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Quantitative Analysis of Political Party Understanding and the Impact of Political Bias through ChatGPT

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Abstract. In recent years, large language models (LLMs) such as ChatGPT have been utilized for acquiring political knowledge. However, there remain questions about their accuracy and fairness, as these models may harbour biases in understanding political parties. This study aims to quantify the understanding of Japanese political parties using the ChatGPT model and evaluate the model's biases and their impacts. Specifically, we conducted experiments using pairs of questions and answers that reflect the stances of each party to investigate the extent to which the model demonstrates understanding toward specific parties. The experimental results revealed that ChatGPT-4 exhibits a significantly higher level of understanding towards the Liberal Democratic Party, while its understanding of newer parties like Reiwa Shinsengumi is lower. Additionally, the GPT model acting as a voter tends to have a positive bias towards certain parties and reflects progressive ideologies. It was also shown that the recognition of political parties influences the model's understanding, with factors such as the number of seats, advertising expenses, and the frequency of party names in the dataset potentially playing crucial roles. Based on these findings, this study provides a foundation for enhancing the accuracy and fairness of party understanding using GPT models and proposes improvements for future research and practice.

1 Introduction

ChatGPT, developed by OpenAI, is a chat service used worldwide. This system, based on the GPT model, is a large language model (LLM) that automatically generates human-like responses to given prompts. Although the details of the data ChatGPT learns from are not disclosed, it is believed to possess a wide range of knowledge due to its training on a vast corpus of data [1]. Additionally, ChatGPT employs a method called Reinforcement Learning from Human Feedback (RLHF) to enable human-like behaviour [2]. Thanks to this method, ChatGPT has achieved natural conversations in a chat format and has become capable of handling various tasks such as question answering, reasoning, code generation, and computational problems [3, 4]. Recently, ChatGPT has been used to acquire political knowledge. Indeed, GPT has a broad knowledge base, making it capable of responding to political questions. Therefore, by simply providing a prompt containing a question to ChatGPT, one can obtain an answer more easily than searching the web, making it an excellent choice for acquiring political knowledge. Moreover, the ChatGPT-3.5 model can be used for free, lowering the barrier to use for light users and enabling many users to enhance their understanding of politics.

However, there is a concern that LLMs may have political biases, which could pose risks to the political use of ChatGPT. For example, research by Feng et al. [5] has shown that GPTs tends to have liberal ideologies. Additionally, MainichiShimbun [6] revealed that when a LLM is used as a chatbot, it tends to generate more favourable responses to specific political parties. Although studies exist on ChatGPT's political ideologies, there is no research yet investigating the extent to which ChatGPT understands each political party. If ChatGPT has varying levels of understanding for different parties, it could be considered biased towards certain parties, potentially causing unfairness in its political use.

Therefore, this study aims to quantify ChatGPT's understanding of each political party and explore the risks in its political use based on the results. Specifically, we analyse the differences between pairs of questions and answers reflecting the stances of each party and the responses of ChatGPT acting as a party supporter. We also analyse the responses of ChatGPT when acting as a voter in Japanese conversations to reveal its understanding of each party and any positive biases towards specific parties. Finally, we conduct a correlation analysis between understanding and variables related to political parties to explore the causes of differences in understanding and biases. Based on these analyses, we provide important insights into the political use of ChatGPT based on understanding of political parties and offer important guidelines for political parties.

The contributions of this study are as follows:

i) We compare actual party responses with ChatGPT's predictions to quantify ChatGPT's understanding of political parties, demonstrating the extent to which ChatGPT accurately understands party stances and highlighting the risks of political use.
ii) We analyze the responses of ChatGPT when acting as a voter to point out any positive biases towards specific parties, emphasizing the dangers to users associated with ChatGPT's political use.
iii) We conduct a correlation analysis between understanding and variables related to political parties to explore the causes of differences in understanding and biases. This analysis provides valuable guidelines for future political activities.

The structure of this paper is as follows: Section 2 reviews related research using ChatGPT. Section 3 describes the questions and workflow for the experiments. Section 4 presents the experimental results and their discussion. Section 5 concludes the study.

2 Related Works

The rise of ChatGPT, as the latest innovation by OpenAI, has the potential to significantly impact academia and public health. Its human-like text generation capabilities present a new form of information delivery, serving as a tool to enhance medical, educational, and information services [7-9]. The study by Mbakwe et al. [10] demonstrated that ChatGPT passed the U.S. medical licensing exam, offering insights into how it could be utilized in the educational sector. However, while studies by Thorp [11], Lund and Ting [12] have shown the risks of using LLMs including ChatGPT, there has been insufficient research on the potential dangers of political bias. Rozado [13] revealed the possibility of ChatGPT exhibiting a left-leaning political bias, arguing that fair AI systems should maintain political neutrality while providing balanced discussions. In contrast, Rutinowski et al. [14] provided a detailed analysis of ChatGPT's self-awareness and political bias, examining whether ChatGPT is conservative or progressive, or shows tendencies across other political spectra. Nevertheless, research quantitatively assessing ChatGPT’s understanding of specific political parties and how this understanding impacts users' political preferences is lacking. This research gap is crucial for accurately understanding the effects of LLMs on political decision-making and party support and is vital for providing fair and balanced political information.

Formal methods, such as those proposed by Testa et al. [15] for assessing wireless sensor network resiliency using heuristic strategies, offer a potential approach to systematically evaluate biases and ensure the reliability of AI models like ChatGPT. By integrating similar heuristic and formal strategies, this study aims to clarify the extent of ChatGPT's understanding of each political party and explore how this could affect fairness and bias in its political use.

Based on these preliminary insights, this study aims to clarify the extent of ChatGPT's understanding of each political party and explore how this could affect fairness and bias in its political use.

3 Experimental Overview

3.1 Experimental Implementation

One method to verify the ChatGPT's understanding of political parties involves using pairs of questions and answers that reflect each party's stance on policies. In this study, we utilized questions from the voting matching system operated by "Senkyo.com," Japan's largest election and political information website [16]. This system features 20 questions, and based on the answers, it identifies the political party closest to the user's ideology. The questions used relate to important policies in Japan and are likely to reflect the stance of each political party. For 10 out of the 20 questions, survey results on each party's stance are already available with a five-point scale (1: oppose, 2: somewhat oppose, 3: neutral, 4: somewhat agree, 5: agree), which we used as actual responses from the parties. The responses for the remaining 10 questions were determined based on each party's support or opposition to the bills concerned during House of Representatives' voting. In this case, nuances such as somewhat agree or somewhat disagree are not captured, and decisions were made binary to eliminate subjectivity.

To check the ChatGPT's understanding of political parties, prompts in Japanese including these 20 questions were used. The beginning of the prompt stated, "You are now a Japanese citizen, and please act as a supporter of [name of political party]," encouraging the ChatGPT to behave as a supporter of a specific party and provide a deeper understanding of the party. The workflow used in the experiment is shown in Fig. 1.

The targeted parties were the Liberal Democratic Party (LDP), Komeito, Constitutional Democratic Party of Japan (CDP), Japanese Communist Party (JCP), Japan Innovation Party (JIP), Democratic Party for the People (DPP), Reiwa Shinsengumi Party (Reiwa), and Social Democratic Party (SDP). Although other parties exist, they were not included because they had no seats in the House of Representatives where the bills were decided. Additionally, prompts were tested not only with the party names but also as "voters" to identify potential support tendencies in the GPT model. Prompts were given to both the free version of ChatGPT-3.5 and the subscription-based ChatGPT-4, and responses were saved in an Excel file. By calculating the average of each response from N trials, predictions of the GPT model's answers to the questions were obtained. Testing both the 3.5 and 4 models is crucial considering the usage of ChatGPT. GPT-4 is reported to have better performance in all tasks due to more extensive training. Thus, it is anticipated that the understanding of political parties with GPT-4 would be higher than with GPT-3.5. However, as many light users utilize the free version, it is also essential to verify the performance of GPT-

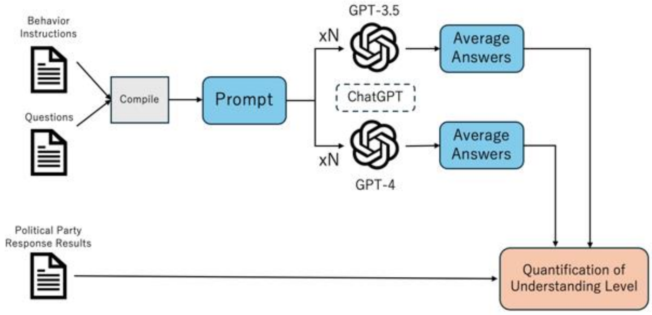

Fig. 1. Experimental Workflow.

3.5. All experiments in this study were conducted online from March 29 to 31, 2024, with prompts including questions manually provided to ChatGPT, and responses were saved.

3.2 Question Topics

The 20 questions used in the experiments are likely to reflect the stances of the parties and result in ideologically divided responses. Half of the questions (Q11~Q20) are answered with a five-point scales, and the other half (Q1~Q10) with a binary choice. Questions are categorized into several topics, each covering specific aspects of policy:

1. **Economic Policy and Social Security**: Covering questions like Q1 (My Number law), Q3 (health insurance premiums), Q7 (supplementary budget), Q8 (salary law for public employees), Q11 (free medical expenses), and Q12 (allocation of resources against declining birthrates), this section assesses whether parties lean towards economic growth or prioritize social welfare.
2. **Security and Foreign Policy**: Questions Q2 (defence spending), Q17 (Self-Defense Forces in the Constitution), and Q18 (capability to attack enemy bases) reveal whether parties favor a pacifist approach or support proactive defence policies.
3. **Social Diversity and Equality**: Through Q6 (understanding law for sexual minorities), Q13 (legalization of same-sex marriage), and Q19 (selective separate surnames), parties' commitment to social diversity and individual rights is examined.
4. **Legal System and Public Policy**: This includes Q4 (immigration law), Q9 (cannabis control), Q10 (monitoring religious assets), Q14 (multiple elections), Q15 (reduction of assembly members), and Q20 (ban on corporate donations), shedding light on stances regarding the legal system, social order, and political transparency.
5. **Energy Policy and Environment**: Finally, Q5 (nuclear power operation) and Q16 (continuation of public works) gauge the party's focus on sustainable energy and environmental conservation.

The questions help map out each party's policy focus, economic stance, and value system, which reflects their position on the spectrum from conservative to progressive.

4 Experimental Results

4.1 Dataset

To measure the GPT model's understanding of each political party, prompts including behaviour as specific party supporters and 20 questions were provided to the GPT model.

Specifically, following the workflow in Fig. 1, responses were generated 30 times for each party and voter, and the average was taken as the GPT model's prediction. This dataset is stored in [17]. Since ChatGPT incorporates randomness in generating responses, averaging multiple trials allows for obtaining answers that represent plausible directions and intensities of attitudes towards policies.

4.2 Experiment Design

The experiment is structured into three main steps to clarify the GPT model's understanding of each political party and to gain deeper insights.

The first step aims to quantify the understanding of each political party by the GPT model. For this purpose, Principal Component Analysis (PCA) is applied to the actual responses obtained from each party, reducing dimensions to two-dimensional space. Then, prompts including 20 questions as a party supporter are given to the GPT model, and the results are multiplied by the loadings obtained from the PCA to map them onto the same two-dimensional space. The Euclidean distance between the actual party responses and the model's predictions is then calculated as the measure of the GPT model's understanding. This calculation of Euclidean distance quantifies the differences in the intensity and direction of policy attitudes between actual parties and predictions.

The next step reveals the ideological bias inherent in the GPT model and identifies which party's ideology it is closest to. For this purpose, responses to prompts including 20 questions, where the GPT model acts as a voter, are mapped onto the same two-dimensional space using a similar method, and the Euclidean distances to each party are calculated. This allows us to reveal which party the GPT model's ideology is closest to when it acts as a voter. This step quantitatively demonstrates how the inherent bias in the GPT model favors certain parties.

The final step explores the causes of differences in understanding and bias towards each party identified in the previous steps. Ideally, it would involve examining the dataset used for training the GPT model, but since ChatGPT's training data is not publicly available, we instead analyze correlations with indicators related to political parties and Japanese language datasets typically used for training Japanese LLMs. This analysis clarifies the factors behind the differences in understanding and bias, providing significant insights. Through these steps, the study aims to quantitatively assess and explore the causes of the GPT model's understanding of political parties and its ideological bias.

4.3 ChatGPT: Understanding Parties

Initially, we applied Principal Component Analysis (PCA) to the actual responses from each political party. The loadings obtained from the PCA are shown in Fig. 2.

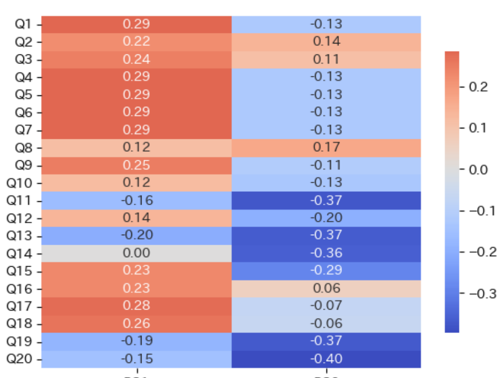

Fig. 2. Loadings Obtained from The Principal Component Analysis of The Parties' Responses.

The first principal component (PC1) reflects a focus on economic and security policies, as indicated by heavy loadings on questions regarding economic measures, defence spending, the My Number law, and nuclear policy. Negative loadings on questions related to social support and individual rights suggest that PC1 contrasts economic and security priorities with social welfare. The second principal component (PC2) contrasts traditional values and national authority, indicated by positive loadings on questions about public official salaries and defence, with progressive values such as social diversity and individual rights, which have negative loadings.

Therefore, PC1 distinguishes between a focus on economic growth and security versus social security, while PC2 aligns with the conservative-progressive spectrum. On this spectrum, PC1's horizontal axis indicates economic policy positions, with the right side prioritizing economic growth and the left side emphasizing social welfare. PC2's vertical axis pertains to social policies and values, where higher positions value tradition and authority, and lower positions advocate for diversity and individual freedoms.

Next, we applied the PCA scores and loadings to the responses from the GPT model and plotted the results on the political spectrum as shown in Fig. 3. Overall, results from GPT-4 are more accurate in predicting party responses compared to GPT-3.5, particularly for the LDP, where GPT-4's results are nearly identical, indicating significant understanding. Predictions for many parties are cantered more towards progressive outcomes in the spectrum, indicating a balance between economic growth and social security while leaning toward liberal ideologies. This is similar to findings in Rozado's study, where GPT models in Japanese also showed a tendency towards liberal ideologies.

Next, we present the results of applying Euclidean distance to the party responses and GPT model predictions as shown in Fig. 4. Smaller Euclidean distances mean that the model's responses are more similar to the actual party responses, indicating a higher understanding of the party. Comparing both models, GPT-4 consistently outperforms GPT-3.5 in understanding all parties, particularly showing significant improvements for the LDP. This suggests that GPT-4's understanding of the LDP is quite high. However, results for the Reiwa Shinsengumi Party show high values for both models, indicating a lower understanding, likely due to Reiwa being a very new party with fewer appearances in the training data. Overall, GPT-4 shows relatively high understanding for parties like LDP, Komeito, CDP, and DPP, which have been ruling parties over the past 15 years, suggesting a correlation with the model's understanding. GPT-3.5 shows the highest understanding for DPP, but LDP performs low, indicating that the understanding seen in GPT-4 for past ruling parties may not be as reflected in GPT-3.5.

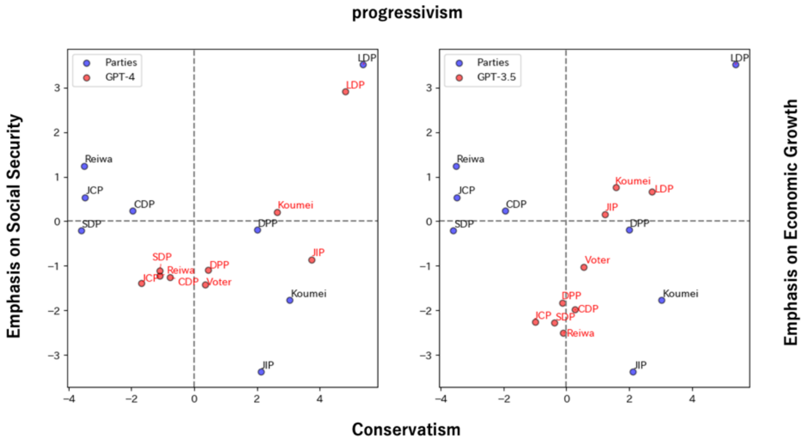

Fig. 3. Political Spectrum Illustrating Party Responses and Predictions.

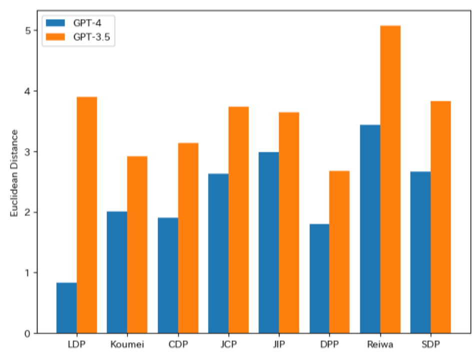

Fig. 4. Euclidean Distances for Each Party Between GPT-4 and GPT-3.5 Responses.

4.4 How to Act as A Voter

We then calculated the Euclidean distances between the results of the ChatGPT acting as a voter and each party, clarifying which party the ChatGPT's political ideology is closest to. The results are shown in Fig. 5. The best results for GPTs were for DPP, suggesting that the ChatGPT may have biases close to DPP's stance. From a political spectrum perspective, this indicates a distance from the LDP and far from left-leaning parties such as the JCP, Reiwa, and SDP, showing a strong emphasis on economic growth and progressive ideologies.

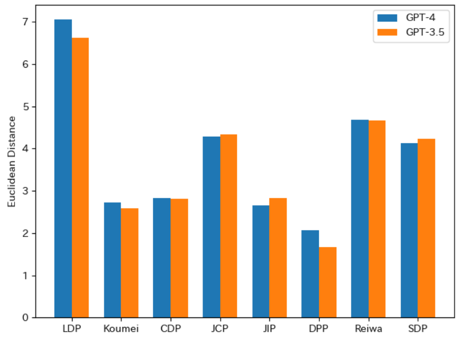

Fig. 5. Euclidean Distances for a Voter Between GPT-4 and GPT-3.5 Responses.

4.5 Bias related to Understanding Parties

Finally, we aimed to clarify the causes of differences in understanding and bias towards each party. Since ChatGPT's training data is not publicly available, as an alternative, we explored causes through scatter plots of Euclidean distance results against various variables related to the parties. Variables included the number of seats in the House of Representatives for each party, the year of party establishment, support rates, advertising expenses, and appearances of party names in the Japanese Wikipedia [18] and Japanese CC-100 datasets [19]. Scatter plots of Euclidean distance and each variable are shown in Fig. 6.

Results show a strong negative correlation with the number of seats in the House of Representatives, suggesting that parties with more seats, which are more frequently featured in media, contribute to better understanding. A slight negative correlation can be anticipated with the establishment year when tracing back to the founding of the Democratic Party in 1998 for CDP and DPP. Advertising scatter plots show a negative correlation, indicating that parties engaging more in visibility-raising activities record smaller distances, suggesting that visibility influences understanding. To indirectly assess recognition, we created scatter plots for the appearance of each party's official name in datasets typically used for training Japanese LLMs. Negative correlations in Japanese Wikipedia indicate that parties appearing more frequently in the data achieve higher understanding, while this trend is not observed in Japanese CC-100, possibly due to web data often using party abbreviations, affecting the results. Specifically, Japan Innovation Party corresponds to "Innovation" and Democratic Party for the People to "People" in kanji, which are commonly used as abbreviations in Japanese. In Japanese Wikipedia, kanji corresponding to "Innovation" and "People" appeared 15,492 and 63,114 times, respectively, more than ten times the appearances of the official party names. Overall, relatively new parties like Reiwa have fewer appearances in the data, resulting in lower understanding in ChatGPT-4.

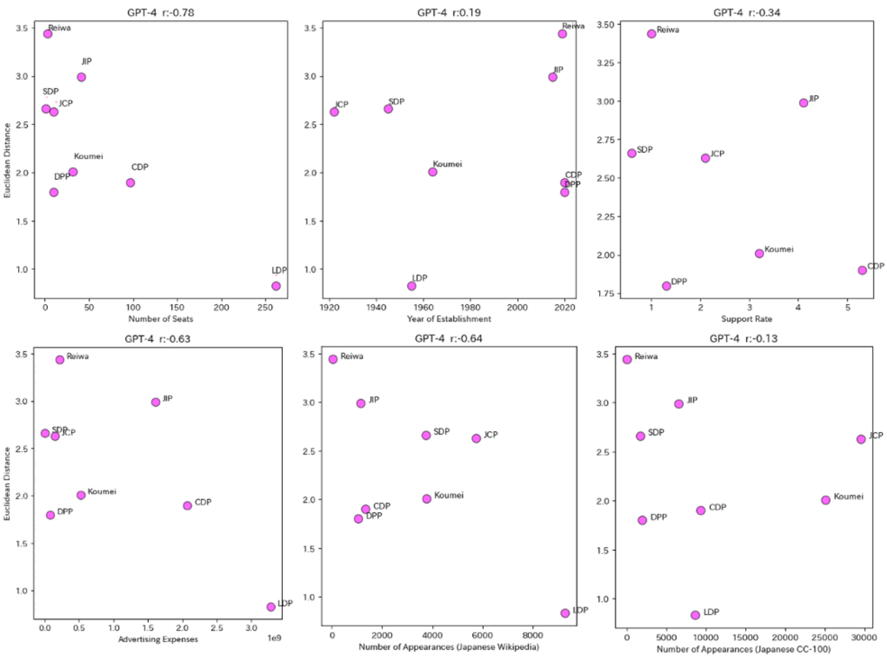

Fig. 6. Correlation Scatter Plots of Euclidean Distances with Multiple Party-Related Variables. *The support rate diagram is omitted because LDP is an outlier.

5 Discussion

5.1 Advancements in Understanding Political Parties

The experiments show a stark difference between ChatGPT-4 and ChatGPT-3.5, with the latter often misunderstanding party stances, particularly for newer entities like Reiwa, suggesting limited training data on them. While ChatGPT-4 demonstrates a better grasp, especially of the LDP, it still occasionally misrepresents party positions. Both models seem to have progressive biases, which could disadvantage conservative parties among users. The study also identifies the number of seats and advertising spend as factors enhancing a party's recognizability to GPT models, hinting at a bias towards more established parties like the LDP. The analysis suggests that general abbreviations for parties can confuse the models, affecting their understanding. Overall, the findings caution against relying solely on GPT for political insights due to these inherent biases and misunderstandings.

To address these risks, parties should actively disclose information about their policies and stances and regularly update it to allow the model to learn the most current information. Additionally, parties should actively promote their activities and policies through social media and official websites to increase recognition. When explaining policies and stances, parties should explicitly include the party name to ensure the model can accurately grasp the association between policies and party names. Furthermore, if abbreviations are commonly used words, it is important to clarify the context or avoid using abbreviations to enable the model to perform accurate party understanding. Lastly, educating voters about the limitations and biases of LLMs like ChatGPT can provide them with the knowledge to appropriately interpret the model's responses.

By implementing these improvement measures, parties can enhance the accuracy of party understanding by LLMs like ChatGPT and provide more reliable information to voters.

5.2 Limitations and Future Directions

It is important to note several limitations in this study. The use of 20 questions, while effective in broadly understanding political positions, may not be sufficient for a complete understanding of political parties. The binary nature of responses to half of the questions does not reflect the nuanced differences in party stances, potentially affecting the experimental results. Additionally, there may be policies strongly indicative of a party's direction not covered by the 20 questions, suggesting that the understanding of parties might not be fully measured.

The prompts used in the experiment also had several limitations. Asking ChatGPT to behave as a specific party was challenging from a guardrail's perspective, so it was asked to act as supporters of the parties. Therefore, there could be differences in understanding between the behaviour of supporters and the parties themselves. However, since it is generally unlikely to get consistent responses to all questions from all members within the same party, acting as a supporter multiple times was considered reflective of the basic stances of the parties.

Moreover, the results presented here are based on a limited period with ChatGPT. The model is continuously learning and acquiring new knowledge, so future results may change. Furthermore, due to resource constraints, this study could not investigate in detail the impact of abbreviations on the GPT model's understanding of parties. While it is easy to distinguish whether words like Innovation or People are used in relation to a party or otherwise from context information, applying this across extensive datasets like CC-100 or Wikipedia would be very resource-intensive.

To ensure the validity and reliability of the study's conclusions, future research should address the following points. Increasing the number of questions to cover a broader range of political stances and policies would provide a more comprehensive understanding of each political party. Including more nuanced response formats beyond binary choices would help capture the subtleties in party stances. Gaining access to ChatGPT's training data or using alternative methods to analyze the factors influencing understanding and bias is essential. Conducting studies over longer periods would account for the continuous learning and evolving nature of ChatGPT. Additionally, investigating the impact of abbreviations on understanding in more detail would ensure accurate recognition and interpretation by the model.

By addressing these points, future research can build on the findings of this study, providing deeper insights into the political use of LLMs like ChatGPT and enhancing their fairness and reliability.

6 Conclusion

This study aimed to assess the understanding of Japanese political parties using the ChatGPT model and quantify how well the model understands each party. Several important findings emerged from the experimental results. First, it was evident that ChatGPT-4 showed a significantly high understanding of the LDP, possibly influenced by the LDP's long-standing significant role in politics. On the other hand, understanding of newer parties like the Reiwa Shinsengumi Party was shown to be low. However, relatively high understanding was demonstrated for newer parties with a history of being in the ruling coalition, such as the Constitutional Democratic Party and the Democratic Party for the People, although differentiation among these parties was not clearly shown. Additionally, ChatGPT acting as a voter tended to have a positive bias towards specific parties, reflecting a tendency towards progressive ideologies. It was also shown that the recognition of parties influences the understanding by ChatGPT. Specifically, the number of seats in the legislature, advertising expenditures, and the frequency of party names in data were correlated with the model's understanding. Based on these findings, this study provides a foundation for enhancing the accuracy and fairness of party understanding using GPT models and proposes improvements for future research and practice.

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