants' views about and use of AI and technology, and ten closed-ended demographic questions. Please see Appendix A for complete question text. Most demographic questions also included open-ended "Prefer to self-describe" options, which we later coded manually. Most quantitative measures were evaluated on a 7-point Likert scale ranging from 1 ("Strongly disagree") to 7 ("Strongly agree") unless otherwise noted. To ensure that the survey questions were easily interpretable, we pilot tested and workshopped the survey with a group of our colleagues and a small group of pilot participants on Prolific, who provided feedback on question wording and survey structure. On average, the survey took participants 25.00 minutes (SD = 18.85). Participants were compensated at a rate at or above $12 per hour (depending on how long they took to complete the survey).

3.2.1 AI attitudes. Eliciting views on emerging technologies through surveys is challenging, because respondents' differing levels of knowledge about the technology can be difficult to separate from their attitudes towards it [53]. Thus, question wording is particularly important [53]. We closely examined several validated scales about AI attitudes, and chose the one that seemed most appropriate.

[3]We used Javascript to disable copy-paste in all open-ended responses, to deter participants from generative AI use.

We measured AI attitudes using four items adapted from Grassini's AI Attitude Scale [38]: "I believe that AI will improve my life," "I believe that AI will improve my work," "I think I will use AI technology in the future" and "I think AI technology is positive for humanity." Since participants may not have been knowledgeable about AI's meaning, we provided them with the following definition to keep in mind as they answered survey questions: "algorithmic systems that can perform tasks that would usually require human intelligence." Prior to defining AI for participants in the survey, we asked them open-ended questions about their perceptions of what AI means. While we leave analysis and reporting of those responses to future work, our AI definition demonstrates face validity in aligning with participants' responses.

3.2.2 Technology use variables. We asked participants about the extent to which they had heard of AI, whether they had experienced algorithmic harm, online privacy, tech enthusiasm, tech anxiety, the extent they had heard about AI in media, the sentiment of AI media coverage they had observed, tech savviness, and AI use in everyday life. Please see Appendix A for complete question text and response options.

3.2.3 Demographics. We asked participants to report their gender, trans status, race/ethnicity, disability status, specific disability or disabilities, how long they had lived in the U.S., sexual orientation, education, income, and political orientation. Please see Appendix A for complete question text and response options, and Table 1 for information about participants' demographics.

3.2.4 Trans and nonbinary identities. Our analysis makes distinctions between trans and nonbinary participants because AI attitudes differ between these groups. We provide some explanation here to help readers understand the differences between these categories. Trans people are those who have a current gender different from that assigned at birth. Nonbinary people are those whose gender falls outside of, or combines aspects of, the two dominant gender categories of male and female. Some trans people identify as nonbinary, and others do not. Some nonbinary people identify as trans, and others do not. Trans is sometimes considered an umbrella term that includes nonbinary people, but it is important to clarify that not all nonbinary people consider themselves trans. Please see Figure 1 for a mapping of participants' trans and nonbinary identities. We asked these questions separately (see Appendix A) to capture the complexities of participants' identities.

3.3 Data analysis

We used t-tests (Tables 4,5,6) and a regression model (Table 3) to analyze relationships between variables of interest and to test our hypotheses. We include more details in Results (Section 4).

3.4 Positionality

Because this paper centers on specific identity characteristics, we believe it is important to share information about our own identities in relation to those we study. Our approach aligns with frameworks such as feminist standpoint theory, which prioritize marginalized experiences and emphasize the importance of acknowledging the social contexts in which research is conducted [42, 43]. Our research and authorship team includes trans and queer individuals, offering

Table 1: Participant demographics and AI attitudes. Participants could choose multiple gender, race/ethnicity, and disability options, so percentages add up to greater than 100%.

	Survey participants (n = 742)	**AI attitudes** mean (*SD*) on a 1-7 scale
representative U.S. sample	297 (40.0%)	5.02 (1.39)
full sample	742 (100.0%)	4.96 (1.45)
Gender		
cisgender	620 (83.6%)	5.12 (1.33)
woman	372 (50.1%)	4.96 (1.38)
cisgender woman	348 (46.9%)	5.00 (1.33)
man	280 (37.7%)	5.32 (1.27)
cisgender man	257 (34.6%)	5.35 (1.24)
nonbinary OR transgender	132 (17.8%)	4.11 (1.72)
transgender	101 (13.6%)	4.12 (1.73)
nonbinary	93 (12.5%)	3.84 (1.67)
nonbinary AND transgender	62 (8.4%)	3.72 (1.65)
transgender NOT nonbinary	39 (5.3%)	4.76 (1.68)
nonbinary NOT transgender	31 (4.2%)	4.08 (1.71)
transgender man	23 (3.1%)	4.90 (1.58)
transgender woman	19 (2.6%)	4.59 (1.85)
unsure or additional gender	8 (1.1%)	3.97 (1.62)
Race/Ethnicity		
person of color	401 (54.0%)	5.15 (1.35)
White only	341 (46.0%)	4.74 (1.54)
Black or African American	167 (22.5%)	5.26 (1.36)
Hispanic or Latino/a/e/x	113 (15.2%)	4.98 (1.40)
American Indian or Alaska Native	45 (6.1%)	5.01 (1.39)
East Asian	35 (4.7%)	5.06 (1.26)
Southeast Asian	29 (3.9%)	5.24 (1.22)
Middle Eastern	23 (3.1%)	4.95 (1.27)
South Asian	15 (2.0%)	5.03 (1.17)
Native Hawaiian or Pacific Islander	10 (1.3%)	4.65 (1.86)
mixed race, multiracial, or biracial	45 (6.1%)	4.47 (1.53)
Disability		
not disabled	468 (63.1%)	5.13 (1.33)
has one or more disabilities	274 (36.9%)	4.68 (1.60)
mental health condition	160 (21.6%)	4.43 (1.67)
neurodivergent	141 (19.0%)	4.28 (1.72)
chronic illness	114 (15.4%)	4.67 (1.52)
mobility limitation	76 (10.2%)	4.98 (1.35)
learning disability	44 (5.9%)	4.19 (1.81)
deaf or have serious difficulty hearing	28 (3.8%)	5.04 (1.15)
motor limitation	23 (3.1%)	5.12 (1.08)
speech or language impairment	16 (2.2%)	4.58 (1.72)
blind or have serious difficulty seeing	14 (1.9%)	5.00 (1.60)
Age		
range: 18 - 82; mean = 39.71 (*SD* = 14.54)		
18-24	120 (16.2%)	4.74 (1.60)
25-34	213 (28.7%)	4.83 (1.58)
35-44	151 (20.4%)	5.09 (1.40)
45-54	108 (14.6%)	5.23 (1.14)
55-64	107 (14.4%)	5.07 (1.32)
65 or older	43 (5.8%)	4.77 (1.44)

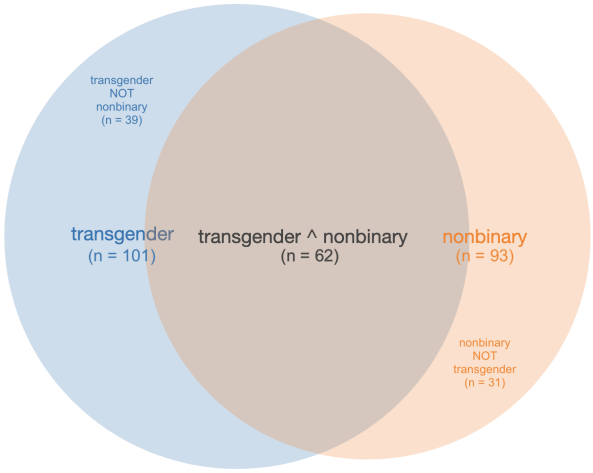


Figure 1: Venn diagram showing the mapping and overlap of participants' trans and nonbinary identities. The diagram shows that there is substantial overlap between the two categories, with many participants who identify as both nonbinary and trans, but also many participants who only identify with one category but not the other.

particular insight into trans experiences with AI. We recognize the absence of nonbinary researchers on our team as a limitation, especially given this study's focus on nonbinary people's attitudes toward AI. The authors are white, Middle Eastern, Asian, and mixed, and several of us have disabilities and/or chronic health conditions.

3.5 Limitations

Our sample, while partially representative of the U.S. population and inclusive of often under-represented groups, could have benefited from larger sample sizes across some disabilities and racial categories. While we controlled for a number of demographic and technology use variables in our regression model, there may be other potential confounding variables that we did not measure. While we took great care in our survey design, surveys about attitudes toward technology are challenging, as it can be difficult to differentiate between participants' acceptance of vs. resignation toward emerging technologies that may involve harmful data practices [53]. Thus, we aim to provide substantial methodological and contextual detail, as recommended by [53]. Further, our results are correlational; future work should address similar questions using a causal approach. Finally, these results are limited in their focus on the U.S.

4 Results

In what follows, we test our hypotheses (see Table 2). We find support for H1 and H3, indicating significantly more negative AI attitudes for several marginalized groups – gender minorities and people with disabilities – when compared with majority groups. H2, related to racial minorities, is not supported, and in fact we find that people of color broadly, and Black participants in particular, had significantly more positive AI attitudes than others.

Before testing our hypotheses, we present descriptive statistics for AI attitudes across each demographic group and overall (see Table 1). In our representative U.S. sample, AI attitudes are on average 5.02 (SD = 1.39), while in the full survey sample, which includes oversampling for gender and racial minorities and people with disabilities, the average AI attitude is slightly lower, at 4.96 (SD = 1.45).

While this paper separates people into demographic categories, as authors we align with intersectionality theory [26] and the matrix of domination [25], both of which describe how people's multiple identity facets cannot truly be separated. Regression models offer a statistical approach to account for how people's identities intersect and shape experiences, as they allow researchers to assess multiple identity variables' combined influence on outcomes [9, 10, 39]. Thus, in addition to t-tests, which consider each demographic variable in isolation, we built a regression model (see Table 3) to understand each variable's relationship with AI attitudes while controlling for participants' membership in other demographic categories.[4]

4.1 Gender minorities and AI attitudes

To test H1 and determine whether gender minorities' attitudes towards AI differ from cisgender people's, we conducted a series of Welch's two-sample t-tests (see Table 4). Welch's t-tests are appropriate for this analysis because the dependent variable is continuous, the two groups being compared are independent, and the samples' variances are not equal.[5] Because we conducted multiple t-tests (a total of ten), we used Bonferroni correction and we use the threshold of p<0.005 for statistical significance.

We find strong evidence that gender minorities have significantly less positive attitudes towards AI than cisgender people, and that women have less positive AI attitudes than men (see Table 4 and Figure 2). Trans participants have significantly lower attitudes towards AI (M = 4.12 on a 1-7 scale, SD = 1.73) compared to cisgender participants (M = 5.12, SD = 1.33), t(120.07) = -5.56, p < 0.0001. Nonbinary participants have even lower AI attitudes (M = 3.84, SD = 1.67) compared to participants who are not nonbinary, t(109.66) = -7.05, p < 0.0001. Finally, we find that women have significantly less positive AI attitudes (M = 4.96, SD = 1.38) than men (M = 5.32, SD = 1.27), t(624.68) = -3.42, p < 0.001.[6] Although women are not technically a gender minority, and men are not a gender majority, we categorize them this way because women are systemically oppressed in relation to men.

Next, we constructed a linear regression model with AI attitudes as the outcome variable (see Table 3). The model includes demographic and technology use control variables to see whether our gender variables are significantly correlated with AI attitudes. This model explains a large portion of the variance in AI attitudes across the sample, with an adjusted R^2 value of 0.45. The nonbinary variable (b = -0.52, p < 0.01) is negative and statistically significant. This indicates that nonbinary people, on average, have AI attitudes 0.52

[4] An even more rigorous intersectional approach could use interaction terms to measure intersectionality [9, 10, 39]. We opted not to take this approach because of the large number of demographic categories that could potentially interact, few of which showed significant effects in trial regression models.
[5] The samples are not normally distributed, but Welch's t-tests are still appropriate because the sample sizes are large enough that the Central Limit Theorem applies.
[6] In this test, we compared all women (cisgender and trans) with all men (cisgender and trans) to understand the differences between these two binary categories.

Table 2: Summary of Hypothesis Testing

Hypothesis	Result
H1: Trans people will have more negative attitudes towards AI than cisgender people.	Supported
H2: Racial minorities will have more negative attitudes towards AI than white people.	Effect in opposite direction
H3: Disabled people will have more negative attitudes towards AI than non-disabled people.	Supported

Table 3: Linear regression model examining factors associated with attitudes towards AI.

Variable	Coefficient	(Standard Error)
heard of AI	0.16	(0.09)
tech savviness	−0.04	(0.04)
tech enthusiasm	0.63***	(0.05)
tech anxiety	0.08*	(0.03)
heard about AI in media	0.06	(0.04)
sentiment of AI media coverage observed	0.07*	(0.03)
experienced algorithmic harm	−0.30 *	(0.13)
unsure if experienced algorithmic harm	−0.24 *	(0.10)
online privacy	−0.15 ***	(0.04)
man (reference category)		
woman	−0.06	(0.09)
nonbinary	−0.52 **	(0.17)
trans	0.08	(0.15)
White-only (reference category)		
Black	0.22*	(0.11)
Latino/a/e/x	0.25*	(0.12)
American Indian or Alaska Native	0.04	(0.18)
East Asian	0.28	(0.20)
Southeast Asian	0.31	(0.22)
Middle Eastern	−0.01	(0.24)
South Asian	−0.17	(0.29)
Native Hawaiian or Pacific Islander	−0.03	(0.36)
mixed race, multiracial, or biracial	−0.04	(0.19)
mental health condition	0.03	(0.13)
neurodivergent	0.03	(0.14)
learning disability	−0.22	(0.19)
age 18-24	−0.33 *	(0.14)
age 25-34	−0.10	(0.12)
age 35-44 (reference category)		
age 45-54	0.11	(0.14)
age 55-64	0.09	(0.14)
age 65+	0.01	(0.20)
LGBQ	0.03	(0.11)
duration living in US	−0.18 *	(0.08)
income	0.07***	(0.02)
education	0.02	(0.04)
very liberal or left	−0.29 **	(0.11)
very conservative	−0.08	(0.22)
intercept	2.04**	(0.66)
adjusted R^2	0.45	

* $p < .05$; ** $p < .01$; *** $p < .001$

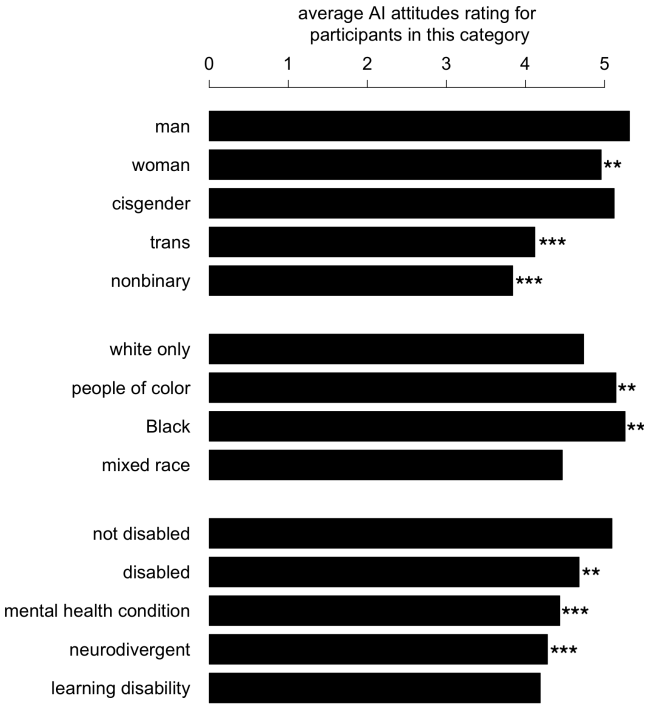


Figure 2: Bar graph showing average AI attitudes for participants in different identity categories. The plot shows that women (including both cisgender and trans women) have lower AI attitudes than men (including both cisgender and trans men); trans and nonbinary participants have significantly lower AI attitudes than cisgender participants; people of color, and Black participants in particular, have significantly higher AI attitudes than white participants; and disabled participants, specifically those who are neurodivergent or have mental health conditions, have significantly lower AI attitudes than participants without those disabilities. We used Bonferroni correction because we conducted multiple t-tests, and we indicate statistical significance based on the following p-value thresholds: * p<0.005; ** p<0.001; *** p<0.0001

units lower (on a scale of 1-7) than cisgender men (the reference group), even after controlling for all demographic and technology use-related variables. The trans variable and woman variable are not statistically significant after controlling for demographics and technology use. Of course, the trans variable and the nonbinary variable are highly correlated[7] because many nonbinary people are also trans, and vice versa (see Figure 1).

Table 4: Comparisons between mean AI attitudes for gender minorities and gender majorities (Welch's two sample t-tests). Results show that all gender minority groups have significantly lower AI attitudes than gender majorities. Although women are not technically a gender minority, and men are not a gender majority, we categorize them this way because women are systemically oppressed in relation to men.

Gender Minority Mean	Gender Majority Mean	Difference	95% CI of Difference	*t*-value	*p*-value
transgender: 4.12	cisgender: 5.12	−1.00 ***	(-1.36, -0.65)	-5.56	<0.0001
nonbinary: 3.84	not nonbinary: 5.12	−1.28 ***	(-1.64, -0.92)	-7.05	<0.0001
woman: 4.96	man: 5.32	−0.36 **	(-0.56, -0.15)	-3.42	<0.001
p-value thresholds after Bonferroni correction: * $p < .005$; ** $p < .001$; *** $p < .0001$					

Table 5: Comparisons between mean AI attitudes for racial minorities and racial majorities (Welch's two sample t-tests). Results show that participants of color overall, and Black participants in particular, have significantly higher AI attitudes than racial majorities.

Racial Minority Mean	Racial Majority Mean	Difference	95% CI of Difference	*t*-value	*p*-value
people of color: 5.15	White-only: 4.74	0.41**	(0.20, 0.62)	3.82	<0.001
Black: 5.26	White-only: 4.74	0.52**	(0.26, 0.79)	3.91	<0.001
mixed race, multiracial, biracial: 4.47	White-only: 4.74	−0.27	(-0.76, 0.22)	−1.11	0.27
p-value thresholds after Bonferroni correction: * $p < .005$; ** $p < .001$; *** $p < .0001$					

4.2 Racial minorities and AI attitudes

To test H2, which posits that racial minorities will have more negative attitudes towards AI than white people, we conducted several t-tests using the same method described in section 4.1 (see Table 5 and Figure 2). We find significant effects in the opposite direction of our hypothesis, suggesting that racial minorities have more *positive* attitudes towards AI than white people.

First, we tested whether people of color overall have different AI attitudes than white people. We find that racial minority participants have significantly more positive attitudes towards AI (M = 5.15, SD = 1.35) compared to white-only participants (M = 4.74, SD = 1.54), $t(682.93) = 3.82$, $p < 0.001$.

We then examined the mean AI attitudes of each racial/ethnic group in our dataset (reported in Table 3), and conducted t-tests for those that were the highest (Black participants) and lowest (participants who are mixed race, multiracial, or biracial). We find that Black participants have significantly more positive AI attitudes (M = 5.26, SD = 1.36) than white-only participants, $t(368.22) = 3.91$, $p < 0.001$, while participants who are mixed race, multiracial, or biracial (M = 4.47, SD = 1.53) do not have significantly different AI attitude levels than white-only participants, $t(56.38)$ = -1.11, $p <$ 0.27.

Next we return to the regression model in Table 3, which includes all demographic and technology use control variables, to see whether race variables are significantly correlated with AI attitudes. We find that even after controlling for other demographic and technology-use related variables, Black participants still have significantly higher AI attitudes than white participants (the reference variable) ($b = 0.22, p < 0.05$). This means that on average, Black participants have AI attitudes 0.22 units higher than white-only participants. We also see a positive significant effect for Latino/a/e/x participants ($b = 0.25$, $p < 0.05$), which indicates that Latinx participants have significantly more positive attitudes towards AI than white-only participants after controlling for potential confounding variables.

4.3 Disabled people and AI attitudes

To test H3 and determine whether disabled people's attitudes towards AI differ from non-disabled people, we conducted t-tests using the same method described in section 4.1 (see Table 6 and Figure 2). We find strong evidence that disabled participants have more negative AI attitudes than those who are not disabled.

We first tested whether disabled participants overall have attitudes towards AI that differ from non-disabled participants. We find that disabled participants do have significantly more negative attitudes towards AI (M = 4.68, SD = 1.60) than non-disabled participants (M = 5.13, SD = 1.33), $t(423.29) = -3.85, p < 0.001$.

Next, we calculated the mean AI attitudes of people with each specific type of disability, and conducted t-tests for those with especially low means (reported in Table 1) and sufficient sample sizes: learning disabilities, neurodivergence, and mental health disabilities. Overall, people who did not have a disability reported AI attitudes with a higher mean than disabled people. Specifically, we find that neurodivergent participants have significantly more negative AI attitudes (M = 4.28, SD = 1.72) than those who are neurotypical (M = 5.12, SD = 1.33), $t(181.19) = -5.41, p < 0.0001$, and participants with mental health conditions have significantly more negative AI attitudes (M = 4.43, SD = 1.67) than those without mental health conditions (M = 5.10, SD = 1.35), $t(219.52) = -4.65, p < 0.0001$. Participants with learning disabilities have more negative AI attitudes (M = 4.19, SD = 1.81) than those without learning disabilities (M = 5.01, SD = 1.41), $t(46.35) = -2.94, p < 0.01$, though this does not meet our Bonferroni-adjusted threshold for statistical significance.

Then we return to the regression model in Table 3, which includes all demographic and technology use control variables, to see

[7] though not enough to introduce problematic levels of multicollinearity into the model, according to the model's variance inflation factors

Table 6: Comparisons between mean AI attitudes for disabled people and those without these disabilities (Welch's two sample t-tests). Results show that disabled participants overall, neurodivergent participants, and participants with mental health conditions have significantly lower AI attitudes than others.

With Disability Mean	Without Disability Mean	Difference	95% CI of Difference	*t*-value	*p*-value
one or more disabilities: 4.68	no disability: 5.13	−0.46 **	(-0.69, -0.22)	−3.85	<0.001
neurodivergent: 4.28	neurotypical: 5.12	−0.84 ***	(-1.14, -0.53)	−5.41	<0.0001
learning disability: 4.19	no learning disability: 5.01	−0.82	(-1.38, -0.26)	−2.94	0.005
mental health condition: 4.43	no mental health condition: 5.10	−0.67 ***	(-0.95, -0.38)	−4.65	<0.0001
p-value thresholds after Bonferroni correction: * $p < .005$; ** $p < .001$; *** $p < .0001$					

whether any disability variables are significantly correlated with AI attitudes after adding control variables. None of the disability categories are statistically significant predictors of AI attitudes after controlling for other variables.

4.4 Additional effects

In Table 3, we see a number of emergent effects that were not part of our initial hypotheses. Related to demographic characteristics, we see that there is an association between age and AI attitudes for participants aged 18-24 ($b = -0.33, p < 0.05$), meaning that these younger participants have more negative AI attitudes than the reference group, people aged 35-44.[8] We also find that participants who have lived in the U.S. longer, or their whole lives, have more negative AI attitudes than those who have moved to the U.S. more recently ($b = -0.18, p < 0.05$). Income is a significant, positive predictor of AI attitudes ($b = 0.07, p < 0.001$), meaning that participants with higher incomes tend to have more positive attitudes towards AI. Finally, those with very leftist or liberal political orientations have more negative AI attitudes ($b = -0.29, p < 0.01$).

Technology use variables also were predictive of AI attitudes. Participants who are more enthusiastic ($b = 0.63, p < 0.001$) as well as more anxious ($b = 0.07, p < 0.05$) about technology in general, and those who have seen more positive coverage of AI in the media ($b = 0.07, p < 0.05$), have higher AI attitudes on average. Participants with higher levels of concern about online privacy ($b = -0.15, p < 0.001$) tend to have more negative AI attitudes. Importantly, those who believe they have experienced algorithmic harm ($b = -0.30, p < 0.05$), or who are unsure if they have experienced algorithm harm ($b = -0.24, p < 0.05$), have more negative AI attitudes on average.

To understand another potential impact or antecedent of AI attitudes, we also examined the extent to which AI attitudes may correlate with participants' AI use in their everyday lives. This was a correlational analysis conducted separately from the regression model. We found that AI attitudes and use of AI use in one's personal and/or work life are highly correlated, $r = 0.66$, $p < 0.0001$.

5 Discussion

We find that some groups of people in our dataset – gender minorities and disabled people – have more negative attitudes towards AI than their majority counterparts. Specifically, the demographic groups most likely to have negative AI attitudes are nonbinary people, trans people, women, neurodivergent people, and those with mental health conditions. Knowledge about how particular marginalized groups think and feel about AI can inform more equitable policies and reduce the disparities that these groups face when using – both with and without explicit knowledge – emerging technologies.

5.1 Differences in AI Attitudes Across Gender, Disability, and Race

Prior research examining AI attitudes and gender found that women have more negative attitudes towards AI than men [18, 30, 32, 38, 55, 74, 91], which this study similarly identifies. It makes sense that women would feel more negatively about AI than men, given a long history of algorithmic discrimination and bias towards women [20, 24, 36, 70]. Given that gender minorities (trans and nonbinary people) also face substantial discrimination and bias, it follows that these groups would have negative AI attitudes, as we show empirically. Yet prior studies did not examine gender minorities' AI attitudes. We extend prior work by analyzing AI attitudes not only among cisgender, binary gender categories but also among nonbinary and trans people. This new empirical evidence enables us to see a more granular picture about the relationship between AI and gender-based marginalization.

Regarding disability, a number of scholars have examined the ways that AI technologies perpetuate biases towards disabled people [14, 82, 89, 100, 103], and a growing body of work is beginning to examine disabled people's experiences with AI [1, 33, 37]. We expand the former and contribute to the latter by quantitatively examining disabled people's attitudes towards AI. Our results indicate that, when disabled people are required to use AI systems (such as in workplace or healthcare settings), they may be doing so while harboring serious concerns and hesitations.

Although we find minoritized genders and individuals with disabilities to have a negative relationship with attitudes toward AI, we see the opposite when looking at race. In fact, we find that marginalized racial groups, and Black people in particular, have significantly more *positive* attitudes toward AI than their White counterparts. This may be partially explained by Black optimism, which Sexton [88] argues serves as a form of resistance by Black individuals and a way to exercise agency in response to oppressive systems. Black optimism has been demonstrated in empirical research; for example, recent work found people with darker skin tones were more likely to use facial recognition technology [72].

[8] While we initially treated age as a continuous variable, upon inspection we found a upside-down-U-shaped relationship between age and AI attitudes, with both the youngest and oldest participants having more negative AI attitudes. Thus, we decided to use age groups as dummy variables, with age 35-44 as the reference variable, to capture these age differences more accurately in the regression model.

Yet other work has highlighted Black participants' mistrust of AI systems, such as when compared with human decisions in healthcare contexts [57], and shown how, for racial minority participants, learning about the concept of algorithmic fairness elicited negative attitudes toward algorithmic systems in the context of racial injustice [105].

The DISCO Network's concept of Afro-skepticism, in their discussion of Blackness and AI, can further help explain these seeming contradictions. Afro-skepticism "acknowledges the brutality of totalizing systems while at the same time recognizing existing capacities for joy, hope, play, and freedom" [68]. That is, rather than assuming that Black people are uncritically accepting AI, instead we must acknowledge their ambivalence, and the resistance inherent in finding playful or joyful ways to co-opt the very same technology that harms them [68]. Given that Black individuals tend to have positive attitudes towards AI and are likely to use AI systems, but at the same time face substantial bias and potential harm when using these systems [11, 20, 47, 48], future work should build from an existing set of work about AI centering Black people and other racial minorities [16, 19, 44, 57, 97, 104] to better understand why those who may experience AI harms tend to have positive attitudes towards AI. While our findings are limited to individuals in the U.S., they corroborate previous work which suggested individuals living in predominantly Black nations (e.g., Ghana and Nigeria) also have positive attitudes about AI in particular contexts [49, 69, 83], despite AI technology design often failing to consider the specific needs of Global South communities [4]. We strongly warn that our findings should not be read as a justification for using AI in racial minority communities when racialized AI harms still persist, regardless of attitudes.

Many aspects of daily life include interacting with AI in some way, across workplaces, education systems, healthcare systems, and more. Our findings that attitudes towards AI vary based on gender, race, and disability mean that those groups with more negative attitudes will likely feel less comfortable using AI in these settings, limiting their participation and meaningful consent. This is problematic given increasingly prevalent discourses that the advancement and deployment of AI across domains is "inevitable" [8] and a universal "positive" [64, 99]. Our findings demonstrate that ubiquitous AI is not a desired direction for all people.

5.2 AI Attitudes, Future AI Use, and Algorithmic Harms

Our results point to a potential preliminary conceptual model in which algorithmic harms may lead to more negative AI attitudes, which in turn may lead to lessened AI use. We have correlational evidence of both of these links: In our regression model (see Table 3), we showed that those participants who stated they had experienced algorithmic harm in the past had significantly more negative AI attitudes than those who had not; and we showed a significant positive correlation between AI attitudes and participants' propensity to use AI in their work or personal lives (see the last paragraph of Section 4.4). We cannot make definitive causal claims in the absence of an experimental or longitudinal study design, and we did not conduct a mediation analysis that may have been able to showcase the mediating role of AI attitudes between previous algorithmic harms and future AI use. But conceptually, it seems logical that those who experience substantial algorithmic harms and thus develop negative attitudes toward AI will tend to use AI less in the future. Future work could examine these effects using a causal experimental study design. If this conceptual understanding is correct, then these groups of people who have experienced algorithmic harms (such as discrimination and bias) are less likely to access any promised benefits of AI, signaling widespread inequities.

Additionally, how and why AI is used across contexts can be opaque [58] and unknown to those impacted by it, limiting meaningful consent [76]. That groups of minoritized people have significant negative attitudes towards AI, as we find, indicates that harmful implications stemming from lack of transparency and consent are likely even more pronounced for these groups. This is particularly important in contexts imbued with power imbalances between those subjected to AI and those imposing its use (e.g., work, healthcare, education, law enforcement) [46, 81]. Opting out of AI use is a luxury available to few, and may be unavailable particularly for minoritized groups – resulting in people being coerced into interacting with AI systems or relying on them for critical aspects of life (e.g., healthcare, education), even when they hold negative attitudes toward these systems.

It is telling – alarming, even – that cisgender people, men, non-disabled people, and those with higher socioeconomic status have significantly more positive attitudes towards AI. These groups are less likely to experience AI harms [55, 70, 74, 75, 100], and are also highly represented in the tech sector developing AI [66] and hyping it up. In many cases, these are the people holding power in deciding if and how AI will be regulated, invested in, and deployed.

5.3 Implications for Policy

Accordingly, the aforementioned implications mean that AI regulation and policy decisions must consider disparate AI attitudes. As the White House's previously published AI Bill of Rights is no longer available and AI regulation will likely not be pursued by the current U.S. federal administration, state-level protections may lead the way in protecting against the harms of AI. For instance, California's AB 2013 (effective 2026) and Colorado's AI Act mandate transparency and bias mitigation, reflecting growing local efforts to combat algorithmic discrimination in the absence of federal enforcement. We call on state-level U.S. policymakers to continue pushing policy that works against AI-driven discrimination, as this may urge companies to adhere to the most stringent state law in order to operate in the U.S. (otherwise referred to as the "California effect" [102]). In creating policy, it will be essential for legislators to consider not only the harms of raw data collection, but the inferences and predictions AI makes about individuals which could reinforce existing inequities [61]. Policy efforts could promote the inclusion of impacted groups in AI development through requiring developers to audit their systems and assess impact on diverse groups, akin to the recent NYC law regarding AI use in hiring [98]. Further, we can prevent forced coercion into using AI systems by bolstering meaningful consent and requiring companies to exercise loyalty toward their consumers, as law scholars have argued [78]. Our finding that more privacy-concerned participants have more

negative attitudes towards AI signals that regulation and system design aimed at improving public trust and attitudes towards AI must prioritize addressing the privacy harms caused by these technologies. Further, it is crucial to prioritize gender minorities, disabled individuals, and other minoritized groups by acknowledging and addressing their attitudes in future AI policymaking to ensure these groups' concerns are taken seriously.

6 Conclusion

In this work, we provide empirical evidence showing that certain groups in the U.S. – gender minorities and people with disabilities – have significantly more negative attitudes towards AI compared to others. In particular, nonbinary individuals, trans individuals, women, neurodivergent individuals, and those with mental health conditions express less positive AI attitudes than dominant groups. These results have major implications when considering AI's widespread adoption across myriad contexts. AI adoption requires many people to use AI, or be subjected to its use, despite significant disparities in attitudes based on gender, race, and disability. We conclude that AI's extensive integration into all aspects of life is clearly is not a desired direction for all.

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A Appendix: Survey Instrument

This appendix only includes parts of the survey that were included in this paper's analysis.

A.1 Screening and basic questions

(1) Do you live in the United States? [Yes; No]
(2) How old are you? [numerical input]
(3) Please verify that you are a person. [Captcha checkbox]

A.2 Technology use measures

(1) **heard of AI**. Which best describes your knowledge about AI? [Never heard of it; Heard of it, but don't know what it is; Know what it is, but not sure how it works; Understand how it works; Expert in it]
(2) **AI attitudes**. Please indicate your agreement with each of the following statements about AI. [38]
  (a) I believe that AI will improve my life.
  (b) I believe that AI will improve my work.
  (c) I think I will use AI technology in the future.
  (d) I think AI technology is positive for humanity.
  [Strongly disagree; Disagree; Somewhat disagree; Neither agree nor disagree; Somewhat agree; Agree; Strongly agree]
(3) **experienced algorithmic harm**. Have you personally experienced harm or unwanted effects from algorithmic systems? [Yes; No; I'm not sure]
(4) **privacy**.Please indicate your agreement with each of the following statements about privacy. [59]
  (a) All things considered, the internet causes serious privacy problems.
  (b) Compared to others, I am more sensitive about the way my personal information is handled.
  (c) To me, it is the most important thing to keep my privacy intact from companies and institutions.
  (d) I believe other people are too much concerned with online privacy issues. (reverse item)
  (e) Compared with other subjects on my mind, personal privacy is very important.
  (f) I am concerned about threats to my personal privacy today.
  [Strongly disagree; Disagree; Somewhat disagree; Neither agree nor disagree; Somewhat agree; Agree; Strongly agree]
(5) **tech enthusiasm; tech anxiety**. Please indicate your agreement with each of the following statements about technology. [2]
  (a) I think new technological gadgets are fun.
  (b) Using technology makes life easier for me.
  (c) I like to acquire the latest models or updates.
  (d) I am sometimes afraid of not being able to use new technical things.
  (e) Today, the technological progress is so fast that it's hard for me to keep up.
  (f) I would try new technologies to a greater extent if I had more support.
  [Strongly disagree; Disagree; Somewhat disagree; Neither agree nor disagree; Somewhat agree; Agree; Strongly agree]
(6) **heard about AI in media**. To what extent have you heard about AI in the media (on TV, on social media, in movies, in magazines/newspapers, etc.)? [Never; Very rarely; Rarely; Occasionally; Frequently; Very frequently; All the time]
(7) **sentiment of AI media coverage observed**. How would you characterize coverage of AI in the media overall (on TV, on social media, in movies, in magazines/newspapers, etc.)? [Very negative; Negative; Somewhat negative; Neither

positive nor negative; Somewhat positive; Positive; Very positive; N/A (I have not seen coverage in the media)]

(8) **tech savviness**. Please indicate your agreement with each of the following statements. [63, 95]
   (a) I am confident using computers, smartphones, or other types of digital technology to do thing things I need to do. (adapted from [63]
   (b) People consider me to be tech savvy.
   (c) I consider myself to be tech savvy.
   [Strongly disagree; Disagree; Somewhat disagree; Neither agree nor disagree; Somewhat agree; Agree; Strongly agree]

(9) **AI use in everyday life**. To what extent do you use AI in your day-to-day life and work? [Never; Very rarely; Rarely; Occasionally; Frequently; Very frequently; All the time]

A.3 Demographic questions

(1) What is your gender? (select all that apply) [Woman; Man; Non-binary; I'm not sure; Prefer to self-describe: _____]

(2) Are you transgender? [Yes; No; I'm not sure; Prefer to self-describe: _____]

(3) Choose one or more races/ethnicities that you consider yourself to be. (select all that apply) [American Indian or Alaska Native; Black or African American; East Asian; Hispanic or Latino; Middle Eastern; Native Hawaiian or Pacific Islander; South Asian; Southeast Asian; White; Mixed race, multiracial, or biracial; Prefer to self-describe: _____]

(4) Please check any of the boxes that apply to you regarding disability status. (select all that apply) [I use disability resources; I self-identify as disabled; I self-identify as disabled in some contexts but not others; I am unsure if I am disabled; I do not consider myself disabled]

(5) Do any of the following disabilities or chronic conditions impact your daily life? A formal diagnosis is not needed. (select all that apply) [None; Deaf/deaf or have serious difficulty hearing; Blind or have seriously difficulty seeing, even when wearing glasses; Mobility limitation including serious difficulty walking or climbing stairs; Motor limitation including manual dexterity; Learning disability; Neurodiverse; Speech or language impediment; Chronic illness that is neurological or physical; Mental health condition; Prefer to self-describe: _____]

(6) How long have you lived in the U.S.? [Less than one year; 1-2 years; 3-5 years; 6-10 years; More than 10 years but not my whole life; My whole life]

(7) What is your sexual orientation? (select all that apply) [Straight; Gay; Lesbian; Bisexual; Pansexual; Queer; Asexual; I'm not sure; Prefer to self-describe: _____]

(8) What is the highest level of school you have completed or the highest degree you have received? [Less than high school; High school or equivalent; Some college or two-year associate's degree; Bachelor's degree; Some graduate school; Master's or professional degree; Doctoral degree]

(9) Information about income is very important to understand. Would you please give your best guess? Please indicate the answer that includes your entire household income in 2023 before taxes. [Less than $20,000; $20,000 to $34,999; $35,000 to $49,999; $50,000 to $74,999; $75,000 to $99,999; $100,000 to $149,999; $150,000 to $199,999; $200,000 to $249,999; $250,000 or more]

(10) In general, how would you describe your political views? [Very conservative; Conservative; Moderate; Liberal; Very liberal; Prefer to self-describe: _____]