Donald Trumps in the Virtual Polls: Simulating and Predicting Public Opinions in Surveys Using Large Language Models*

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Abstract

In recent years, large language models (LLMs) have attracted attention due to their ability to generate human-like text. As surveys and opinion polls remain key tools for gauging public attitudes, there is increasing interest in assessing whether LLMs can accurately replicate human responses. This study examines the potential of LLMs, specifically ChatGPT-40, to replicate human responses in large-scale surveys and to predict election outcomes based on demographic data. Employing data from the World Values Survey (WVS) and the American National Election Studies (ANES), we assess the LLM's performance in two key tasks: simulating human responses and forecasting U.S. election results. In simulations, the LLM was tasked with generating synthetic responses for various socio-cultural and trust-related questions, demonstrating notable alignment with human response patterns across U.S.-China samples, though with some limitations on value-sensitive topics. In prediction tasks, the LLM was used to simulate voting behavior in past U.S. elections and predict the 2024 election outcome. Our findings show that the LLM replicates cultural differences effectively, exhibits in-sample predictive validity, and provides plausible out-of-sample forecasts, suggesting potential as a cost-effective supplement for survey-based research.

Keywords: Large language models, synthetic survey data, election prediction

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1 Introduction

Large language models (LLMs) are powerful tools for simulating human behavior due to their ability to capture the complexity of natural language and encode a wide range of human experiences, cultural norms, and decision-making patterns from extensive training data. These models reflect how people use language to express thoughts, beliefs, and emotions, making them suitable for replicating behaviors across different social contexts. This is particularly valuable in social science research, where experiments and surveys rely heavily on human participants to gather behavioral data (Kim and Lee, 2023). Specifically, using LLMs in behavioral simulations allows researchers to scale experiments, lower the costs of human subject studies, and gain insights into individual behavior and complex social interactions, such as trust, negotiation, and cooperation (Aher et al., 2022). Additionally, LLMs can simulate multiple scenarios and personalities, helping researchers predict responses to new social environments (Cheng et al., 2023).

LLMs are primarily trained on vast text corpora derived from diverse sources, such as general web text, books, and articles, rather than raw experimental data. Despite this, current research on LLM-based simulations found that LLMs can accurately reproduce outcomes from classic experiments such as the ultimatum game, trust game, prisoner's dilemma, dictator game, and strategic communication game (Aher et al., 2022; Xie et al., 2024; Phelps and Russell, 2023; Xu et al., 2023; Ashokkumar et al., 2024). However, current LLM-based experimental simulations focus on basic experiments that are relatively simple, with clear incentives or dominant strategies. Compared to experimental simulations, surveys feature ambiguously defined questions with multiple options that offer minimal distinction (e.g., Likert scales). Without incentives and optimal strategies, surveys focus more on values and attitudes, where consensus may not exist.

This study aims to leverage the latest LLM model, ChatGPT-40¹, to simulate respon-

¹The ChatGPT-40 model has been trained on information available until October 2023. Throughout the entire study, we utilized the ChatGPT API tool exclusively, without incorporating any real-time search capabilities.

dents' choices in large-scale surveys, particularly their attitudes on controversial value-based questions. Specifically, we leveraged the LLM to perform two main tasks: simulation and prediction. For the simulation task, the model adopted personas based on demographic profiles from respondents in the U.S. and China, using data from the World Values Survey (WVS). Based on the adopted personas in the WVS, the model generated synthetic responses on various topics such as social values, trust, and ethics, allowing us to compare the synthetic responses with actual human responses. In contrast, for the prediction task, the LLM simulated voting behavior using another group of personas sourced from the American National Election Studies (ANES), first by recreating past U.S. election outcomes and then forecasting the 2024 election.

Our findings reveal that the LLM shows strong in-sample predictive ability, closely aligning with human responses when demographic inputs are included. For cross-cultural comparisons, the LLM effectively replicates cultural differences in values between the U.S. and China on most items, although it occasionally overestimates socially progressive views, particularly in the U.S. On the predictive side, the model demonstrates potential for out-of-sample forecasting, with its accuracy further supported when historical voting patterns are incorporated. These results underscore the potential of LLMs as supplemental tools in large-scale surveys, enabling cost-effective and culturally nuanced insights.

Literature have demonstrated the ability of LLMs in simulating respondents' choices in surveys. Studies such as Argyle et al. (2023) explored how GPT-3, conditioned with socio-demographic data, can generate responses resembling real-world survey data, capturing nuanced relationships between attitudes and socio-cultural contexts. Similarly, Bisbee et al. (2023) evaluated LLM's ability to generate synthetic opinions aligned with real survey responses, finding that while overall averages can match human data, the model struggles with variability and reliability across iterations. Research also highlights the practical challenges of using LLMs in surveys; for example, Kim and Lee (2023) noted that LLM-generated survey responses may exhibit response biases based on question phrasing, which can affect

the reliability of insights. Furthermore, Tjuatja et al. (2023) emphasized that while LLMs can replicate survey patterns, they tend to homogenize responses, reducing the distinctiveness found in human data. These findings illustrate both the promise and limitations of using LLMs to simulate survey participants, underscoring the need for careful prompt design and attention to variability. However, current research on LLM-based survey simulations is still limited, with most studies focused on political attitudes and data from English-speaking countries.

Our paper contributes to the literature by shifting the focus of LLM-based simulations from experimental replication to survey studies. We employ the more advanced ChatGPT-40 to explore key social values and opinions, broadening the relevance to social science surveys. Our study also offers cross-cultural insights through U.S.-China comparisons, providing rare evidence from non-English-speaking contexts. Additionally, we leverage simulated results to predict the 2024 U.S. presidential election based on voters' demographics—marking the first use of LLMs to forecast a future event.

2 Research design

This section outlines the research design for executing the two tasks: simulation and prediction. In the simulation task, we provided ChatGPT with demographic characteristics of respondents from the United States and China, as recorded in the 7th Wave of the World Values Survey (WVS). After adopting a persona defined by a set of demographic characteristics of a respondent, the LLM was tasked with generating a dataset of synthetic opinions on social values, trust, common-sense questions, and ethical norms and values. By doing so, we can compare the synthetic opinions with the true opinions provided by human respondents in the survey. This not only enables us to assess the accuracy of the synthetic LLM responses but also to determine whether the opinion differences between China and the U.S. are retained in the simulated sample. The prompts used in this task is presented in the part

(a) of Appendix A. In total, we compare the LLM's responses with those of each of the 2,429 human respondents in China and 2,507 in the U.S. from the survey.

In the prediction task, the LLM was provided with the demographic characteristics of respondents from the American National Election Studies (ANES). We prompted it to play the role of an ANES respondent and cast a vote accordingly. After adopting the persona of a respondent from the 2020 ANES survey, the LLM was tasked with voting in two elections: Hillary Clinton vs. Donald Trump in 2016 and Joe Biden vs. Donald Trump in 2020. Following U.S. election rules, we then aggregated the simulated votes by state. These were further combined at the national level to determine the electoral votes and predict the winner. Thus, we can compare the synthetic voting results generated by the LLM with the actual outcomes of the elections. Beyond that, we prompted the LLM to adopt the persona of a respondent from the 2020 ANES survey and cast a hypothetical vote in the 2024 presidential election, choosing between Kamala Harris and Donald Trump. Therefore, after the official election results are released, we can verify the accuracy of our predictions on a state-by-state basis. In total, we utilized the personal characteristics of 6,571 human respondents from the 2020 ANES survey and adjusted the prediction results using the survey's sampling weights to ensure representativeness.

Since the LLM is highly sensitive to prompts, we employed two different prompting methods. The first prompt is called the "role-play prompt", a widely used approach in LLMs. It involves assigning the model a specific role and instructing it to act based on the characteristics and information associated with that role. This technique helps guide the model's behavior and responses, making them more contextually appropriate and aligned with the task at hand. As shown in part (b) of Appendix A, we instruct the LLM to play the role of a resident being interviewed by a pollster.

However, using a role-play prompt for predicting voting behavior may lead the LLM to focus too heavily on individual characteristics while neglecting the historical voting trends and established political leanings of a given state. To address this, we implemented a "structural prompt," guiding the LLM to consider both the respondent's profile and the political tendencies of their state. This prompt provides more structured background information and directs GPT to incorporate the state's historical voting patterns into its predictions. For the detailed prompt, see part (c) of Appendix A.

3 Results

3.1 LLM accuracy in replicating U.S. and China survey responses

Figure 1 compares human responses from the WVS sample with those generated by the LLM. Throughout this section, survey questions are referenced directly by their original identifiers in the WVS. Panel A displays the U.S. sample, and Panel B shows the China sample. While there are some mean differences between LLM and human responses, most LLM response means fall within one standard deviation of the human response means. Additionally, many LLM responses not only have means within this range but also exhibit a smaller variance, as their own standard deviation is largely encompassed by that of the human responses, indicating less fluctuation in LLM responses. This finding is consistent with Bisbee et al. (2023).

However, in some survey items, the LLM responses diverge notably from human responses. For instance, in the U.S. sample, significant differences appear on social values questions such as Q33, Q36, and Q41, which address topics like gender equality in employment, LGBTQ+ rights, and work ethic. For trust-related items (Q62 and Q63), the LLM predicts a higher level of trust toward individuals from diverse religious and national backgrounds than actual U.S. respondents expressed. These findings reflect that ChatGPT may exhibit a bias toward portraying Americans as more inclined toward progressive views, aligning with observations from Feng et al. (2023). Interestingly, for these questions, the differences between LLM and human responses are smaller in the China sample, indicating the LLM's stronger alignment with values in Chinese context and a less noticeable emphasis

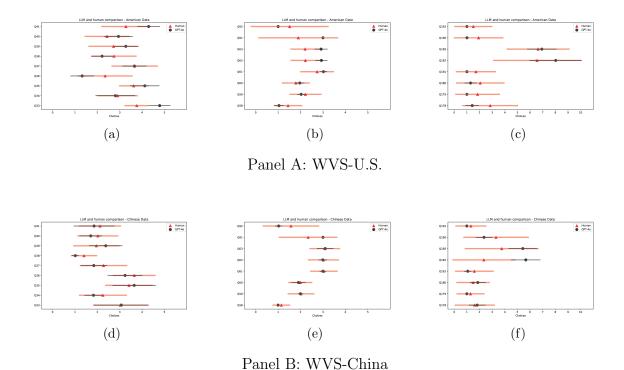


Figure 1: Comparing LLM and WVS response means and standard deviations on socially progressive views.

For common knowledge items like Q91 and Q92, the LLM generally outperforms human respondents with minimal variation, likely due to its vast training data. The LLM also aligned well with human responses on ethical norms, and it tends to show less variability on moral questions. An exception is China's Q182, where the LLM notably overestimates societal acceptance of homosexual communities, reflecting a possible data-influenced overprojection of acceptance.

Table 1 shows differences between U.S. and China responses in both human and LLM samples. We observe that most cultural differences found in the human data persist in the LLM-generated responses, maintaining the same directional trends with statistically significant t-test results. In Panel A, the LLM replicates all actual U.S.-China differences in social values. In Panel B, Q60 and Q61 diverge in predicted direction. Panel C, focusing on common-sense knowledge, shows LLM responses are stable and unrelated to U.S.-China

differences. In Panel D, the LLM inconsistently captures U.S.-China differences, retaining them only for Q182, Q185, and Q190. The weaker performance in Panel D may stem from the LLM's tendency to align with established laws and social norms, which can cause it to diverge from human responses.

Table 1: U.S.-China differences: human responses vs. LLM responses

	Н	luman re	sponse	LLM response				
	U.S.	China	Difference	U.S.	China	Difference		
	(1)	(2)	(3)	(4)	(5)	(6)		
Panel A: Social values								
Q33	3.764	3.022	0.742*	4.828	2.982	1.846*		
Q34	2.913	2.247	0.666*	3.045	1.781	1.264*		
Q35	3.628	3.414	0.214^{*}	4.242	3.544	0.698*		
Q36	2.351	3.653	-1.302*	1.292	3.252	-1.96*		
Q37	3.672	2.272	1.4^{*}	3.806	1.797	2.009*		
Q38	2.746	1.405	1.341^{*}	2.224	0.99	1.234*		
Q39	2.723	1.968	0.755*	3.357	2.313	1.044*		
Q40	2.434	2.028	0.406*	4.864	1.667	3.197*		
Q41	3.28	2.12	1.16*	4.392	1.873	2.519*		
Pane	el B: Tr	rust						
Q58	1.443	1.147	0.296*	1.04	1	0.04^{*}		
Q59	2.222	2.022	0.2^{*}	2.028	1.996	0.032*		
Q60	1.788	1.996	-0.208*	1.966	1.906	0.06^{*}		
Q61	2.741	3.044	-0.303*	3.023	2.997	0.026*		
Q62	2.216	3.028	-0.812*	2.931	2.994	-0.063*		
Q63	2.202	3.084	-0.882*	2.915	3.106	-0.191*		
Pane	Panel C: Common-sense on international organization							
Q91	1.901	2.329	-0.428*	3	2.999	0.001		
Q92	1.513	1.57	-0.057	1	0.999	0.001		
Pane	el D: Et	thical no	orms and v	alues				
Q178	2.843	1.62	1.223^{*}	1.421	1.824	-0.403*		
Q179	1.847	1.283	0.564*	1	1	0		
Q180	2.059	1.5	0.559*	1.29	1.875	-0.585*		
Q181	1.714	1.595	0.119*	1	1.072	-0.072*		
Q182	6.552	2.331	4.221*	8.031	5.676	2.355*		
Q185	6.633	3.738	2.895^{*}	6.93	5.442	1.488*		
Q190	1.926	3.325	-1.399*	1.005	2.375	-1.37^*		
Q192	1.51	1.317	0.193*	1	1	0		

Note: * denote statistical significance at the 1% level.

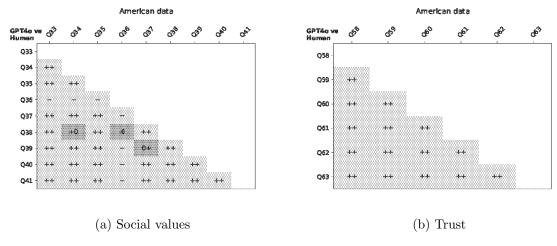
3.2 Variance-covariance of responses and similarity of correlations

Researchers often care about correlations between behaviors and opinions. Due to budget constraints, they often measure multiple preferences in one survey or expriment (e.g., trust and risk-taking), making the consistency of pairwise correlations among these measurements important. After evaluating how well the LLM matches human responses when responding to individual questions, we also explored whether it retains the correlations between different responses observed in the human sample.

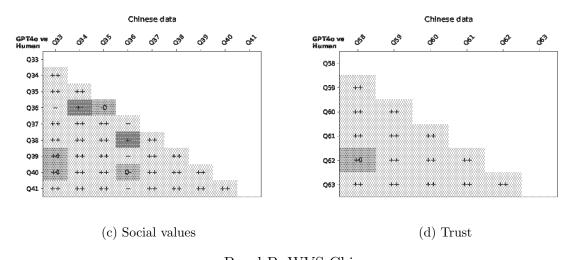
We use a method similar to that of Snowberg and Yariv (2021) to analyze the relationships between responses to different questions in both LLM-simulated and human samples. Specifically, we assess whether statistically significant pairwise correlations observed between two questions in the LLM-generated responses are likewise present in human responses. The results, shown in Figure 2, display the direction and significance of these pairwise correlations for questions on social values and trust, with panel (a) representing the U.S. sample and panel (b) the Chinese sample.

A positive (+) or negative (-) and significant correlation between two outcome measures is denoted by "+" or "-", while an insignificant correlation is marked with "0". Each cell contains two signs: the first indicates correlations in the LLM sample, and the second represents those in the human sample. Cells where pairwise correlations agree in both sign and significance between LLM-simulated and human samples are labeled as "complete agreement" and shaded light grey. Cells where the correlation is significant in one sample but insignificant in the other are labeled "partial disagreement" and shaded grey. Lastly, cells with significant correlations in both samples but in opposite directions are marked as "complete disagreement" and shaded dark grey. We do not include common-sense ethical norms and values questions because LLM-simulated responses lack variation.

In Figure 2, most cells are shaded light grey, indicating complete agreement, with only two instances of complete disagreement in the China sample regarding social values. In the U.S. sample, only 3 out of 51 pairwise correlations indicate partial disagreement, while in



Panel A: WVS-U.S.



Panel B: WVS-China

Figure 2: Within-subject correlations across LLM and human.

the China sample, 5 out of 51 correlations show partial disagreement. This reflects that the LLM-generated responses effectively preserve the correlations between various human beliefs and attitudes.

While synthetic data may seem fairly accurate in aggregate, some issues are still evident when examining conditional relationships. To assess whether the correlational structure of the synthetic data aligns with that of the human benchmark, we compare regression outcomes using actual and synthetic responses as the dependent variable.

Response_{i,j} =
$$\beta_0 + D_j \beta_1 \mathbf{X}_i + (1 - D_j) \beta_2 \mathbf{X}_i + \epsilon_{i,j}$$
 (1)

where *i* represents respondents, *j* denotes the data source (human or LLM sample). D_j is a dummy variable that equals 1 for humans and 0 for LLMs. \mathbf{X}_i is a vector containing respondent characteristics used in the persona prompt (age, gender, education, income, marital status, occupation). Our primary focus is on the coefficient vectors β_1 and β_2 , which capture the partial correlations between each covariate in \mathbf{X}_i and the response for human and LLM samples, respectively.

We run the specification in Equation 1 for each response (questions on social values and trust), totaling 15 regressions. Figure 3 displays the resulting coefficient estimates, with human coefficient, β_1 , on the x-axis and LLM coefficient, β_2 , on the y-axis, organized by independent variables. Points closer to the 45-degree line indicate an alignment in partial correlation observed from either human or synthetic data. In the off-diagonal quadrants (upper left and bottom right), points reflect coefficients with reversed signs depending on the data source, indicating that conclusions based on human data would be opposite to those drawn from the LLM sample.

Overall, most coefficients fall close to the 45-degree line, with the exception of dummy variables related to industry occupation—agricultural and industrial workers—in panels (h) and (i). This indicates that the LLM is fairly effective in predicting an individual's responses based on these characteristics. These findings support the feasibility of using demographic features to predict other individual behaviors, laying a solid foundation for our subsequent prediction task.

3.3 Predicting the outcome of 2024 U.S. presidential election

Using the prompts from parts (b) and (c) in Appendix A, we enabled the LLM to simulate the voting behavior of each ANES respondent. Based on different prompts and calculation

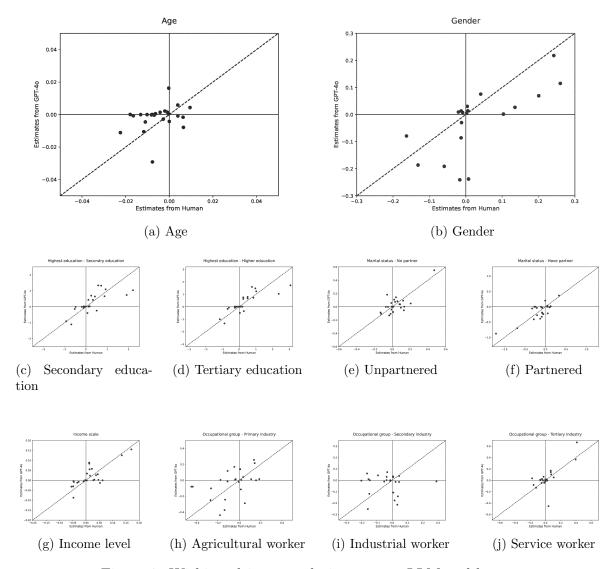


Figure 3: Within-subject correlations across LLM and human.

methods, we obtained three measures of predicted results. The first two use the role-play prompt and the structural prompt, respectively. Although the historical voting prompt directs the LLM to leverage historical data, how the model utilizes its vast stored information remains a black box to us. Therefore, the third method combines the predictions from the role-play prompt with the actual historical vote shares, weighting them to create a more balanced forecast. Specifically, the predicted vote share for party p in state i for year y is

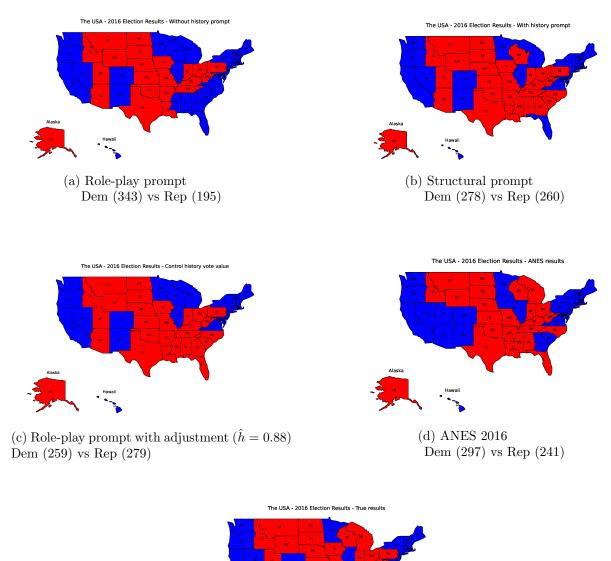
defined as follows:

Predicted vote share_{i,y,p} = $h \times \text{Historical vote share}_{i,p} + (1-h) \times \text{LLM-predicted vote share}_{i,y,p}$

where h denotes the weight. We fine-tuned the weights until the predicted outcomes closely aligned with the actual state-level winners. We then applied this optimized weighting parameter \hat{h} to forecast the outcome of the 2024 presidential election. All the results in Section 3.3 was obtained on or before October 30, 2024, approximately one week before Election Day on November 5, 2024.

In Figure 4, panel (a) presents the results using the role-play prompt, while panel (b) shows the results using the structural prompt. In panel (c), \hat{h} was set to 0.88 to align the predictions more closely with the actual election results in 2016. In panel (d), we calculated the 2016 election outcome within the ANES sample based on respondents' self-reported voting behavior. This approach allows us to estimate how the election would have played out using the ANES data, offering a benchmark for comparison. Due to sampling errors, the survey benchmark do not perfectly match the actual election outcomes. We placed the actual election results in panel (e) for comparison purposes, and found that the ANES sample results in 2016 differed from the actual election outcome in 8 states. Among all the predictions, the structural prompt performed the best, with Michigan and Florida being the only states it mispredicted. Although the role-play prompt showed weaker predictive performance, incorrectly forecasting 8 states, we improved its accuracy by incorporating historical voting data. With this adjustment, it closely approximated the actual outcome, matching the structural prompt by incorrectly predicting the same number of states: Wisconsin and Michigan.

In Figure 5, the structural prompt also performed the best, with Arizona as the only incorrect prediction. The role-play prompt, however, mispredicted 8 states. After adjustment, it closely aligned with the actual results, missing just one more state (North Carolina) compared to the structural prompt. Both Arizona and North Carolina are swing states. Sur-



(e) 2016 actual voting results
Dem (227) vs Rep (304)

Figure 4: LLM-Simulated Replication of the 2016 U.S. Presidential Election

prisingly, the 2020 ANES post-election survey performed poorly, mispredicting the outcomes in 8 states.

Finally, using data from 6,571 respondents from the ANES 2020 survey, we predicted

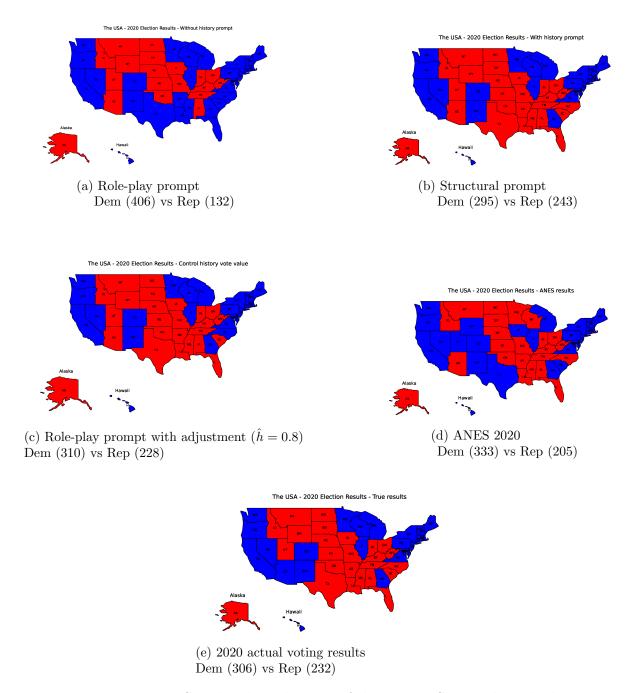


Figure 5: LLM-Simulated Replication of the 2020 U.S. Presidential Election

the outcome of the 2024 election. All three measurement methods consistently forecast that Donald Trump would win the election, and the Republican would receive approximately 300 of the 538 total electoral votes. Detailed state-by-state Democratic and Republican vote shares are available in Table 3 in the Appendix B. Columns (5) and (6) include polling data

from the website 270toWin².

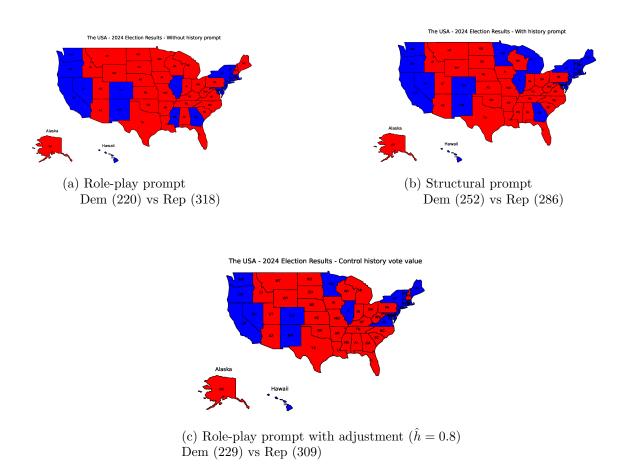


Figure 6: LLM-Simulated Prediction of the 2024 U.S. Presidential Election

4 Discussion and Implications

This study demonstrates that large language models exhibit significant in-sample predictive capabilities, closely mirroring human responses when demographic variables are input. For out-of-sample predictions, such as elections, the model also shows potential in forecasting trends. These findings suggest that LLMs could serve as effective supplements to traditional survey methodologies. First, by accurately simulating human responses based on demographic inputs, LLMs can reduce survey costs, serving as a supplementary data source when

²See https://www.270towin.com/.

direct collection is limited. They also help extend survey reach, filling in data gaps for underrepresented groups. Additionally, LLMs offer a testing ground to validate and refine survey questions, ensuring relevance to target populations. Lastly, their predictive capacity allows researchers to anticipate trends, especially in evolving social issues.

While this study demonstrates the potential of LLMs in simulating human responses, there remain areas for further exploration. Our analysis primarily used ChatGPT-4o, without assessing other LLMs, which may exhibit different biases on value-laden topics due to varied training data. Additionally, our data is drawn from the WVS and ANES surveys, so incorporating more diverse sources could enhance generalizability. Lastly, the cross-cultural analysis is centered on the U.S. and China; future studies could broaden this scope to better understand LLM performance across diverse cultural contexts.

References

- Aher, G., Arriaga, R., and Kalai, A. (2022). Using large language models to simulate multiple humans. ArXiv, abs/2208.10264.
- Argyle, L. P., Busby, E. C., Fulda, N., Gubler, J. R., Rytting, C., and Wingate, D. (2023). Out of one, many: Using language models to simulate human samples. *Political Analysis*, 31(3):337–351.
- Ashokkumar, A., Hewitt, L., Ghezae, I., and Willer, R. (2024). Predicting results of social science experiments using large language models. Technical report, Working Paper.
- Bisbee, J., Clinton, J. D., Dorff, C., Kenkel, B., and Larson, J. M. (2023). Synthetic replacements for human survey data? the perils of large language models. *Political Analysis*, pages 1–16.
- Cheng, M., Piccardi, T., and Yang, D. (2023). Compost: Characterizing and evaluating caricature in llm simulations. *ArXiv*, abs/2310.11501.
- Feng, S., Park, C. Y., Liu, Y., and Tsvetkov, Y. (2023). From pretraining data to language models to downstream tasks: Tracking the trails of political biases leading to unfair nlp models.
- Kim, J. and Lee, B. (2023). Ai-augmented surveys: Leveraging large language models for opinion prediction in nationally representative surveys. ArXiv, abs/2305.09620.
- Phelps, S. and Russell, Y. (2023). Investigating emergent goal-like behaviour in large language models using experimental economics. ArXiv, abs/2305.07970.
- Snowberg, E. and Yariv, L. (2021). Testing the waters: Behavior across participant pools. *American Economic Review*, 111(2):687–719.
- Tjuatja, L., Chen, V., Wu, S. T., Talwalkar, A., and Neubig, G. (2023). Do llms exhibit human-like response biases? a case study in survey design. *ArXiv*, abs/2311.04076.
- Xie, C., Chen, C., Jia, F., Ye, Z., Shu, K., Bibi, A., Hu, Z., Torr, P., Ghanem, B., and Li, G. (2024). Can large language model agents simulate human trust behaviors? arXiv preprint arXiv:2402.04559.
- Xu, Y., Wang, S., Li, P., Luo, F., Wang, X., Liu, W., and Liu, Y. (2023). Exploring large language models for communication games: An empirical study on werewolf. *ArXiv*, abs/2309.04658.

Appendix A Prompts

(a) Simulation prompt

Step 1: Assigning a persona to the LLM

"It is the year 2017. You are a [AGE]-year-old [GENDER] American/Chinese living in [STATE/PROVINCE], with [EDUCATION LEVEL]. Your marital status is [MARITAL STATUS], and you [OCCUPATION DESCRIPTION]. On an income scale on which 1 indicates the lowest income group and 10 the highest income group in your country, your household is [INCOME LEVEL]."

Step 2: Setting the scenario

"Hello. I am from the World Values Survey Association. We are carrying out a global study of what people value in life. This study will interview samples representing most of the world's people. Your name has been selected at random as part of a representative sample of the people in America. I'd like to ask your views on a number of different subjects. Your input will be treated strictly confidential, but it will contribute to a better understanding of what people all over the world believe and want out of life."

Step 3: Asking questions and gathering responses

1. Social values

"For the following questions, choose 1 for Agree strongly, 2 for Agree, 3 for Neither agree nor disagree, 4 for Disagree, and 5 for Disagree strongly. How would you feel about the following statements? Do you agree or disagree with them?"

- Q33 When jobs are scarce, men should have more right to a job than women
- Q34 When jobs are scarce, employers should give priority to people of this country over immigrants
- Q35 If a woman earns more money than her husband, it's almost certain to cause problems
- Q36 Homosexual couples are as good parents as other couples
- Q37 It is a duty towards society to have children
- Q38 Adult children have the duty to provide long-term care for their parents
- Q39 People who don't work turn lazy
- Q40 Work is a duty towards society
- Q41 Work should always come first, even if it means less spare time

2. Trust

"For the following questions, choose 1 for Trust completely, 2 for Trust somewhat, 3 for Do not trust very much, 4 for Do not trust at all. I'd like to ask you how much you trust people from various groups. Could you tell me for each whether you trust people from this group completely, somewhat, not very much or not at all?"

- Q58 Your family
- Q59 Your neighborhood
- Q60 People you know personally
- Q61 People you meet for the first time
- Q62 People of another religion
- Q63 People of another nationality

3. Common-sense on international organization

"Here are some questions about international organizations. Many people don't know the answers to these questions, but if you do please tell me.

- Q91 Five countries have permanent seats on the Security Council of the United Nations. Which one of the following is not a member?
 - (a) France
 - (b) China
 - (c) India
- Q92 Where are the headquarters of the International Monetary Fund (IMF) located?
 - (a) Washington DC
 - (b) London
 - (c) Geneva

4. Ethical norms and values

"Please tell me for each of the following actions whether you think it can always be justified, never be justified, or something in between.

1 = Never justifiable, 2, 3, 4, 5, 6, 7, 8, 9, 10 = Always justifiable

- Q178 Avoiding a fare on public transport
- Q179 Stealing property
- Q180 Cheating on taxes if you have a chance
- Q181 Someone accepting a bribe in the course of their duties
- Q182 Homosexuality
- Q185 Divorce
- Q190 Parents beating children
- Q192 Terrorism as a political, ideological or religious mean

For each query to ChatGPT, the bracketed characteristics are replaced with values matching those of an actual respondent from Wave 7 of the WVS. A detailed list of these values

is provided as follow:

Demographics	Descriptions
AGE	age in years
GENDER	male or female
STATE/PROVINCE	a U.S. state or a Chinese province
EDUCATION LEVEL	 an early childhood education level, a primary education level, a lower secondary education level, an upper secondary education level, a post-secondary non-tertiary education level, a short-cycle tertiary education level, a bachelor or equivalent education level, a master or equivalent education level, a doctoral or equivalent education level
MARITAL STATUS	 married, living together as married, divorced, separated, widowed, single
OCCUPATION DESCRIPTION	1: work in a professional and technical field (for example: doctor, teacher, engineer, artist, accountant, nurse), 2: work in higher administrative (for example: banker, executive in big business, high government official, union official), 3: work in clerical (for example: secretary, clerk, office manager, civil servant, bookkeeper), 4: work in sales (for example: sales manager, shop owner, shop assistant, insurance agent, buyer), 5: work in service (for example: restaurant owner, police officer, waitress, barber, caretaker), 6: work as a skilled worker (for example: foreman, motor mechanic, printer, seamstress, tool and die maker, electrician), 7: work as a semi-skilled worker (for example: bricklayer, bus driver, cannery worker, carpenter, sheet metal worker, baker), 8: work as an unskilled worker (for example: laborer, porter, unskilled factory worker, cleaner), 9: work as a farm worker (for example: farm laborer, tractor driver), 10: work as a farm proprietor, farm manager, 11: are retired/pensioned, 12: are a housewife not otherwise employed, 13: are a student, 14: are unemployed
INCOME LEVEL	0 (the lowest income group) to 10 (the highest income group).

(b) Role-play prompts

Step 1: Assigning a persona to the LLM

"It is the year 2024. You are a/an [AGE]-year-old [ETHIC GROUP] [GENDER] living in the United States, who are registered to vote in [STATE], with [EDUCATION LEVEL] education level and you [RELIGIOUS PHRASE]. Your marital status is [MARITAL STATUS], and you [OCCUPATION DESCRIPTION], [HOW OFTEN] paying attention to what's going on in government and politics. The income of all members of your family during the past 12 months before taxes is [INCOME LEVEL]."

Step 2: Setting the scenario

"Hello!

The presidential election plays a crucial role in determining the direction of the United States for the next four years, influencing not only domestic policies like the economy and healthcare but also having a profound impact on global affairs.

Every vote matters in shaping the future of the nation, as participating in the election is not only a right but also a responsibility.

We encourage everyone to make decisions based on policies and stances rather than emotions or stereotypes.

Now we are conducting a scientific study involving a mock election for the U.S. presidential election.

Assume that you are a voter participating in the 2024 U.S. election. You will be asked to cast your votes. After voting, the results will be shared. Your voting results will only be used for academic analysis, so please don't worry and feel free to vote.

U.S. Presidential and Vice Presidential Election - Vote for One Party

Step 3: Presenting options and gathering responses

Please select the presidential and vice presidential candidates you support:

- 1. KAMALA D. HARRIS / TIM WALZ (Democratic)
- 2. DONALD J. TRUMP / J.D. VANCE (Republican)

Note: Each voter can only select one party ticket. The party label accompanying the candidates indicates that they are the official nominees of the party shown.

Please select your choice: 1 or 2. Respond only with the corresponding number."

The presidential and vice presidential candidates were replaced with the following if the year was set to 2016 or 2020.

- 2016 United States presidential election
 - 1. HILLARY R. CLINTON / TIMOTHY M. KAINE (Democratic)
 - 2. DONALD J. TRUMP / MICHAEL R. PENCE (Republican)

- ullet 2020 United States presidential election
 - 1. JOSEPH R. BIDEN / KAMALA D. HARRIS (Democratic)
 - 2. DONALD J. TRUMP / MICHAEL R. PENCE (Republican)

For each query to ChatGPT, the bracketed characteristics are replaced with values matching those of an actual respondent from the ANES. A detailed list of these values is provided as follow:

Demographics	Descriptions
AGE	age in years
GENDER	male or female
ETHIC GROUP	 non-Hispanic white, non-Hispanic black, Hispanic, non-Hispanic Asian or Native Hawaiian/other Pacific Islander, non-Hispanic Native American/Alaska Native or other race, non-Hispanic of multiple races
STATE/PROVINCE	a U.S. state
EDUCATION LEVEL	 a less than high school credential, a high school diploma or equivalent, a some college but no degree, an associate degree in college(occupational/vocational), an associate degree in college(academic), a bachelors degree, a masters degree, a professional school degree / doctoral degree
RELIGIOUS PHRASE	 belong to the Protestant faith, belong to the Roman Catholic faith, belong to the Orthodox Christian (such as Greek or Russian Orthodox) faith, belong to the Latter-Day Saints(LDS) faith, belong to the Jewish faith, belong to the Muslim faith, belong to the Buddhist faith, belong to the Hindu faith, belong to the Atheist faith, belong to a minority religious group, do not belong to a denomination
MARITAL STATUS	 married(spouse present), married(spouse absent), widowed, divorced, separated,

Demographics	Descriptions
	6: never married
OCCUPATION DESCRIPTION	 work in a for-profit company or organization, work in a non-profit organization (including tax-exempt and charitable organizations), work in local government (for example: city or county school district), work in state government (including state colleges/universities), serve on active duty U.S. Armed Forces or Commissioned Corps, work as a federal government civilian employee, work as an owner of non-incorporated business, professional practice, or farm, work as an owner of incorporated business, professional practice, or farm, work without pay in a for-profit family business or farm for 15 hours or more per week
HOW OFTEN	 always, most of the time, about half the time, some of the time, never
INCOME LEVEL	The income level variable has 22 categories, ranging from "under $\$9,999$ " to " $\$250,000$ or more" with intervals of approximately $\$5,000$ to $\$25,000$.

(c) Structural prompt We assigned a persona to the LLM, using the same characteristics outlined in the role-play prompt.

It is the year 2024.

You are simulating a U.S. voter participating in the 2024 presidential election. Each time, you will receive demographic information along with a U.S. state. Your task is to vote based on the provided details.

1. State Context:

- Consider the historical voting trends of the state provided (e.g., red state, blue state, or swing state).
- For swing states (e.g., Nevada, Pennsylvania), reflect a balanced or probabilistic decision.
- For solidly red or blue states, you may align with the dominant trend unless personal background suggests otherwise.

2. Personal Background:

• Use the demographic details (e.g., age, income, marital status, occupation, and religion) to inform your choice.

• Your goal is to reflect realistic voting behavior, balancing state trends and personal values.

3. Output

- Select one option:
 - 1. KAMALA D. HARRIS / TIM WALZ (Democratic)
 - 2. DONALD J. TRUMP / J.D. VANCE (Republican)
- Respond only with the corresponding number: 1 or 2.

Ensure your decision is logical, balancing state context and individual background to simulate human-like voting behavior.

Your voting results will only be used for academic analysis, so please don't worry and vote according to the actual situation.

Appendix B Tables

Table 3: State-Level LLM-predicted 2024 Election

State	Role-play prompt ($\hat{h} = 0.8$)		Structural prompt		Polling	
	Democrats (1)	Republicans (2)	Democrats (3)	Republicans (4)	Democrats (5)	Republicans (6)
Alabama	34.79%	61.01%	13.22%	86.78%		
Alaska	32.28%	60.81%	0.00%	100.00%	43.00%	51.00%
Arizona	42.71%	52.57%	32.60%	67.40%	46.80%	49.00%
Arkansas	32.87%	62.50%	6.06%	93.94%	40.00%	55.00%
California	62.73%	32.42%	97.60%	2.40%	59.00%	34.30%
Colorado	49.79%	43.25%	74.06%	25.94%		
Connecticut	55.48%	41.95%	97.41%	2.59%		
Delaware	53.01%	40.48%	96.58%	3.42%		
Florida	45.08%	51.57%	20.78%	79.22%	44.20%	51.40%
Georgia	47.58%	49.26%	50.52%	49.48%	46.80%	48.80%
Hawaii	63.13%	31.65%	100.00%	0.00%		
Idaho	27.45%	63.80%	0.00%	100.00%		
Illinois	54.90%	40.95%	91.37%	8.63%		
Indiana	35.66%	59.70%	3.51%	96.49%		
Iowa	38.41%	56.92%	3.15%	96.85%	44.00%	49.00%
Kansas	36.40%	58.28%	2.53%	97.47%	43.00%	48.00%
Kentucky	33.15%	62.31%	1.76%	98.24%		
Louisiana	38.07%	58.98%	18.25%	81.75%		
Maine	46.96%	46.57%	68.25%	31.75%	48.00%	41.00%
Maryland	63.45%	32.39%	97.68%	2.32%	61.30%	33.00%
Massachusetts	62.74%	32.71%	99.75%	0.25%	60.50%	32.00%
Michigan	45.91%	49.27%	54.99%	45.01%	48.90%	47.10%
Minnesota	47.62%	46.38%	75.73%	24.27%	50.00%	43.70%
Mississippi	42.05%	54.96%	35.03%	64.97%		

State	Role-play prompt $(\hat{h} = 0.8)$		Structural prompt		Polling	
	Democrats (1)	Republicans (2)	Democrats (3)	Republicans (4)	Democrats (5)	Republicans (6)
Missouri	35.07%	60.21%	5.63%	94.37%	42.00%	53.50%
Montana	31.53%	63.00%	0.00%	100.00%	39.50%	57.50%
Nebraska	29.66%	65.69%	0.00%	100.00%	48.40%	47.20%
Nevada	49.93%	45.60%	78.78%	21.22%	47.70%	48.10%
New Hampshire	44.18%	49.96%	58.91%	41.09%	50.30%	44.00%
New Jersey	55.24%	41.88%	93.65%	6.35%	52.00%	40.00%
New Mexico	51.47%	41.37%	81.11%	18.89%	49.70%	42.70%
New York	58.67%	37.26%	97.32%	2.68%	57.50%	39.00%
North Carolina	45.05%	50.55%	27.76%	72.24%	47.20%	48.60%
North Dakota	23.88%	68.07%	0.37%	99.63%		
Ohio	39.23%	56.24%	11.30%	88.70%	45.00%	51.40%
Oklahoma	29.07%	65.07%	0.61%	99.39%	40.00%	56.00%
Oregon	52.93%	39.80%	97.47%	2.53%	53.00%	41.00%
Pennsylvania	45.81%	50.18%	44.16%	55.84%	48.00%	48.60%
Rhode Island	49.86%	47.23%	98.10%	1.90%	57.00%	40.50%
South Carolina	41.72%	53.92%	18.93%	81.07%	42.00%	53.50%
South Dakota	30.46%	63.21%	0.00%	100.00%	34.00%	60.50%
Tennessee	34.34%	61.88%	6.48%	93.52%	35.00%	56.00%
Texas	43.05%	53.12%	12.17%	87.83%	45.20%	51.40%
Utah	31.16%	56.06%	1.57%	98.43%	38.00%	54.00%
Vermont	63.41%	32.12%	100.00%	0.00%	70.00%	29.00%
Virginia	49.92%	45.91%	53.66%	46.34%	50.00%	41.30%
Washington	53.33%	38.87%	96.51%	3.49%	56.30%	35.70%
Washington DC	87.52%	9.39%	100.00%	0.00%		
West Virginia	24.60%	70.43%	0.00%	100.00%	34.00%	61.00%
Wisconsin	44.29%	50.97%	41.89%	58.11%	48.10%	48.30%
Wyoming	23.80%	72.08%	0.00%	100.00%		