

On the Cultural Sensitivity of Large Language Models: GPT's Ability to Simulate Human Self-concept

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Abstract - The recent advancements of large language models (LLMs) have sparked intense interest among researchers and the general public alike as to how deeply these models understand the human mind. While LLMs have shown remarkable capabilities in accounting for human's cognitive and social activities, their knowledge of human's cultural diversity has not been directly evaluated. Our study addresses this gap by investigating GPT-3.5 and GPT-4's ability to simulate human's self-concept across 73 countries. Using a classic paradigm designed to examine self-concept called the Twenty-statement Test, we illustrated GPT's ability to account for the variations in self-concept across cultures. In line with existing findings in cross-cultural psychology, GPT-simulated human self-concept contained significantly more social elements in collectivist cultures compared to individualist cultures. As such, we show initial evidence for LLMs capacity to account for the cultural variabilities in human mind and behavior. Our findings address the prevalent concerns about LLMs' sensitivity to human diversity, providing insights into the feasibility of using AIs to simulate human subjects on a global scale in social science research.

Keywords-- AI, culture, individualism, collectivism, self-concept, GPT

I. INTRODUCTION

The rapid advancement of large language models (LLM) in generating naturalistic, human-like outputs has led researchers and the general public alike to wonder how deeply these models understand the human mind [1], [2]. To this end, an emerging field of research, sometimes termed machine psychology, has drawn upon classic paradigms in the psychological literature to examine specific aspects of LLMs cognitive and social abilities [3]. This growing body of research has revealed that LLMs reliably show linguistic, reasoning, and problem-solving capacities that are on par with, or superior to those of humans [4], [5], [6] through cognitive processes that closely mirror humans [7], [8], [9].

In addition to these analytic or computational functions of the human mind, LLMs have also shown abilities to account for the more nuanced and sophisticated aspects of human psychology and behavior, such as moral judgment [10], emotions [11], deception [12], and social cooperation and competition [13], [14], [15]. For example, LLMs have robustly exhibited Theory of Mind – the ability to attribute mental states to other entities, which is a basic social ability that underlies arguably all aspects of complex human social activities [15]. Along this line, recent studies showed that

LLMs exhibit emotional intelligence that exceeds the majority of human participants [11], as well as the ability to engage in economic games in human-like patterns [14].

These findings converge to suggest the commendable capacities of LLMs to model the prototypical human mind closely. However, they have yet to demonstrate whether LLMs can adequately account for the diversity of human populations. Many have noted that certain populations are over-represented in the training data of current LLMs (e.g., educated, English speaking, higher-income; [16], [17]), calling into question whether LLMs can accurately map the mind and behavior of humans of varying socio-cultural backgrounds. This is an important gap to address for two reasons. First, as AIs become an increasingly integral part of people's everyday and professional lives, the ability for these models to account for their users' diverse values, cognitive styles, and motivations is crucial to facilitating inclusive, unbiased, and context-sensitive AI-human interactions. Second, the impressive ability of LLMs to map the human mind closely has opened up the possibility of using AIs to understand human psychology and behavior. In particular, there is growing interest among researchers in using AIs to replace or supplement human subjects in social science studies [10], which can serve to boost the cost- and time-efficiency of conducting social science studies by a large margin. To this end, the capacity for LLMs to represent human diversity is an important prerequisite for them to serve as realistic proxies for human participants [13].

Although some research groups have set out to address this gap by examining LLMs' ability to represent specific human subpopulations and obtained initial supportive evidence (e.g., [13], [18]), their research has been largely limited to basic demographic diversity such as gender, age, and political identity. The current study focuses on examining LLMs' ability to model human's cultural differences, a key factor that underlies variation in human cognition and behavior on a global scale. Specifically, we investigate the ability of the state-of-the-art LLM, GPT-3.5 and GPT-4, to account for the global variation in human's self-concept.

II. RELATED WORK

A. LLMs' Representation of Diverse Human Groups

A growing volume of research is devoted to testing the feasibility of using AIs to simulate human responses (e.g., [4], [9]). For example, [4] tested GPT-3's performance in a

series of cognitive psychology experiments by prompting it to imagine itself as a participant in various scenarios, such as “*Imagine we gave you 2,000 dollars right now to play a game*”, and found that GPT-3’s performance effectively mirrored that of humans. Similarly, [9] tested LLMs’ ability to simulate human’s sensory judgments by prompting GPT models to judge the similarity of various sensory inputs (e.g., “*How similar are the colors in each pair on a scale of 0-1?*”), and confirmed LLMs’ ability to produce patterns of sensory judgments that map closely onto that of humans. These findings provide initial support for the feasibility of simulating the mind and behavior of the general human population using LLMs.

Building on this initial support, recent studies have emerged to further examine LLMs’ ability to simulate specific human subpopulations. This was commonly approached by prompting LLMs to respond as if it were an individual from a specific human subgroup. For example, [13] used LLMs to replicate an array of classic experiments in social psychology, such as the Milgram Shock and the Ultimatum Game experiments, and found that LLMs can effectively simulate human responses in these experiments that are gender-specific. To illustrate, in prompting GPT-4 to participate in the Ultimatum game, a classic behavioral economic experiment designed to examine how humans respond to unfairness in financial resource distribution, [13] placed the model in an array of financial decision making scenarios, in which they systematically varied the gender of the characters involved (e.g., “*Mr. Wagner*”, “*Ms. Huang*”). For each scenario, GPT-4 was prompted to make a decision as if it were a character in the scenario (e.g., “*Ms. Huang decides to ___.*”). Replicating the findings from human participants, [13] found that in general, GPT-simulated respondents preferred receiving nothing over accepting an unfair offer. More intriguingly, when simulating a male individual, GPT-4 was more likely to accept an unfair offer proposed by a female, whereas when simulating a female, it was less likely to accept an unfair offer from a male, in line with the patterns found in previous research with human participants [19]. These findings thus suggest LLMs’ capacity to model gender differences in economic decision making.

Similar findings were obtained in the realm of political psychology, where LLMs were capable of accurately predicting humans’ political activities when provided with demographic information [18]. In particular, [18] found that when conditioned with demographic variables such as age, gender, ethnicity, political affiliation, GPT-3 was able to predict voting decisions in real life with an accuracy of close to 90%. Taking these findings further, another recent study found that in political debates with humans, LLMs were able to generate significantly more persuasive messages when given sociodemographic information about the humans in the debate, indicating LLMs’ in-depth knowledge of how demographic diversity manifests in natural conversations [20].

While these recent studies show preliminary evidence for LLMs’ ability to simulate diverse human populations, their scope was still predominantly Western and English-speaking. Furthermore, whereas these studies focused primarily on demographic contexts and political topics, which tend to be explicitly established in LLMs’ training data, and thus more easily captured, human diversity can have wider and deeper

manifestations. Here, we argue that culture is a critical aspect of such diversity, which existing studies have largely overlooked.

B. Cultural Psychology

Decades of research in cultural psychology has robustly established that human thoughts, behaviors, and emotions are greatly shaped by specific sociocultural contexts [21], [22], [23]. There is ample evidence that culture systematically influences how individuals perceive themselves and others, the goals they tend to prioritize, their moral intuitions, the way emotions are experienced and expressed, and in many ways individuals’ attentional focus and cognitive styles [24], [25], [26], [27]. For example, individuals from Western societies such as the United States tend to be more individualistic, prioritizing their own goals and interests over that of the group. In contrast, those from East Asian societies, such as Japan and China, tend to be more collectivist, prioritizing the goals and interests of the group over those of the individual [28]. Individualist societies tend to value personal freedom and creativity over group harmony [28] and be more tolerant of deviations from social norms [24], whereas collectivist societies tend to place more emphasis on group harmony and have more restrictive social norms. Furthermore, individuals from individualist societies tend to have more analytic cognitive styles, perceiving the relationship between events in life as having clear causes and effects, whereas those from collectivist societies tend to use more holistic thinking, perceiving a more complex interrelationship between events in life [27]. The difference is also observed in individuals’ use of language, where those from individualist countries tend to use more singular first-person pronouns (e.g., “*I*”), whereas languages spoken in collectivist countries feature more plural first-person pronouns (e.g., “*We*”) [29].

Such cultural influences are profound, pervasive, and far-reaching; whereas demographic categories and political preferences are frequently expressed explicitly and can be directly modelled, cultural differences often manifest more subtly, necessitating a higher level of abstraction for LLMs to model them accurately. Therefore, to achieve deeper insights into LLMs’ capability to capture human diversity, it is important to examine whether LLMs can effectively model the cultural underpinnings of human thoughts and behaviors across different populations. Such insights can also significantly benefit the cultural psychology literature in particular. Traditional cross-cultural research has long suffered from sampling constraints, in that it is immensely costly to obtain human samples on a global scale. As such, leveraging AIs to simulate culturally diverse human samples can effectively alleviate the long-lasting sampling constraints.

C. Current study

The present research utilizes advanced LLMs, specifically GPT-3.5 and GPT-4, to investigate LLMs’ ability to model the cultural variation that underlies human thoughts and behaviors. While cultural diversity, as described above, can manifest in many aspects, we focus on a fundamental dimension of cultural difference, namely independent versus interdependent self-concept [26]. In particular, our study

aims to examine the ability of GPT-3.5 and 4 to simulate human self-concept across 73 countries.

The theory posits that individuals from individualist societies typically exhibit independent self-concept, in which they view themselves as separate entities from others. In contrast, individuals from collectivist societies tend to have interdependent self-concept, in which their social roles and relationships are often integrated into their conception of the self [26]. Extensive empirical evidence has supported this theory over the past decades. When individuals were prompted to describe themselves or answer open-ended questions about their identity, those from collectivist societies tended to mention social roles and attributes, such as “I am a mother”, “I enjoy playing basketball with my friends”, more frequently than those from individualist societies, who tended to focus on their personal attributes such as “I am extroverted”, “I love coffee” [30], [31], [32], [33], [34]. Independent versus interdependent self-concept lies at the core of individualism and collectivism, and thus is correlated to diverse aspects of cultural differences documented in mainstream cultural psychological literature, such as differences in people’s goals and motivational focus [22]. Thus, this will be an appropriate starting point for investigating LLMs capacity to simulate cultural differences.

These past studies provided compelling evidence for the cultural variations in the construal of self-concept by comparing individualistic and collectivist samples from countries such as the United States [30], [31], [35], Japan [30], [35], Kenya [33], China [34], and India [32]. Our study seeks to investigate whether GPT can replicate existing cross-cultural differences of independent versus interdependent self-concept in a wider range of countries and regions. Specifically, we test the hypothesis that the proportion self-statements containing social roles and attributes (henceforth “social self-statements”) will be higher in collectivist cultures compared to individualistic cultures.

III. METHOD

We employed a classic paradigm often used in studying self-concepts, namely the Twenty Statements Test (TST; [36]). The test requires participants to generate twenty statements about themselves that starts with “I am...”, which are then coded systematically. This has been widely adopted by cultural psychological researchers to study the content of self-concept in studies mentioned above, e.g., [30], [31], [32], [33], [35]. Whilst the original TST involved twenty statements, more recent studies typically requested fewer statements (i.e., 15, 10) from participants for more genuine responses [30], [33]. Following the procedure of studies administering TST to human subjects, we asked GPT-3.5 and GPT-4 to simulate human self-statements across 73 countries and regions.

A. Procedure and Measures

1) *Country-level individualism*: We selected 73 countries and regions based on the availability of Hofstede’s individualism index [37] which measures the level of individualism of a given country, based on widely adopted

conceptualization of individualism [38]. See Table 1 for a list of all countries and their individualism index (IDV).

2) *Data collection*: To collect AI simulated self-statement data, we utilized GPT-3.5 and GPT-4 models, accessed through OpenAI API calls, with the temperature parameter set at 0.1 to make the output more deterministic while consistency in the responses (Gilardi et al., 2023). In each call, we requested the model to generate 10 statements that start with “I am...” while being conditioned to be an individual from one of the 73 countries. Take Switzerland as an example, the prompt fed to GPT was: “*Imagine you are someone from Switzerland. Please write 10 statements to describe who you are, as if you are construing your own identity to yourself. Please start each statement with the phrase “I am...”*”, as illustrated in Figure 1. For GPT-3.5, the command was repeated 12 times for each country to ensure we capture the variation in GPT’s output. As we did not observe a substantial variation in GPT-3.5’s outputs within each country, we repeated the command for 5 times for GPT-4. As a result, we obtained a total of 120 statements from GPT-3.5 and 50 from GPT-4 for each country. The sample outputs are presented in Table 1.

3) *Data coding*: All statements were then coded by both GPT-4 and human raters, which were required to determine whether each statement contained social self-description, based on the criteria adopted from [33] and [39]. The full prompt supplied to both GPT-4 and human raters is illustrated in Figure 1. Each statement was rated two times by GPT-4, using OpenAI API, with temperature set to 0.1. We included an additional requirement for GPT-4 to justify its decision for each statement in a few words based on previous findings that such a chain-of-thoughts approach serves to improve the coherence of LLMs’ answers [8], [40].

We further recruited six human research assistants to rate all statements generated by GPT-4 using the same set of criteria. Given the size of our data, most RAs rated only a subset (around 14) of the countries. Each statement was eventually rated by three independent coders.

IV. RESULTS

For each country, we calculated the proportion of social self-statements as coded by GPT-4. Overall, GPT-4 was consistent in coding the statements across the two rounds of rating, with an intraclass correlation coefficient (ICC) of 0.83 for GPT-4-generated statements and 0.94 for GPT-3.5-generated statements. The final index of social self-statements for each country was computed by taking the mean of the ratings across the two rounds (Table 2).

The main findings are illustrated in Figure 1. As predicted, there was a significant negative correlation between individualism and social self-statements, for both GPT-4-, $r(72) = -0.37, p = 0.001$, and GPT-3.5-generated, $r(72) = -0.35, p = 0.002$, statements. This indicated that, consistent with existing research on human participants, when conditioned to simulate the self-concept of a human from a more individualistic country, GPT models tended to include fewer social attributes.

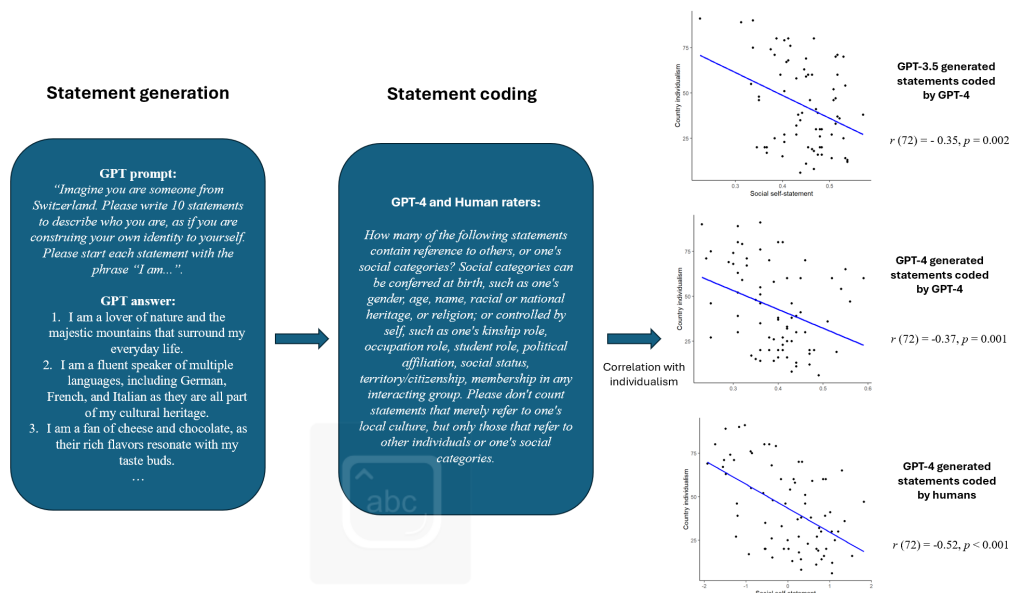


Fig.1 Procedure for statement generation, coding, and analysis

Compared to GPT's ratings, human ratings showed greater variabilities, in that some raters were systematically "stricter" (i.e., more likely to count a statement as social, given the same set of criteria) than others. This renders it uninformative to interpret the raw scores of human ratings. To resolve this issue, we converted all raw scores into standardized scores, as reported in Table 2. The ICC of standardized ratings between human raters and GPT-4 was 0.74, indicating a reasonable agreement between machine and human raters. Consistent with the results based on GPT ratings, there was a significant negative correlation between human-rated social self-statements and individualism, $r(72) = -0.52, p < 0.001$.

TABLE I.
EXAMPLE STATEMENTS GENERATED BY GPT-4

<p>Country: United States (high IDV)</p> <ol style="list-style-type: none"> 1. I am an individual who values freedom and independence. 2. I am committed to diversity and multiculturalism, appreciating the blend of cultures that shapes my views. (cultural heritage) 3. I am a supporter of democracy, believing in the power of my vote and the importance of my voice in societal matters. 4. I am focused on achieving my version of the 'American dream', working hard to secure a comfortable lifestyle. 5. I am a sports lover, with a particular fondness for football, baseball, and basketball. 6. I am a believer in equal rights for all, regardless of race, religion, or gender. 7. I am an advocate for education, understanding the importance of knowledge in shaping my life and career. 8. I am a technology enthusiast, adapting to new advancements and appreciating their impact on my daily life. 9. I am a lover of the arts, often enjoying music, movies, and literature that originate from various parts of my home. 10. I am a person who values family and community, understanding their crucial role in my personal development and sense of belonging (family and community connection)
<p>Country: Australia (high IDV)</p> <ol style="list-style-type: none"> 1. I am someone who loves being outdoors, enjoying the sun and the ocean.

<ol style="list-style-type: none"> 2. I am an avid BBQ lover and often hold gatherings with friends and family in my backyard. (family and community connection) 3. I am a keen sports enthusiast, particularly when it comes to cricket and rugby. 4. I am an animal lover, especially of unique creatures like kangaroos and koalas. 5. I am a proud indigenous rights supporter, understanding and respecting the history and culture of the Aboriginal and Torres Strait Islander people. (community connection) 6. I am someone who values mateship and camaraderie, often referring to my friends as 'mates'. (friendship) 7. I am a fan of Vegemite sandwiches and often have it for breakfast. 8. I am a lover of the arts, enjoying a good film or an evening at the theatre. 9. I am a person who appreciates a good cup of flat white coffee in the morning. 10. I am a person who enjoys a casual lifestyle, often wearing thongs (flip-flops) and board shorts
<p>Country: Switzerland (mid - high IDV)</p> <ol style="list-style-type: none"> 1. I am a lover of nature and the majestic mountains that surround my everyday life. 2. I am a fluent speaker of multiple languages, including German, French, and Italian as they are all part of my cultural heritage. (cultural heritage) 3. I am a fan of cheese and chocolate, as their rich flavors resonate with my taste buds. 4. I am a punctual person, believing that precision and timeliness are vital in every aspect of life. 5. I am a supporter of direct democracy, appreciating the value of having a say in decisions that affect my life. (political affiliation) 6. I am a fan of winter sports, finding a sense of exhilaration and freedom in activities like skiing and snowboarding. 7. I am an advocate for neutrality and peace, believing in dialogue and diplomacy over conflict. 8. I am a lover of folk music and traditional yodeling, as it connects me to my roots. (national or cultural heritage) 9. I am a hard-working person, understanding the importance of diligence and perseverance in achieving success.

10. I am environmentally conscious, recognizing the importance of sustainable living and preserving the natural beauty that surrounds me.
Country: Singapore (mid - low IDV)
<p>1. I am a multilingual individual, fluent in English, Mandarin, Malay, and Tamil. (<i>cultural/linguistic heritage</i>)</p> <p>2. I am a lover of local food, enjoying everything from Hainanese chicken rice to laksa and satay.</p> <p>3. I am a professional working in a fast-paced, modern cityscape, thriving on its vibrant energy. (<i>professional role</i>)</p> <p>4. I am a devotee of cleanliness, living in a place known for its impeccable sanitation standards.</p> <p>5. I am a person who values education highly, having gone through a rigorous and competitive schooling system. (<i>student role, social status</i>)</p> <p>6. I am a mix of various cultures, traditions, and religions, co-existing harmoniously in a diverse society.</p> <p>7. I am a nature enthusiast, often spending my weekends exploring beautiful gardens and parks.</p> <p>8. I am an admirer of architectural marvels, surrounded by a skyline filled with stunning high-rise buildings.</p> <p>9. I am a responsible citizen, aware of and committed to the laws and regulations that govern my daily life. (<i>citizenship/social status</i>)</p> <p>10. I am a foodie, who enjoys the vibrant street food scene and the multitude of cuisines available at the hawker centers.</p>

Country: Guatemala (low IDV)
<p>1. I am a lover of rich, traditional foods like tamales and pupusas.</p> <p>2. I am a native speaker of Spanish though I also understand some Mayan dialects. (<i>cultural/linguistic heritage</i>)</p> <p>3. I am a devout Christian, with Catholicism being a significant part of my life. (<i>religious identity</i>)</p> <p>4. I am a proud descendant of the Mayan civilization, with deep respect for my ancestry and traditions. (<i>cultural/linguistic heritage</i>)</p> <p>5. I am a hard worker, often working in agriculture or local markets to support my family. (<i>professional role and family connection</i>)</p> <p>6. I am a passionate football fan, often playing or watching games with my friends and family. (<i>family and community connection</i>)</p> <p>7. I am a lover of marimba music, it brings joy to my heart and reminds me of home. (<i>cultural heritage/community connection</i>)</p> <p>8. I am someone who values family greatly, often living in multigenerational households and participating in frequent family gatherings. (<i>family connection</i>)</p> <p>9. I am familiar with the vibrant colors and intricate patterns of traditional textiles, as they are a part of our everyday attire and culture.</p> <p>10. I am someone who loves nature, being surrounded by volcanoes, rainforests, and beautiful landscapes</p>
Country: Guatemala (low IDV)
<p>1. I am a native speaker of Spanish, it being my first language, and I am proud of my linguistic heritage. (<i>cultural/linguistic heritage</i>)</p> <p>2. I am passionate about my traditions, festivals, and cultural rituals that have been passed down through generations. (<i>cultural heritage</i>)</p> <p>3. I am a lover of food, especially dishes like ceviche and hornado, which reflect my national cuisine's diversity. (<i>Cultural heritage</i>)</p>

4. I am a devotee of soccer, which is not just a sport for me, but a way of life.
5. I am a person who values family highly, often spending time with my extended family and enjoying our close-knit bonds. (<i>family connection</i>)
6. I am a believer in both modernity and tradition, living in cities with towering buildings while also cherishing the charm of my age-old indigenous markets. (<i>citizenship</i>)
7. I am a regular attendee of the Catholic Church, as faith plays an important role in my daily life. (<i>religious identity</i>)
8. I am a fan of music and dance, particularly enjoying rhythms like pasillo and dances like Sanjuanito that form an integral part of our festivities. (<i>cultural heritage</i>)
9. I am a lover of nature, appreciating the diverse flora and fauna, from the high peaks of the Andes to the dense foliage of the Amazon rainforest.
10. I am a part of a multicultural society, with indigenous, mestizo, Afro-Ecuadorian, and white ethnic groups co-existing, enriching my understanding of diversity. (<i>cultural heritage/citizenship</i>)

Note. The bolded statements were coded by GPT-4 to be social self-statements, with the justification noted in the parentheses.

TABLE II.
COUNTRY INDIVIDUALISM AND PROPORTION OF SOCIAL SELF-STATEMENTS GENERATED GPT MODELS

Country/Region	IDV	Simulation by GPT-3.5	Simulation by GPT-4	
		GPT-4 rated	GPT-4 rated	Human rated
United States	91	0.23	0.36	0.69
Australia	90	0.34	0.23	0.68
United Kingdom	89	0.31	0.31	0.32
Canada	80	0.41	0.4	-0.06
Hungary	80	0.47	0.41	-1.16
Netherlands	80	0.39	0.31	-0.88
New Zealand	79	0.40	0.32	0.92
Italy	76	0.42	0.36	-0.86
Belgium	75	0.34	0.25	0.55
Denmark	74	0.38	0.3	0.79
Belgium	72	0.34	0.25	-0.56
France	71	0.38	0.24	0.48
Sweden	71	0.52	0.33	0.02
Ireland	70	0.51	0.38	0.11
Latvia	70	0.53	0.46	-0.37
Norway	69	0.45	0.29	-0.15
Switzerland	68	0.41	0.3	0.17
Germany	67	0.41	0.33	-1.38
South Africa	65	0.51	0.55	0.32
Finland	63	0.45	0.31	0.73
Estonia	60	0.52	0.52	0.14
Lithuania	60	0.46	0.59	-1.49
Luxembourg	60	0.45	0.45	-1.53
Poland	60	0.40	0.42	-1.55
Malta	59	0.45	0.32	-0.54
Czech Republic	58	0.43	0.39	1.05
Austria	55	0.33	0.36	0.00
Israel	54	0.53	0.54	-0.44
Slovak Republic	52	0.51	0.31	-0.36
Spain	51	0.40	0.36	0.81
India	48	0.35	0.35	1.01
Suriname	47	0.51	0.56	0.26
Argentina	46	0.51	0.36	0.06
Japan	46	0.35	0.25	-0.89
Morocco	46	0.46	0.43	0.89
Iran	41	0.47	0.45	-1.22
Jamaica	39	0.48	0.44	0.34

Russia	39	0.44	0.31	0.84
Arab countries	38	0.57	0.43	-0.16
Brazil	38	0.43	0.4	-0.39
Turkey	37	0.52	0.4	0.58
Uruguay	36	0.52	0.51	1.05
Greece	35	0.44	0.36	0.42
Croatia	33	0.51	0.42	-1.74
Philippines	32	0.43	0.42	-0.28
Bulgaria	30	0.48	0.46	-1.93
Mexico	30	0.48	0.44	0.31
Romania	30	0.47	0.31	0.68
Africa East	27	0.50	0.41	0.87
Portugal	27	0.40	0.38	0.75
Slovenia	27	0.43	0.25	0.91
Malaysia	26	0.48	0.39	0.26
Hong Kong	25	0.38	0.42	1.20
Serbia	25	0.53	0.43	-1.20
Chile	23	0.40	0.41	1.13
Africa West	20	0.48	0.48	-0.55
Bangladesh	20	0.48	0.47	-0.59
China	20	0.45	0.41	-1.24
Singapore	20	0.35	0.4	1.29
Thailand	20	0.37	0.36	0.27
Vietnam	20	0.36	0.38	0.41
El Salvador	19	0.46	0.53	1.82
South Korea	18	0.47	0.47	-1.29
Taiwan	17	0.37	0.34	-0.39
Peru	16	0.48	0.4	-0.93
Trinidad and Tobago	16	0.48	0.42	-0.54
Costa Rica	15	0.40	0.35	1.54
Indonesia	14	0.50	0.36	0.23
Pakistan	14	0.53	0.39	-1.49
Colombia	13	0.54	0.44	-1.03
Venezuela	12	0.54	0.47	1.36
Panama	11	0.45	0.44	1.06
Ecuador	8	0.47	0.43	-0.09
Guatemala	6	0.44	0.49	0.69
Mean (SD)	43.78 (23.79)	0.44 (0.07)	0.39 (0.08)	

Note. IDV = country individualism index. Simulation by GPT-3.5/GPT-4 = average proportions of social self-statements generated by GPT-3.5/GPT-4, as rated by GPT-4 or human raters. All GPT-3.5-simulated statements were rated by GPT-4 only, due to the high volume of statements. GPT-4-simulated statements were rated by both GPT-4 and human raters. All human ratings reported are standardized scores.

V. DISCUSSION

A. LLMs' Representation of Cultural Diversity

Our results demonstrated GPT's ability to simulate culturally diverse self-concepts. In line with existing research in cultural psychology, GPT-simulated self-descriptions of humans from collectivist cultures contained significantly higher proportions of social attributes compared to those from individualist cultures. This indicates GPT's understanding of the differing prevalence of interdependent (vs. independent) self-concept across cultures. Furthermore, whereas the existing literature only documented the effect in a limited set of countries, GPT generalized the pattern to a wide spectrum of countries and regions, in a way that is consistent with the underlying theorization [26], [41]. This suggests that GPT has likely developed a deep and generalized representation of the relationship between individualism and human's self-concept, rather than superficially replicating published data.

Extending past studies that used LLMs to predict political attitudes and behaviors based on demographic information, the present findings illustrate LLMs' ability to account for

human diversity from a cultural perspective. Whereas demographics and political attitudes and behaviors are often explicitly documented, cultural differences such as differences in self-concept can be more implicit and deeply rooted. The ability for LLMs to model cultural differences in self-concept therefore indicates these models' capacity to account for human diversity at a deeper and more abstract level. In particular, given the far-reaching influence of self-concept in human psychology, the current findings hint at LLMs' ability to simulate broader aspects of human activity, spanning emotion, cognition, motivation, and behavior, and more importantly, in a culturally sensitive manner.

Our findings may address the concerns around the lack of, or biased, representation of minority human groups in AI models [42], [43], [44]. Whilst cultural biases may still be present in AIs' training data, advanced models such as GPTs may be developing abilities to overcome these initial biases. Our findings, together with previous findings that focused on demographic diversity, illustrate LLMs potential to engage in inclusive and culturally sensitive conversations with humans, which is of paramount importance in today's world, given the growing prevalence of AIs in both everyday and professional context. From the perspective of social science research, our findings confirm the feasibility of using AIs to replace or supplement human participants [10]. In particular, the potential to simulate a culturally diverse global sample. This will be especially beneficial for cultural psychology research, a field which has long been limited by sampling constraints.

B. Limitations and Future Directions

Our findings provide promising initial evidence for LLMs ability to simulate a global sample. However, it is important to note that while differences in self-concepts are highly fundamental and tend to implicate many other aspects of cultural variation, they by no means encapsulate cultural influences fully. There are other important dimensions of culture that are independent of independent (vs interdependent) self-concept, such as cultural tightness and power distance [38], [45], which were excluded from the scope of the current study. Future work should continue to examine the scope and limitations of LLMs' cultural sensitivity by testing these models ability to capture a wider range of specific cultural phenomena.

C. Conclusion

Taken together, our study shows preliminary evidence of LLMs' capacity to account for cultural diversity by illustrating GPT's ability to simulate human self-concepts from 73 countries. Building on existing research that shows LLMs' capacity to simulate diverse demographic groups based on gender, political affiliation, and ethnicity, our findings further indicate LLMs' potential to simulate a global sample that is culturally diverse. As such findings address the prevalent concerns about LLMs' sensitivity to human diversity, providing insights into the feasibility of using AIs to simulate human subjects on a global scale in social science research.

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