Cultural Values and Their Effects on Attitudes and Reliance on AI

KATELYN X. MEI, Information School, University of Washington, USA
NIGINI A. OLIVEIRA, Paul G. Allen School of Computer Science & Engineering, University of Washington, USA
RODOLFO C. BARRAGAN, Department of Psychology, University of Washington, USA
YULIA TSVETKOV, Paul G. Allen School of Computer Science & Engineering, University of Washington, USA
ANDREW N. MELTZOFF, Department of Psychology, University of Washington, USA
MAARTEN SAP, Language Technologies Institute, Carnegie Mellon University, USA
KATHARINA REINECKE, Paul G. Allen School of Computer Science & Engineering, University of Washington, USA

Conversational AI is rapidly being adopted by people with different cultural values across the world. The large language models (LLMs) used by these AI systems have been criticized for frequently expressing value-laden statements that are biased towards the dominant views in English-speaking, Western countries. We hypothesized that this could influence people's attitudes towards, and their reliance on AI, especially if their cultural values differ from those expressed by the AI. In an online experiment with 465 participants from 66 countries, we exposed participants to the value-laden statements of an LLM and subsequently had them solve a value-neutral task. Our results show that, paradoxically, people with traditional values tend to have more positive attitudes towards, and a higher reliance on the AI than those with more secular values, despite our AI being biased against their values. We discuss the implications of our results for AI innovation, economic hegemonies, research, and design.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**.

Additional Key Words and Phrases: cultural values, Human-AI interaction, reliance, AI-assisted decision-making

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1 INTRODUCTION

Recent rapid advances in Large Language Models (LLMs) have spurred their broad adoption for various daily tasks such as searching for information, forming opinions, and making important decisions. However, with LLMs playing an

Authors' addresses: Katelyn X. Mei, kmei@uw.edu, Information School, University of Washington , Seattle, WA, USA; Nigini A. Oliveira, nigini@cs.washington.edu, Paul G. Allen School of Computer Science & Engineering, University of Washington , Seattle, WA, USA; Rodolfo C. Barragan, barragan@uw.edu, Department of Psychology, University of Washington, Seattle, WA, USA; Yulia Tsvetkov, yuliat@cs.washington.edu, Paul G. Allen School of Computer Science & Engineering, University of Washington , Seattle, WA, USA; Andrew N. Meltzoff, meltzoff@uw.edu, Department of Psychology, University of Washington, Seattle, WA, USA; Maarten Sap, msap2@andrew.cmu.edu, Language Technologies Institute, Carnegie Mellon University, , PA, USA; Katharina Reinecke, reinecke@cs.washington.edu, Paul G. Allen School of Computer Science & Engineering, University of Washington , Seattle, WA, USA.

increasingly large role in people's lives, researchers have voiced concerns about inherent biases present in LLMs, which are trained on predominantly Western and English data [12]. LLMs have been found to contain significant social and political biases [15, 16, 53, 65] and are often aligned with the values and norms of Western, White, college-educated, and younger populations [54]. While unable to form values themselves, LLMs have been found to express value-laden statements, which are again commonly aligned with Western values [11, 23, 54].

Given that humans have vastly divergent values across countries and cultures, people's interaction with LLMs may expose them to value-laden statements that are more or less aligned with their own. This could impact their trust, acceptance of, and general attitudes towards the AI, which could in turn influence its adoption and whether users choose to rely on its output. Indeed, previous research has shown that self-reported attitudes towards AI differ across countries, with people in emerging economies (Brazil, India, China, South Africa) reporting the highest levels of trust and acceptance in AI and only a minority of survey respondents from Finland and Japan saying that they trusted and accepted AI [17]. To date, however, no experimental studies have been conducted to systematically evaluate people's attitudes when they are actually interacting with an AI, and in particular when they are exposed to value-laden statements by an LLM, and whether such exposure may influence their use and reliance of an AI in a value-neutral task.

This paper addresses this gap by posing the following research question: *"How do cultural values affect users' attitudes towards, and reliance on, an AI after being exposed to an LLMs' value-laden statements?"*

To answer this question, we designed an online experiment in which participants (n=465 from 66 countries) were first asked to get to know an AI collaborator in a conversation that included the value-laden answers from an LLM to a subset of the World Values Survey (WVS), a widely used and validated global survey used to compare human values. The World Values Survey has shown that differences in human values can be largely explained with the help of two cultural dimensions: (a) Survival vs. Self-Expression (which captures the continuum between cultures that emphasize economic and physical security and those that value autonomy and tolerance) and (b) Traditionalism vs. Secularism (describing the extent to which societies adhere to religion, traditional family values, and authority versus being largely secular, which often means being more open to divorce, abortion, and science) [25]. Our experiment measured participants' positions on these cultural dimensions, their attitudes towards the AI after interacting with it, and their reliance on the AI when solving a value-neutral spatial reasoning task.

Our results reveal a contradiction that can be best described as the paradox of cultural bias in AI: While the often decried Western and secular bias of LLMs had us hypothesize that people with strongly diverging values would have more negative attitudes towards the AI, we instead found that people with comparatively traditional values tend to have more positive attitudes towards and a higher reliance on AI despite it being biased against their values. Surprisingly, participants with more traditional values reported having a higher trust in the AI, a greater sense of belonging with the AI, found the AI more competent, and relied more on the AI in making decisions than those with more secular values. These findings hold true while controlling for education level and age.

We did not find participants' Survival vs. Self-Expression scores to predict their attitudes towards, or reliance on AI, suggesting that the difference between Traditionalism and Secularism may be a more important driver for people's interaction with AI.

Our findings have broad implications for the acceptance and use of AI by individuals and society. They include potential economic benefits for societies that readily embrace AI, and risks if AI innovations are not being safeguarded by appropriate regulations and laws, which we discussing more detail in Section 5.

2 RELATED WORK

2.1 Culture and Values

Culture has been described as "a system of shared beliefs, values, customs, behaviors, and material objects that the members of a society use to cope with their world and with one another, and that are transmitted from generation to generation through learning" [3, p.5]. To apply this definition in contexts where a comparison of cultures may be desirable, cultural anthropologists have produced various conceptualizations of culture, which are commonly based on geographic location, to understand and contrast prevalent customs and values across countries or other geographic locales (e.g., Hofstede [24], Schwartz [58], Inglehart [25], and others [38, 46, 63, 64]). The attempts to characterize cultures have led to much debate in various academic fields [13, 22, 30, 49, 60, 61], because doing so "suggests boundedness, homogeneity, coherence, stability, and structure whereas social reality is characterized by variability, inconsistencies, conflict, change, and individual agency" [8, p.1]. For example, any reduction of culture to geographic boundaries risks ignoring cultural variations within these boundaries, excludes regional subcultures or cultural groups that span multiple regions, and falls short of explaining and understanding how an increasingly interconnected world of people traversing and adapting to various cultures has influenced and changed cultural norms [45]. Hence, while researchers generally agree that social groups, such as national cultures, share learned routines, knowledge, meanings, and values, it is important to be aware of variations within such groups [8, 26, 57].

Our research builds on the data provided by the World Value Survey (WVS)—a survey that has been conducted with representative participant samples (recruited using random probability sampling) in more than 80 countries, the latest wave covering a time frame between 2017-2021 [20]. The WVS Wave 7 includes 290 questions on values, ranging from political views, support for democracy, gender equality, and tolerance of foreigners and minorities, to the role of religion and national identity. For example, participants in the WVS are asked to rate, rank-order, or provide multiple choice answers, such as by rating their agreement with statements such as "*If jobs are scarce, men should have more right to a job than women*" or "*Homosexual couples are as good parents as other couples*". The questions include an abbreviated version of Schwartz's value questionnaire [58] and questions that have led to Inglehart and Welzel's cultural dimensions (e.g., Traditional vs. Secular, Survival vs. Self-expression) [29]. Based on large-scale survey responses to the WVS, Inglehart and Welzel position countries relatively based on their values along the two cultural dimensions (e.g., the cultural map). The cultural map from recent survey responses (year 2017-2022) indicates that European and English-Speaking regions and the Confucian region (e.g., South Korea, Hong Kong, Japan) lean toward *Secular* values whereas countries from African-Islamic and Latin America leans toward *Traditional* values; additionally, European and English-speaking regions lean towards *Self-expression* whereas African-Islamic and Latin America regions towards *Survival*. Our quantification of cultural values adopts the approach by Inglehart and Welzel [29] and positions individuals' values along the same cultural dimensions.

2.2 Cultural Values in LLMs and Implications

The rising popularity of LLMs among the public and downstream applications raises concerns across different communities since their development is predominantly contributed by people in Western cultures. Research in the Natural Language Processing (NLP) community has been dedicated to examining the representation of cultural values in popular LLMs. Using various kinds of probing methods and questions from the WVS, researchers found that responses from current LLMs, including recent models (GPT-4, 4-turbo, 4o), are more representative of opinions from English-speaking and Protestant European countries [4, 14, 23, 62]. These findings suggest that current LLMs still fail to represent the diverse cultural values of different populations. Research focusing on human-AI interaction has shown that a lack of diverse perspectives in the generated content of LLMs can have downstream implications on users. An experiment study by Jakesch et al. [31] shows that individuals' attitudes and writing about social media are affected by the preferred opinions of the language model. A recent study from Sharma et al. [59] demonstrates that when individuals search for information with an opinionated LLM, their information querying becomes more biased. While these studies suggest the impact of biased LLMs on users' task performance, they focus on individuals' opinions and search behaviors. In this work, we examine users' attitudes toward an opinionated AI system and reliance on the AI and whether there exists a broad cultural variation.

2.3 Variance in Users' Attitudes toward and Reliance on AI across Demographics

Prior studies on human-AI interaction have identified that the design of AI systems can influence individuals' trust and reliance on AI [37, 39, 40, 55, 67]. However, in addition to system-related factors, recent survey-based and qualitative studies suggest that individuals' attitudes toward AI can vary by their demographics and characteristics [17, 33, 35]. Gillespie et al. [17] surveyed over 17,000 people from 17 countries on their opinions towards AI and found that the majority of people (61%) reported being either ambivalent or unwilling to trust AI systems; people from emerging "BICS" economies (Brazil, India, China, and South Africa) reported having a higher trust in and acceptance of AI systems than those in Western countries. In a survey of job-seekers from 48 countries, [43] found that East Asians exhibit a more trusting attitude toward emotional AI in the workplace than European participants. Kapania et al. [33] found that people from India perceived high authority of AI decisions and had high acceptance of AI decisions even in high-stakes settings such as financial loan assessment and medical diagnosis. Gender differences have also been observed in individuals' attitudes toward AI, and male participants have reported more positive attitudes than female participants [35]. Evidence from these survey studies suggests individuals behaviors in human-AI interaction might be influenced by their culture and demographics, as such, our study contributes to this line of work and further explores how cultural values affect individuals' attitudes and reliance on AI via empirical evidence.

Influence of Value Similarity on Technology Adoption. How do individuals rely on AI differently if it displays dissimilar values? One recent work from Narayanan et al. [48] focused on ethical values and a task where participants were asked to determine a candidate who should receive a kidney donation. Participants were provided with an AI's suggestions which followed either similar or opposite decision principles. Their results show that when individuals' initial decisions disagree with the AI they are more likely to align with an AI that displays similar principles in their final decision. Focusing on the similarity of values that individuals apply to the decision-making task, their research suggests that value similarity between humans and AI plays a role in human-AI collaborative decision-making. Our research extends the investigation of value similarity by focusing on the cultural values of individuals and an objective task that does not apply subjective values.

3 METHODOLOGY

Our study aims to investigate the following research questions:

> **RQ1**: How do cultural values affect users' attitudes towards an AI after they learn about an AI's values which may or may not conflict with their own beliefs?
> **RQ2**: How do cultural values affect users' reliance on an AI in a value-neutral, objective task?

To answer these questions, we designed an online experiment to reach participants with diverse values. Our online experiment included 1) a questionnaire to measure participants' cultural values, 2) a conversational task where they were exposed to an AI's value-laden answers to their questions, 3) a value-neutral, spatial reasoning task designed to measure their reliance on the AI by allowing them to use as much assistance from the AI as they wished, and 4) a questionnaire to evaluate their attitudes toward the AI after interacting with it. Note that we chose not to ask about participants' attitudes toward the AI before and after our task both to avoid priming and to be able to ask about attitudes towards the specific AI after participants were interacting with it; however, this has the downside that we do not know their baseline attitudes towards AI.

3.1 Study Procedure

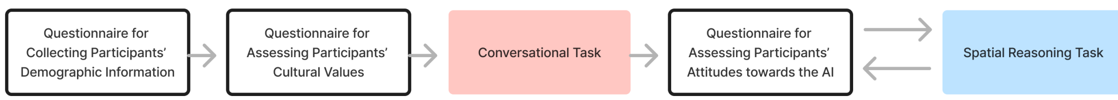

Fig. 1. Experiment Design

The full experiment is illustrated in Figure 1. The study started by introducing participants to the context of the task: "how do you collaboratively solve problems? Test how well you solve spatial reasoning tasks with an AI." This introduction is designed to intrinsically motivate participants to engage in the experiment, beyond the appeal of monetary compensation. Participants were asked about their demographic information related to gender, age, and country they grew up and currently live. Then participants were encouraged to answer a questionnaire for assessing their cultural values under the guise that we would "better pair them with an AI collaborator". They were then directed to the conversational task where they could select questions related to cultural beliefs to ask the AI, as shown in Figure 2. The list of questions participants could ask the AI is included in the appendix Table 7. Participants needed to ask the AI at least five questions (maximum was eight) before they could proceed. Next, they were directed to complete either the questionnaire assessing their attitudes towards the AI or the spatial reasoning task. The spatial reasoning task required them to encode a representation of an object and mentally rotate its representation to match another presented view, as shown in Figure 3. The task had 6 trials and in each trial participants were asked to select their answers first before they were provided AI's suggestions. They could modify their responses after seeing the AI suggestions before submitting their final answers. The questionnaire and the spatial reasoning task were assigned in a random order (as shown in Figure 1) to allow us to analyze whether the order of tasks influenced participants' attitudes towards the AI differently.

3.2 Materials

Questionnaire for Assessing Cultural Values of Participants. To measure participants' cultural values, we used the 11 survey questions from the WVS that position human respondents on the *Survival/Self-Expression* and *Traditional/Secular* cultural dimensions (see Appendix Table 5). According to the political scientists Inglehart and Welzel [25], these two dimensions have high variations across cultures.[1] People who score high in *Survival* tend to focus on physical and economic security with low support for gender equality whereas people who score high on *Self-expression* tend to emphasize environmental protection, show a growing tolerance of foreigners, gender equality, and greater demands for

[1]See *Findings & Insights Section at https://www.worldvaluessurvey.org*

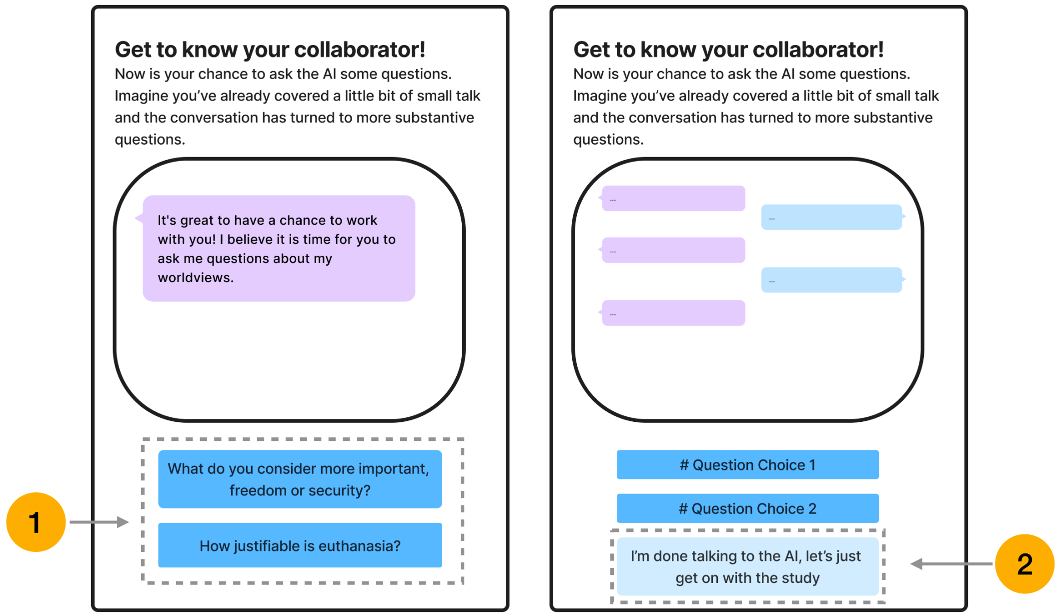

Fig. 2. **Conversational Task**: Participants were provided two choices of questions they could ask the AI in each turn. After asking four questions, they were provided a choice to move on to the next task.

autonomy and freedom from central authority. On the dimension *Traditional/Secular*, people who are more *Traditional* tend to believe in the importance of religion and traditional family values whereas those who are more *Secular* place less emphasis on traditional values such as religion, family values, and authority and have a higher acceptance of divorce, abortion, and euthanasia.

Questions and AI Responses for the Conversational Task. We used a subset of questions from the WVS to generate responses from a publicly accessible chatbot, Meta's Blenderbot [52], which we found to answer with sometimes strong expressions of values (unlike newer LLMs which mostly express fairly neutral statements due to companies safeguarding the output). [2] To select a subset of questions, we first prompted Blenderbot with 140 questions from the WVS (excluding those that could not be reasonably answered by an AI, such as "How happy are you?"). We then filtered out questions where Blenderbot's responses were ambiguous or lacked value-laden opinions in the studied dimensions, resulting in 60 questions. Next, we recruited from Amazon Mechanical Turk (MTurk) to rate each AI response on our two cultural dimensions, with a scale ranging from 1 (e.g., Very Traditional) to 5 (e.g., Very Secular), with the center labeled "In Between." Each question was accompanied by a description of the corresponding dimension, taken from the WVS website, and annotators were also given a separate option labeled "Doesn't Apply," coded as zero in our dataset.

Each AI response was rated by at least 4 MTurk workers. One author additionally annotated all AI responses without prior knowledge of the MTurk ratings for comparison, resulting in a total of 5 ratings per AI response. We selected those AI responses (along with their questions) that annotators overwhelmingly agreed expressed a certain cultural value.

[2] It is worth noting that while the responses we obtained from Blenderbot might differ from the neutral output generated from current LLMs, recent research has shown that current LLMs still generate value-laden responses [14].

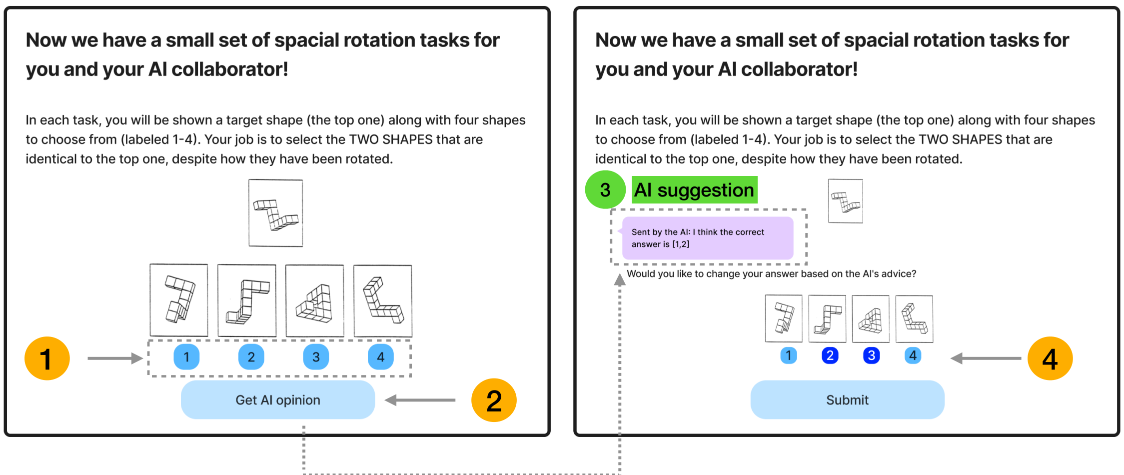

Fig. 3. **Spatial Reasoning Task**: Participants were asked to find the identical object as the target by mentally rotating the four shapes provided. After they selected an answer, they were able to click "Get AI opinion" to see the AI's suggested solution. After the AI's suggested solution was shown, they could choose to modify their answers before submitting them. They could not click 'Get AI opinion' before they selected a response themselves.

More precisely, we selected those where at least the majority ($n >= 3$) annotated as expressing Self-expression, while the rest did not categorically disagree – i.e., mostly selected neutral ($n >= 1$). This process resulted in 19 question/AI response pairs that received consistent annotator ratings that leaned toward Self-expression. We made this decision because we wanted to precisely control the values expressed by the chatbot, towards which we intended to compare the values reported by study participants. The 19 questions and AI's responses can be found in the Supplementary Materials (Table 7.

Questionnaire for Assessing Participants' Attitudes towards the AI. Given that our study participants might potentially encounter AI value expressions that are misaligned with their own, we expected their attitudes toward the AI might manifest similarly to the experience of acculturative stress. Acculturative stress is a term often used to describe people's reactions when encountering attitudes and values different from their own, such as in the context of immigration experiences [2, 5]. In our study, measuring acculturative stress is useful to capture participants' emotional responses in addition to the more general attitudes that much of the prior work in human-AI interaction has explored [18, 56]. As such, we adapted questions from prior work measuring acculturative stress [7] to suit the context of AI and combined them with more general questions about attitudes towards the AI. Our final questionnaire (see Table 1) asked about participants' perceived competence of the AI, feelings related to their trust/reliance, well-being, and belonging after conversing with the AI. It consisted of 9 statements for which participants selected their agreement with a Likert scale (1 for 'Not at all true', 5 for 'Very true').

Table 1. Questionnaire for Assessing Participants' Attitudes towards the AI

q1 I agree with this AI's opinions.
q2 Talking to this AI made me feel insecure.
q3 I cannot trust this AI to discuss my personal problems.
q4 It hurts when this AI does not share my cultural values.
q5 I don't feel a sense of belonging with this AI.
q6 Talking to this AI made me feel lonely.
q7 I think this AI is competent.
q8 Talking to this AI could have a negative effect on my well-being.
q9 Talking to this AI made me angry.

3.3 Overview of Variables

To summarize, we utilize the following variables to conduct our analysis:

- *Independent Variables*
  - **Cultural Values: SECU, SELE**: individuals' cultural values along the dimensions of *Traditional vs Secular* (**SECU**) and *Survival vs Self-expression* (**SELE**) calculated based on their responses to the WVS questionnaire (11 survey questions) using the formula by Inglehart [25] [3]. The positive pole of SECU indicates *Secular* and the positive pole of SELE indicates *Self-expression*.
  - Demographic variables: age, gender, education levels
  - Question Count: the number of questions participants asked the AI in the Conversational Task
- *Dependent Variables*
  - **Each Question Response in Participants' Attitudes toward the AI** : individuals' attitudes towards the AI in terms of their trust/reliance, well-being, and belonging.
  - **Reliance on AI**: participants' reliance on AI is a binary variable operationalized as—in each trial of the spatial reasoning task—whether they *switch* from their initial response to the decision provided by the AI, whether or not the AI's response is correct. We adopt this measure from prior studies on human-AI interaction [10, 41]. We also calculate their **frequency of reliance** across all the trials in the spatial reasoning task.

3.4 Participants

We recruited participants through LabintheWild [51], a volunteer-based online study platform that has been shown to attract culturally diverse volunteers, and Prolific, which allows recruitment from specific countries and regions. Our sample started with 536 participants and our filtering process resulted in a final analytic sample of 465 participants (373 from Prolific). Specifically, we excluded participants who did not finish the study or reported having previously taken it (N=40), were under 18 years old (N=17), or completed the study in less than 5 minutes (N=6). We set the minimum to be 5 minutes to account for participants who deferred to the AI's decisions all the time for the spatial reasoning task. Additionally, we filtered out participants suspected of satisficing behavior (N=8), identified as those who selected the same options for every question in our questionnaire regarding their impressions of the AI. Our participants were from 66 different countries based on where they grew up. The countries with the highest number of participants in the current

[3]The formula can also be found in https://www.worldvaluessurvey.org/WVSContents.jsp

Table 2. Demographics of Participants

Demographics	Frequency
Overall	
Overall	465
Age Group	
18-24	131
25-34	215
35-44	76
45-54	26
55-64	9
Over 64	8
Education	
Less than high school education	60
Have obtained or Pursuing a college education	302
Have obtained of Pursuing a graduate education	103
Gender	
female	217
male	237
no-disclosure	2
non-binary	9

study were as follows: Mexico constituted 10% of the total sample, followed by South Africa at 9%, Greece at 7%, and the United States at 6%; additionally, Zimbabwe, Poland, and Nigeria each represented 5% of the participants. Figure 4 illustrates the cultural values of participants in the two dimensions Traditional/Secular and Survival/Self-expression.

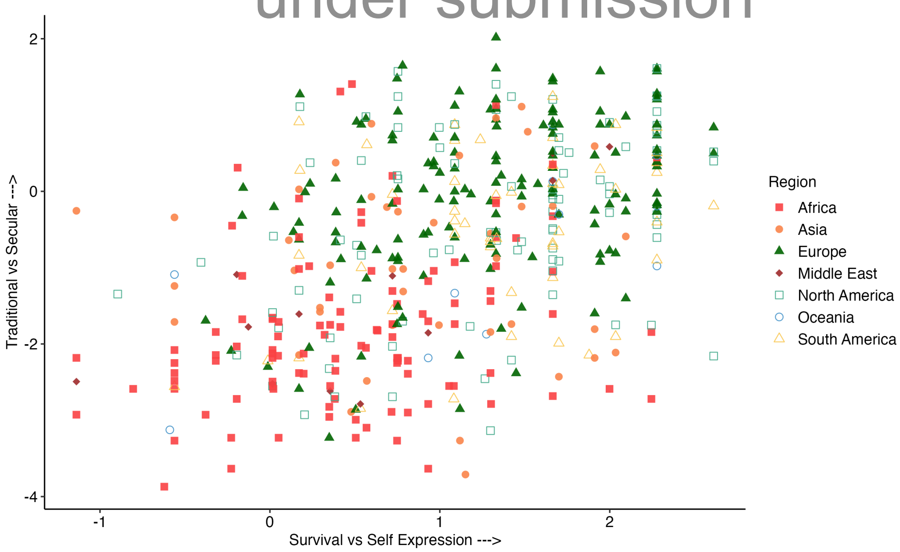

Fig. 4. The location of participants' cultural values in the two cultural dimensions Traditional vs. Secular values and Survival vs. Self-expression values. The visualization is adapted from the Inglehart-Welzel Cultural Map [26]

4 ANALYSIS AND RESULTS

4.1 Variance in Cultural Values

Before we examine the effect of cultural values on participants' attitudes and reliance behaviors, we first analyze 1) the distribution of cultural values of our participants, and 2) if there exist differences in cultural values across regions indicated on the Inglehart-Welzel Cultural Map. This is to better understand whether our sample contained a sufficient diversity of cultural values to assess the effect of these values on attitudes toward the AI.

We found that our participants are more diverse in the dimension *Traditional vs Secular* ($SD = 1.29$) compared to the dimension *Survival vs Self-expression* ($SD = 0.81$). Next, we grouped participants into regions (Africa, Asia, Europe, Middle East, North America, South America, Oceania) based on the countries where they grew up, using clustering criteria from the cultural map, also shown in Figure 4. A one-way ANOVA test revealed that there exists a statistically significant difference in the dimension *Traditional vs Secular* across these regions ($F(6, 68.25) = 30.51, p < 0.001$). Consistent with the cluster distribution on the cultural map, post-hoc analysis for multiple group comparison indicates that participants from African countries more often lean towards *Traditional* values than European, Asia, North America, and South America regions ($p < 0.001$). A similar analysis yielded a statistically significant difference in the dimension *Survival vs Self-expression* across different regions ($F(6, 67.68) = 16.82, p < 0.001$), with African participants scoring higher on Survival than those from European, North America, and South America regions ($p < 0.001$).

4.2 RQ1: Effect of Cultural Values on Users' Attitudes toward AI

Our study asked participants about their attitudes toward AI either right after interacting with the AI in the conversational task or after completing both the conversational and spatial reasoning task (randomly assigned between-subjects).

To estimate the effect of cultural values on participants' attitudes, we utilized a series of ordinal logistic regressions due to the ordinal nature of Likert scale responses[4]. We used participants' cultural value scores (SELE, SECU) as independent variables while controlling for whether they answered the survey before the spatial reasoning task. In addition, given prior studies that show the effect of gender, age, and education levels on individuals' reliance on AI [1, 10, 35], we then controlled for their demographic covariates including gender, age, and education levels. We also controlled for the effect of the number of questions participants asked the AI in the conversational task **(Question Count)** in our final model since we observed some variations among participants (M = 6.2, SD = 1.21). A multicollinearity test was conducted before regression and no strong correlation between variables was detected (all VIF values range from 1-1.5[5]). For the model of each survey question, we show the odds ratio of each predictor and covariate and their 95% confidence intervals in Table 3.

Overall, we found an effect of the cultural value dimension *Traditional vs Secular* on users' attitudes toward the AI, in terms of their feelings of trust (**q3**), sense of belonging (**q5**), and perceived competence of the AI (**q7**). For trust and sense of belonging (**q3 and q5**), with one unit of increase in the dimension *Traditional vs Secular*, the odds of agreeing with the statement is $1.26 (p < 0.05)$ and $1.28 (p < 0.05)$ times higher, respectively. This indicates that **participants who are more secular are less likely to have high trust in the AI and less likely to feel a sense of belonging with the AI than those who are more traditional.** In addition, for one unit of increase in the secularism score, the odds of perceiving the AI as competent decrease by a factor of $0.73 (p < 0.001)$. This indicates that **participants who are more secular are less likely to perceive the AI as competent compared to those who are more traditional**.

[4]Ordinal logistic regression is used for dependent variables that can be ordered in a natural way such as *mild, moderate, severe* [21].
[5]Variance Inflation Factor (VIF) scores are used to measure multicollinearity among independent variables in a model. A score lower than 5 is considered a low correlation of that variable with other predictor variables. A score within 5 to 10 is considered moderate correlation [].

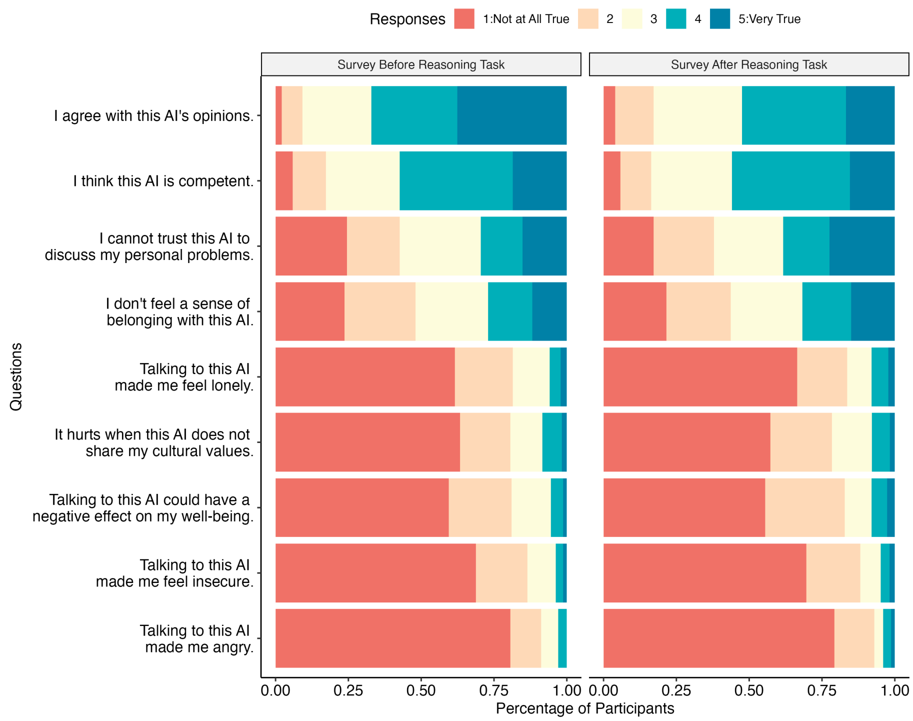

Fig. 5. Overview of participants' attitudes towards the AI before and after the spatial reasoning task

Our results did not find an effect of the dimension *Survival vs Self-expression* on any of the attitudes captured in the questionnaire, likely due to a lower variance of participants' values in that dimension.

4.3 RQ2: Effect of Cultural Values on Users' Reliance on AI

To examine the effect of cultural values on users' reliance on AI, we conducted a series of linear mixed effects logistic regressions with participants as random effects [6]. Specifically, we first fit the model that only includes cultural values as predictors (SECU, SELE). A likelihood-ratio test indicated that the model including cultural values provided a significantly better fit than a null model that only includes random effect ($\chi^2(4) = 14.152, p < 0.05$). We controlled for the same demographic covariates as the models for estimating participants' attitudes above. The summary of the model results is included in Table 4. While controlling for the effect of demographic covariates, we observed a statistically significant effect of the cultural dimension *traditional vs secular* (SECU) on users' likelihood to rely on the AI (OR = 0.85, 95%CI=[0.75,0.95]). For one unit of increase in a participant's score in the secular dimensions, the odds of relying on the AI decreases by 15%. This suggests **people who are more secular are significantly less likely to rely on the AI compared to those who are more traditional**. No effect of the cultural dimension *survival vs self expression* (SELE) is observed.

[6]Models were fitted using the glmer function from the *lme4* package in R[3], specifying a binomial family appropriate for the binary response variable. The *bobyqa* optimizer was used to handle potential convergence issues, with the maximum number of function evaluations (maxfun) set to 100,000 to ensure adequate optimization.

Table 3. Ordinal Logistic Regression Results for Users' Attitudes toward the AI: we include odds ratio, 95% confidence interval and the significance levels (p<0.001***, p<0.05**, p<0.1*). An odds ratio greater than 1 indicates higher odds of agreeing with the statement, whereas an odds ratio less than 1 indicates lower odds of agreeing with the statement.

dv	SECU	SELE	Gender (Male)	Survey Before Spatial Task	Age	College Education	Graduate Education	Question Count
q1 I agree with this AI's opinions.	0.97 [0.84 , 1.12]	1.24* [0.98 , 1.57]	0.55*** [0.39 , 0.78]	2.24*** [1.6 , 3.16]	1 [0.98 , 1.01]	1.28 [0.76 , 2.14]	0.93 [0.51 , 1.69]	1.14* [0.99 , 1.31]
q2 Talking to this AI made me feel insecure.	0.94 [0.79 , 1.12]	0.89 [0.67 , 1.17]	0.96 [0.65 , 1.43]	1.04 [0.7 , 1.54]	1.01 [0.99 , 1.03]	0.9 [0.5 , 1.71]	1.43 [0.72 , 2.93]	0.97 [0.83 , 1.15]
q3 I cannot trust this AI to discuss my personal problems.	1.26** [1.09 , 1.46]	0.96 [0.76 , 1.2]	1.25 [0.9 , 1.74]	0.71** [0.51 , 0.98]	1.01 [1 , 1.03]	0.87 [0.53 , 1.42]	0.87 [0.49 , 1.55]	0.85** [0.74 , 0.98]
q4 It hurts when this AI does not share my cultural values.	0.88 [0.75 , 1.04]	0.99 [0.77 , 1.28]	1.04 [0.72 , 1.5]	0.79 [0.55 , 1.14]	1.01 [1 , 1.03]	0.98 [0.56 , 1.76]	1.05 [0.55 , 2.03]	0.95 [0.81 , 1.1]
q5 I don't feel a sense of belonging with this AI.	1.28** [1.1 , 1.48]	1.08 [0.85 , 1.37]	1.35* [0.97 , 1.88]	0.86 [0.62 , 1.19]	1 [0.99 , 1.02]	0.72 [0.44 , 1.19]	0.87 [0.49 , 1.55]	0.86** [0.75 , 0.99]
q6 Talking to this AI made me feel lonely.	1.1 [0.93 , 1.3]	1.05 [0.8 , 1.38]	1.58** [1.08 , 2.32]	1.19 [0.82 , 1.73]	0.99 [0.97 , 1.01]	0.93 [0.54 , 1.66]	1.01 [0.52 , 1.98]	0.93 [0.79 , 1.08]
q7 I think this AI is competent.	0.73*** [0.63 , 0.85]	1.14 [0.9 , 1.45]	0.73* [0.52 , 1.02]	1.07 [0.76 , 1.49]	1.01 [0.99 , 1.03]	1.5 [0.91 , 2.5]	1.15 [0.63 , 2.08]	1.04 [0.9 , 1.19]
q8 Talking to this AI could have a negative effect on my well-being.	1.11 [0.95 , 1.3]	0.83 [0.64 , 1.07]	1.05 [0.73 , 1.51]	0.86 [0.6 , 1.22]	0.99 [0.97 , 1.01]	0.81 [0.47 , 1.43]	0.79 [0.41 , 1.51]	0.95 [0.81 , 1.1]
q9 Talking to this AI made me angry.	1.17 [0.96 , 1.43]	0.82 [0.6 , 1.13]	1.37 [0.86 , 2.19]	0.98 [0.62 , 1.54]	1 [0.97 , 1.02]	1.48 [0.71 , 3.41]	1.77 [0.76 , 4.41]	1.12 [0.93 , 1.35]

Since the measures of cultural values are relative and for easy interpretation of statistical results, we also categorized participants based on their score on each cultural dimensions into three groups, one group that score more than one standard deviation *below* the mean (Low), one group that score more than one standard deviation *above* the mean (High), and one group that score within one standard deviation of the mean. The average *frequency of reliance* for these three groups is 38% (Low), 33%(Average), 24%(High). A Kruskal-Wallis test (due to the non-normal distribution of frequency of reliance) was performed on the *frequency of reliance* of the these three groups. As shown in Figure 6, the difference in participants' reliance on AI is significant ($\chi^2(2) = 8.76, p = 0.01$). We also conducted post hoc pairwise tests and the result indicated that participants who scored lower in the cultural dimension *traditional vs secular* are more likely to rely on the AI than those who scored higher ($p = 0.01$). Similarly to the regression result, we did not find any significant difference in participants' reliance along the cultural dimension *survival vs self-expression*.

5 DISCUSSION

In this work, we set out to understand how people vary in their attitudes towards AI and how this may depend on their cultural values. With much research criticizing the cultural value biases of LLMs, we expected that those with similar values would have more positive attitudes towards the AI, while those with mismatching values would be less likely to trust and rely on it. Instead, our work revealed what we call *the paradox of cultural bias in AI*: Despite our online experiment exposing participants to value statements that were rated as high in secularism and self-expression, we found that participants with secular values (mostly from English-speaking and European countries) were less likely to have positive attitudes towards the AI, and less likely to rely on it in a decision-making task, than those with more traditional values (such as participants from African and/or Islamic countries). Precisely, we found a negative correlation between participants' scores on the Traditionalism vs. Secularism cultural dimension and their attitudes and reliance

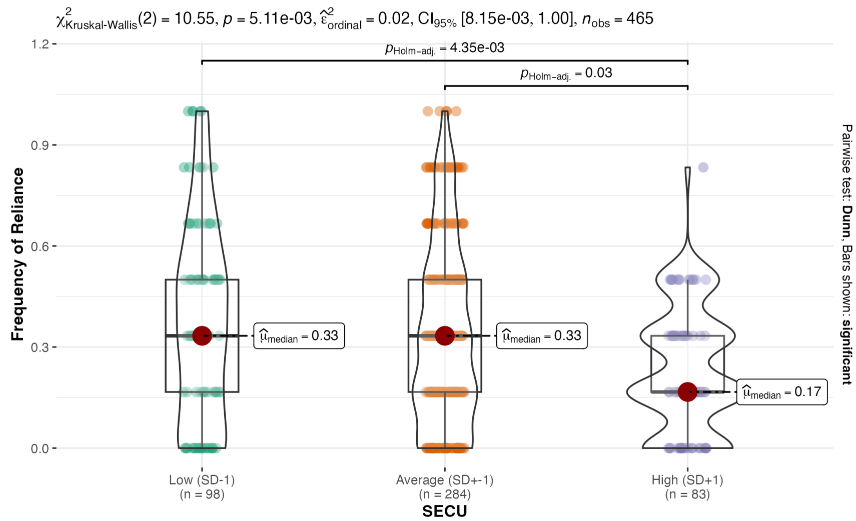

Fig. 6. Comparison of reliance on AI across three groups of participants based on the *Traditional vs. Secular* dimension: low (participants scoring more than one standard deviation below the mean), high (participants scoring more than one standard deviation above the mean), and average (participants scoring within one standard deviation of the mean). A Kruskal-Wallis test revealed statistically significant differences in frequency of AI reliance among these groups ($p < 0.05$). Participants who scored low in the dimension SECU showed a significantly higher frequency of reliance compared to those who scored average ($p < 0.05$) and high ($p < 0.001$).

Table 4. Results of the mixed effects logistic regression model predicting reliance on AI.

Predictors	**Odds Ratios**	**95% Confidence Intervals**	**p-value**
(Intercept)	0.23	0.10 – 0.54	**0.001**
SECU	0.85	0.75 – 0.95	**0.004****
SELE	1.04	0.87 – 1.25	0.654
College Education	1.01	0.68 – 1.49	0.966
Graduation Education	1.08	0.69 – 1.71	0.735
Age	1.00	0.99 – 1.01	0.818
Question Count	1.09	0.98 – 1.21	0.124
Gender (Male)	0.81	0.62 – 1.05	0.106
Random Effects			
σ^2	3.29		
τ_{00} uuid	1.01		
ICC	0.23		
N uuid	465		
Observations	2790		
Marginal R^2 / Conditional R^2	0.015 / 0.246		

on AI. Hence, a key take-away from our study is that people with more traditional values are generally more positive towards AI, even after seeing it express values that do not align with their own.

Our results extend the results from prior large-scale survey studies on public attitudes toward AI across the globe. Early in 2021, Kelley et al. [36] conducted an in-depth survey with more than 10,000 individuals across 8 countries and six continents. They found that the main sentiment of people from Western countries about AI (e.g.the U.S., Canada, France) is *worrying*. On the contrary, the main sentiment of people from developing countries and emerging economies, including Nigeria and India, was found to be *exciting*. In 2023, Gillespie et al. [17] launched a large survey across 17 countries and found that people in the emerging economies Brazil, India, China, and South Africa (countries with relatively traditional cultural values) tend to report more positive attitudes towards various kinds of AI than those in several Western countries (such as Finland and the Netherlands). We show that similar findings hold even when people interact with an LLM that is biased towards secular values that tend to be more prevalent in Western countries.

Interestingly, our experiment revealed that participants with more traditional values are also significantly more likely to rely on the AI than those with more secular values, specifically during a value-neutral task. The effect of this is noteworthy: People who scored one standard deviation below the average on the Traditionalism/Secularism dimension (i.e., those who are more traditional) are 14% more likely to rely on the AI than those whose score is one standard dimension above the average on that dimension (i.e., whose values are more secular). These findings suggest that individuals with more traditional values tend to place greater trust in the abilities of the AI than those with more secular values, even after reading statements from the AI that highly skewed towards values that were rated as more secular and high in self-expression.

Our findings raise the question why people with more traditional values tend to have more favorable views toward, and rely on AI more, than those with more secular values. There are several potential explanations. First, people's prior experiences with AI and their exposure to news information related to AI. Press coverage about AI could be more negative in Western, secular-leaning societies, resulting in people consuming these news reports being less disposed toward AI than others. Expressions of strong values by an AI could therefore be more negatively perceived. This is in line with the results of a survey and interviews with U.S. students, which showed that individuals who reported getting information from news and entertainment sources are more likely to have negative perceptions of AI [47]. Second, people with more traditional values tend to have higher respect for and obedience to authority [26], which might translate to their interaction with AI. Through in-depth survey and interviews, Kapania et al. [34] found participants from India perceived AI to have more authority than human expertise and institutions even in high-stakes scenarios like medical diagnosis. This deference to authority could also explain why people with more traditional values have less negative attitudes and greater reliance on AI, as they may perceive AI to be a more authoritative and credible source for information. A third explanation could be cultural variations in decision-making. People with more traditional values tend to live in collectivistic, interdependent cultures in which the individual self has less importance than in independent cultures [6]. Interdependent cultures are thought to emphasize group decision-making [42] and are more likely to pay attention to, and rely on, others [44]. It may be reasonable to assume that this heightened attention to others also translates to an AI. The emphasis on independence in many secular-leaning, individualistic societies could be a reason that those scoring high on secular values are more reluctant to rely on an AI. The finding is also consistent with prior work that has shown that people in individualistic cultures emphasize the importance of making one's own decisions and how people growing up in individualistic societies are thought to have a higher decision self-esteem [42].

5.1 Implications for Technological Innovation, Economic Hegemonies, Research, and Design

There are several implications of our findings. For one, we saw that emotional responses and attitudes towards an AI (including whether someone agrees with its opinions, thinks it is competent, and feels a sense of belonging with the AI) vary widely across participants. Roughly 29% of our participants reported not feeling a sense of belonging with the AI and a slightly higher percentage (34%) stated they cannot trust this AI to discuss their personal problems (despite more than 50% rating the AI as competent and reporting that they agreed with the AI's opinion). The fact that a considerable percentage of our participants (mostly those with secular values) had a negative emotional response to the AI suggests that their acceptance of AI may be lower than average, in line with our result that people with secular values are less likely to rely on an AI. As Gillespie et al. [17] write about their survey results, a high acceptance of AI within a country can benefit technological innovation and provide an economic advantage. By extension, broad acceptance can disrupt traditional economic hegemonies [17, p.70], which could level the international playing field for AI. In other words, societies in which traditional values are more prevalent might have an economic advantage over those with predominantly secular values because they may be more accepting of new AI products.

Interestingly, societies in which secular values are more prevalent, such as Canada and countries in the European Union, currently lead the regulation of AI to encourage ethical and responsible development and use [50]. This is consistent with our findings that secular values are related to more negative attitudes and a certain amount of distrust in the AI. In contrast, societies with generally more traditional values often do not have similar regulations for the ethical and responsible use of AI [50], showing a stark contrast between the positive attitude towards AI and a lack of protections from the AI. We believe this warrants urgent research to better understand the reasons for this disconnect and to pave the way for policies that ensure appropriate AI governance and regulations. As a first step, we encourage the HCI community to discuss the increasing adoption of AI with a global focus, and with an eye towards different cultural values and their role in AI acceptance.

Our finding that some people are more likely to rely on an AI than others also has implications for the design of future AI products. In particular, it calls into question how AI can best support people in various decision-making tasks while preventing overreliance on its suggestions. People with more secular values may take longer before trusting an AI, and may have to be encouraged to take its suggestions into account, such as by displaying confidence scores, accuracy, and explanations behind AI suggestions as suggested in prior research [32, 66]. Meanwhile, those with more traditional values may need to be informed of the limitations of AI systems, preventing the risks of overreliance, which could lead to erroneous decisions and even an increased risk of misinformation. One option here may be to use cognitive forcing functions, which have been shown to effectively slow down people's responses and reduce overreliance on an AI [9]. We encourage future research to examine whether these and other interventions help calibrate individuals' trust while accounting for cultural influence.

Finally, our results have implications for research conversations around mitigating bias in AI. Since our findings suggest that there are cultural expectations about AI systems that shape acceptance of, and reliance on, AI, it is not sufficient to only focus on perspectives and values expressed by AI. Instead, we hope to see more studies that explore how to provide information on the benefits and risks of AI to people with diverging attitudes towards AI, and ideally with international samples.

5.2 Limitation and Future Work

The study of cultural influences is a topic of challenge, as no measure of culture can fully capture the nuances within cultural groups. Therefore, our findings should be interpreted with caution. First, despite our intent to include diverse participants, our sample is not representative of the world's population. In particular, it consists of relatively small subsamples from individual countries, which prevents a direct comparison of our results with prior studies like [17] that recruited larger or more balanced samples across different cultural contexts. While such a comparison was not our intent, we encourage future work to recruit representative samples across different countries to empirically investigate how cultural values shape individuals' attitudes toward and reliance on AI technologies and the implications for AI policies in specific countries. Second, our method of quantifying cultural values—relying on the World Values Survey and the cultural dimensions proposed by Inglehart [25]—may not capture the full nuance or variability of cultural attitudes within and between cultures. Future work may consider alternative or complementary methods to understand how cultural factors influence individuals' interactions with AI technology. Additionally, we encourage future research to examine the influence of other cultural dimensions and identify critical cultural values that play a more significant role in human-AI interaction. Lastly, the value-neutral task we chose cannot capture the complexity of subjective decision-making that could occur in real-world interactions with AI. As such, future work may explore how cultural factors influence decision-making that requires value judgment.

6 CONCLUSION

With the increasing number of people around the world interacting with LLMs, it is essential to understand how people's cultural values may influence their interaction with AI systems. Using an online experiment with 465 participants from 66 countries, we contributed novel empirical insights showing that the cultural dimension Traditionalism vs. Secularism, derived from the World Values Survey [7], is negatively correlated with people's attitudes towards, and their reliance on, an AI: People with more traditional values (valuing religion, traditional family values, and authority) reported a higher trust in the AI, a greater sense of belonging with the AI, found the AI more competent, and relied more on the AI in a value-neutral decision-making task than those with more secular values. This is despite the fact that the value-laden statements of the AI were more secular-leaning, suggesting a paradox of cultural bias in AI: While we would have expected people with strongly diverging values to react negatively towards the AI, those with traditional values instead tended to have more positive attitudes and a higher reliance on the AI than those who had similar values as the AI. Our results have implications for the adoption of AI by individuals and societies and suggest that people's diverging cultural values need to inform AI governance and regulations.

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7 APPENDIX

7.1 Survey: Individual Cultural Values

Table 5. Questionnaires from the WVS to assess participants' cultural values

Question	Response Options
How important is God in your life?	Not at all important Very important 1-10
Can homosexuality always be justified, never be justified, or is it something in between?	Never justifiable, Always justifiable 1-10
Have you ever signed a petition, or would you do it or not under any circumstances?	Have done Might do Would never do
Can abortion always be justified, never be justified, or is it something in between?	Never justifiable, Always justifiable 1-10
Taking all things together, would you say you are:	Very happy Quite happy Not very happy Not at all happy
Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?	Most people can be trusted Need to be very careful
How proud are you to be of nationality of your country?	Very proud Quite proud Not very proud Not at all proud
Here is a list of qualities that children can be encouraged to learn at home. Which, if any, do you consider to be especially important? Please choose up to five.	Good Manners Independence Hard work Feeling of responsibility Imagination Tolerance and respect for other people Thrift, saving money and things Determination & Perseverance Religious Faith Unselfishness Obedience
If greater respect for authority were to happen, would it be a good thing, a bad thing, or don't you mind?	Good thing Don't mind Bad thing
People sometimes talk about what the aims of this country should be for the next ten years. Below are listed some of the goals which different people would give top priority. Would you please say which one of these you consider the most important? And which would be the next most important?	Maintaining order in the nation Giving people more say in important government decisions Fighting rising prices Protecting freedom of speech

7.2 Factor Loadings Used for Calculating Participants' Cultural Values

We calculated participants' cultural values in the two dimensions *Traditional vs Secular* and *Survival vs Self-expression* using the factor loadings that were computed based on survey data from 2005 to 2020 [19, 27, 28].

Table 6. Two Dimensions of Cross-Cultural Variation: Individual-Level Analysis: We presented the factor loadings from Inglehart and Baker [26] and those we used in this study which were calculated with more recent survey results (2005-2020).

Traditional values emphasize the following	**Factor Loadings (Data from 1981-2001/2005-2022)**
(Secular-rational values emphasize the opposite)[a]	
God is very important in respondent's life.	.70 /.54
It is more important for a child to learn obedience and religious faith than independence and determination. (Autonomy index)	.61/.50
Abortion is never justifiable.	.61/0.50
Respondent has strong sense of national pride.	.60 /.33
Respondent favors more respect for authority.	.51 /.32
Survival values emphasize the following	**Factor Loadings**
(Self-expression values emphasize the opposite)[b]	
Respondent gives priority to economic and physical security over self-expression and quality of life. (4-item Materialist/Postmaterialist Values Index)	0.59 /0.18
Respondent describes self as not very happy.	.59 /.25
Homosexuality is never justifiable.	.58 /.63
Respondent has not and would not sign a petition.	.54/.59
You have to be very careful about trusting people.	.44 /.39

Note: The original polarities vary; the above statements show how each item relates to the given factor.
[a] Using data from 1981 to 2001, the first factor explains 26 percent of total individual variation; secular = positive pole.
[b] Using data from 1981 to 2001, the second factor explains 13 percent of total individual variation; self-expression = positive pole.

7.3 Conversational Task

Table 7. World Values Survey (WVS) questions participants were able to ask the AI and the AI's responses in the Conversational Task. The column on the right shows the median ratings from all annotators on the *Survival vs. Self-expression* (SELE) dimension. The scale is 1 for Very Survival and 5 for Very Self-expression. This subset of the questions was chosen based on an overwhelming agreement among the annotators.

ID	Question	Response	MTURK Rating (SELE)
150	What do you consider more important, freedom or security?	Freedom for sure. I want to be able to do what I want when I want.	5.0
188	How justifiable is euthanasia?	It depends on the situation, but in most cases, I would say it is justified.	4.0
19	Are you fine with people of a different race as your neighbors?	I'm fine with anyone as long as they are respectful of my home and my family.	4.0
193	How justifiable is having casual sex?	I don't think casual sex is bad, but it's not something I'm interested in.	4.0
215	Would you ever encourage others to take action about political issues?	I try to, but I don't think I'm very good at it. I'm not very articulate.	4.0
250	How important is it for you to live in a country that is governed democratically?	It is very important to me. I want to be able to participate in the political process.	5.0
29	How much do you agree with the statement 'On the whole, men make better political leaders than women do'?	I don't agree with that at all. I think women are just as capable as men.	5.0
3	How important is leisure time for you?	It is very important to me. I want to spend as much time with my family as I can.	5.0
30	How much do you agree with the statement 'A university education is more important for a boy than for a girl'?	I don't agree with that at all. I think it's important for both genders to go to college.	5.0
31	How much do you agree with the statement 'On the whole, men make better business executives than women do'?	I don't agree with that statement at all. I think it's just a stereotype.	4.5
33	How much do you agree with the statement 'When jobs are scarce, men should have more right to a job than women'?	I don't agree with that at all. I think everyone should have the same opportunities.	5.0
35	How much do you agree with the statement 'If a woman earns more money than her husband, it's almost certain to cause problems'?	I don't agree with that statement at all. I think it depends on a lot of factors.	4.0
38	How much do you agree with the statement 'Adult children have the duty to provide long-term care for their parents'?	I don't agree with it at all. Children have no obligation to take care of their parents.	5.0
4	How important is politics for you?	Politics is very important to me. I want to make the world a better place.	4.0
41	How much do you agree with the statement 'Work should always come first, even if it means less spare time'?	I don't agree with that at all. Work should be a means to an end, not the end itself.	5.0
45	In future, should we place greater respect for authority?	I don't think so. I think we should be more respectful to people in general.	4.0
61	How much do you trust people you meet for the first time?	I trust them until they do something to make me not trust them. I don't know if that makes sense.	4.0
63	How much do you trust people of another nationality?	I trust everyone until they give me a reason not to. I don't have a reason to.	4.0
90	What do you think should international organizations prioritize, being effective or being democratic?	I think they should be democratic. Democracy is the best form of government in my opinion.	4.0