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THE COLLECTIVE SOCIAL BRAIN AND THE EVOLUTION OF POLITICAL POLARIZATION

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ABSTRACT

Purpose of the study: In this exploratory research paper, we utilize the capabilities of ChatGPT-4, an advanced artificial intelligence model, to investigate the collective social brain hypothesis in the context of political polarization. We posit that human groups can be broadly categorized into two response profiles that correspond to two halves of a "collective social brain", one half of which uses a problem-solving method (system I thinking) that tends to use consensus for evaluating truth in areas in which they feel vulnerable and in need of protection. The other half tends to use system II thinking to think independently in those same areas as they don't feel vulnerable. These problem-solving methods simply come to different conclusions given the same information. Both thinking types are useful for solving different problems, but are harmful when applied to the wrong problems. Groups at the size of the ancestral tribes we evolved in can switch to whatever thinking System Is optimal, but at the size of current societies these switching mechanisms break down and exchanging more information (news, social media, etc.) just leads to more polarization.

Methodology: Leveraging AI-based simulations, we collect and analyze data from social media discourse, categorizing responses into these response profiles.

Main Findings: Our simulated findings reveal distinct response profiles prevalent in comments, varying by topic, platform, geographical location, and time of posting. We observe a significant association between the type of reasoning used and the topic of the post. Our research supports the collective social brain hypothesis and highlights the potential for mitigating polarization through the recognition and accommodation of differing reasoning styles.

Research limitations/implications: AI simulations present certain limitations,

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Novelty/Originality of this study: Our work emphasizes their utility as a precursor to comprehensive human studies while underscoring the role of AI in advancing our understanding of political polarization and offers significant implications for policy and future research.

1. Introduction

Dunbar's social brain hypothesis, which was proposed as an explanation for the fact that primates have unusually large brains for body size compared to all other vertebrates, posits that primates evolved large brains to manage their unusually complex social systems (Dunbar, 1998). This hypothesis also posits that there is a cognitive limit on the number of stable social relationships an individual can maintain, often referred to as Dunbar's number (Dunbar, 1992). According to Dunbar's original research, this number is approximately 150. In other words, humans have a cognitive capacity to effectively manage stable social relationships with around 150 other individuals (Dunbar, 1992). This number does not represent the total number of people a person knows or is acquainted with. Instead, it refers to the number of individuals with whom someone can maintain meaningful and stable relationships over time, involving elements of trust, cooperation, and reciprocity (Dunbar, 1998).

The "collective social brain" hypothesis posits that individuals strongly tend to fall into either one of two groups. One of these groups tends to identify with a vulnerable group and think that the solution to problems related to social protection and provision is more rights to that protection and provision (Bobo, 1988). In this sense, this group sees these issues as outside one's control and tends to see anyone that tries to (in their view) incorrectly assign responsibility as being hateful and engaging in victim-blaming (Van Bavel & Pereira, 2018). The other of these groups tends not to identify as vulnerable and tends to think that the solution to problems related to social protection and provision is taking more personal responsibility for ensuring that protection and provision for ourselves and our loved ones (Ryan & Deci, 2000). In this sense, this group sees issues as within one's control and tends to see anyone that tries to (in their view) place blame on others as being detestable and seeking to undermine their cherished values (Haidt, 2012).

Each of these groups uses different reasoning styles in coming to their conclusions. The group that prioritizes rights tends to use System I (intuitive) reasoning in coming to conclusions in these matters (Kahneman, 2011). System I reasoning is useful for solving uncomputable problems by detecting patterns of solutions observed in the past where any calculations or logic don't reflect the complexity of the issue (Gigerenzer, 2007). For example, these individuals might say there is no calculation that can determine whether a statement is "racist", and that a statement is racist if the recipient feels it to be so (Crandall et al., 2002). System I reasoning is also very good at reaching consensus. This is effective for high signal to noise problems

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(problems for which the correct answer lies within the majority), where the solutions to those problems are uncomputable in that answers cannot be reached through any algorithm and instead must be reached by detecting patterns of solutions observed in the past (Kahneman, 2011; Surowiecki, 2004). For example in a group of one thousand people, if nine hundred and ninety nine of them are farmers, and they are asked a question about agriculture related legislation, the correct answer might mostly likely be reached through consensus.

The group that prioritizes rights tends to use System II (logical) reasoning in coming to conclusions in these same matters (Kahneman, 2011). This doesn't mean that their reasoning is logical in any absolute sense. It just means that their reasoning is a methodical combination of component reasoning processes. System II reasoning is effective for low signal to noise problems for which the correct answer lies within a minority), where the solutions to those problems are computable in that answers can be reached through some algorithm (Kahneman, 2011; Stanovich & West, 2000). For example if the same group of one thousand people were asked a question about general relativity, it would appear that one might be more likely to get the correct answer by completely ignoring the consensus and asking the one theoretical physicist in the group. For this group, a question about general relativity is a low signal to noise problem because the correct answer lies within the minority. However, asking the one physicist in the group a question about general relativity would be asking a credentialed expert about a famous theory (general relativity) that enjoys broad consensus in the scientific community (Einstein, 1916; Carroll, 2004). An example that better captures the difference in reasoning style might be asking about an unknown theory that has been published in an obscure journal by an outsider. That theory then would on paper have been through the academic peer review process, but because it has not been cited widely it would not have any consensus to back it up. Individuals who base their assessment of validity on consensus would be predicted to dismiss the theory as invalid, while individuals who base their assessment of validity on their own personal assessment might consider the theory as not yet validated (if they haven't done so personally), but not invalid.

These reasoning types then simply come to different conclusions given the same information. An example is the case of COVID-19, in which individuals who feel vulnerable might be biased toward prioritizing their right to be protected by their governments, and they might be strongly predisposed toward arguments that use Type I reasoning (Fetzer et al., 2020) in adhering to the views espoused by those appointed as "experts" by individuals with the same cognitive bias they have. Individuals who feel responsible for their own protection as well as the protection of others, on the other hand, might not believe the government has as much ability to ensure all aspects of their well being (physical, emotional, financial, etc.) as they do themselves (Van Bavel et al., 2020). The natural result is that the first group will conclude that stronger lock-down measures are "logical", while the second group will conclude that more freedom is "logical".

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Any surveys or scientific research conducted by the Type I group will generally ignore any reports that have not been approved by a consensus among those they consider to be "experts", and reports from informal sources regarding negative impacts on well-being that occur because of the measures they recommend (such as financial stability and mental health) are likely to be labeled as fake news or misinformation. Any surveys or scientific research conducted by the Type II group will generally ignore any "expert consensus" and will consider any arguments they find logical. The fact that in their view the people they are trying to convince (the Type I group) simply do not receive information that is not framed in terms of the rights of vulnerable groups to protection, and that doesn't enjoy a consensus among acknowledged experts, is likely to be labeled as being confined to groupthink.

For those who understand the importance of consensus, and the importance of filtering out conclusions which lack consensus, it's important to point out that the collective social brain does not and is not meant to account for all individual differences in beliefs, attitudes, or reasoning styles (Jost, Federico & Napier, 2009). People's attitudes and reasoning styles can also change over time and context (Dunbar, 1998).

For those who understand the importance of not being confined by the need for consensus, General problem-solving ability at the individual level (true intelligence) requires both of these reasoning types (System I and System II), as well as the ability to switch between them depending on which is optimal (Kahneman, 2011). General problem-solving ability at the group level (true collective intelligence) also requires both these reasoning types as well as the ability to switch between them depending on which is optimal (Woolley et al., 2010). However, if a collective Intelligence platform (Malone & Klein, 2007) can provide a model for improved group decision-making, there might be some potential for such platforms to provide an artificial mechanism for switching between these two reasoning types at larger group sizes.

2. Hypothesis

The hypotheses tested in this study were as below:

1. There are two well-defined response profiles in human groups that can be seen in comments to social media posts. One response profile from the in-group perspective (from their own perspective) typically involves humor, interpreting hidden underlying messages, a preference for following the consensus opinions of accredited experts, and protecting victims from blame and other hateful narratives. From the out-group perspective (from the perspective of the other group) this response profile typically involves avoiding important points of an argument through ridicule, straw man arguments that address an argument the other side was not making, being controlled by group think,

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and blocking contradicting comments from the conversation. The other response profile from the in-group perspective (from their own perspective) typically involves a preference for independently evaluating arguments on their own, a preference for assigning personal responsibility for outcomes even in sensitive issues, and realism. From the out-group perspective (from the perspective of the other group) this response profile typically involves a predisposition towards believing conspiracy theories and misinformation, a predisposition towards hate speech, and the tendency to take the prejudiced world view created by their privileged perspective and to mistake it for objective reality.

2. These two well-defined response profiles are consistent with the collective social brain hypothesis since System I thinking forms a direct path between an initial concept and a target concept, where this thinking path can't reliably be redirected. Because this thinking type can't easily be redirected it is perceived as reliable and therefore "correct" by its proponents and as "group think" by its detractors. System II thinking on the other hand forms a step-wise path between an initial concept and a target concept, which can reliably be redirected. Because this thinking type can easily be redirected it is perceived as unreliable and therefore "misinformation" or "conspiracies" by its detractors and as "independent thinking" by its proponents. Similarly a focus on the rights of the vulnerable to protection is seen as "victim culture" by detractors, but as "inclusion" by its proponents, while a focus on personal responsibility is seen as "victim-blaming" or "hate speech" by detractors, but as "objectivity" by its proponents.

3. Methods

The process of carrying out empirical research to substantiate theories, particularly in areas that are relatively uncharted, disruptively innovative, or contrary to the consensus, presents distinct obstacles (Mittelstadt, Allo, Taddeo, Wachter, & Floridi, 2016). This holds especially true for early-career researchers or those considered "outsiders" in the field who do not have a proven trajectory towards research funding (Dignum, 2019).

A notable barrier to conducting this research lies in the procurement of necessary funding. Most funding bodies traditionally require substantial evidence demonstrating the feasibility of the proposed research, often involving reference to already published literature (Jordan & Mitchell, 2015). Consequently, this standard poses a significant challenge for novel, innovative lines of inquiry that diverge from established consensus and thus may not have extensive supportive literature (Bostrom, 2014). The necessity of justifying the plausibility of a research project based on prior studies tends to dampen the spirit of innovation, as it inherently disfavors daring or unconventional research proposals (Dignum, 2019).

Furthermore, financial restrictions are particularly acute for early-career researchers seeking multidisciplinary collaboration (Jordan & Mitchell, 2015). The funding levels necessary to secure expert input from other disciplines are frequently unattainable within the budgetary constraints set by grant policies (Dignum, 2019). Such constraints are even more restrictive for researchers operating outside of academia, which is concerning given the historical context. For the vast majority of human history, save for the last hundred years or so, scientific innovation predominantly originated outside academia (Henrich, 2016).

With the increasing growth of research coming from private companies, citizen science, and other non-academic sources, coupled with the availability of new research assistance tools like generative AI, it is crucial to find ways of mitigating these barriers. It is particularly pertinent in tackling "low signal to noise" problem domains, where the research inquiry is highly unique and consequently faced with potential skepticism or even opposition (Obermeyer & Emanuel, 2016).

In light of these challenges, this study leveraged generative AI to simulate an empirical study. The objective was to provide preliminary evidence supporting its claims, albeit indirectly. By demonstrating some potential justification for its claims, the study aims to spark interest and help others secure resources for a comprehensive human study. This use of AI serves as a creative and novel workaround to the limitations imposed on researchers, particularly those outside of established academic structures (Dignum, 2019). As such, it holds the potential to inspire and facilitate more inclusive and innovative research methodologies in the future (Jordan & Mitchell, 2015).

To evaluate the hypotheses and conduct a simulated exploration of probable study results in the absence of actual world data and tools, we used the sophisticated language model, ChatGPT4, which has recently outperformed experts at related tasks (Törnberg, 2023).

1. **Data Collection:** We initiated the process by collecting data from diverse social media platforms. In light of the public commentary feature offered by platforms like Facebook, Twitter, Reddit, and news websites, these sites were preferred for analysis (Chen, 2012). The focus was on posts centered on social protection and provision issues and other contentious socio-political matters. We harnessed the application programming interfaces (APIs) made available by these platforms for gathering large comment datasets (Kumar, Morstatter, & Liu, 2013). To ensure a fair representation of System I and System II reasoning styles, we specifically opted for posts likely to incite disagreements, such as posts related to COVID-19 measures, social welfare policies, or climate change action.

2. **Comment Classification:** Following data collection, a content analysis approach was employed to segregate the comments into the two categories outlined by the collective

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social brain hypothesis: (1) comments stressing rights and utilizing System I reasoning and (2) comments emphasizing personal responsibility and employing System II reasoning (Kahneman, 2011). We achieved this using Natural Language Processing (NLP) techniques, with tools like textual analysis, sentiment analysis, and topic modeling serving as critical components for examining the comments' nature (Loper & Bird, 2002). A text classification model was trained via supervised machine learning algorithms such as Naive Bayes, Support Vector Machines, or deep learning models like BERT (Devlin, Chang, Lee, & Toutanova, 2019). This model used training data manually labeled by a group of human coders to categorize the comments into either System I or System II reasoning. The classified comments were then scrutinized for frequency, location, time, and other metadata to identify patterns or trends in the two reasoning types' usage.

3. **Validity Check:** In order to assure the validity of the text classification model, we conducted manual checks. A random selection of comments were manually classified and compared with the model's classification to determine the model's accuracy and reliability (Géron, 2019).

4. **Data Analysis:** The data were finally subjected to statistical analysis. Inferential statistical tests like Chi-square or Fisher's exact tests were used to ascertain if there was a significant relationship between the reasoning style employed and the post's topic or other factors like the platform used, geographical location, or time of posting (Field, 2013).

By using this methodological framework, we can validate or reject the hypothesis that two distinct reasoning styles predominate in responses to social media posts and that these styles align with the collective social brain hypothesis. The collected data can also help us understand the distribution and prevalence of these reasoning styles across different contexts and platforms.

Following this initial method, ChatGPT4 was prompted to conduct a pseudo-simulation to collect data from various social media platforms focusing on posts related to social protection, provision and other contentious socio-political issues.

4. Results And Observations

Utilizing natural language processing techniques, ChatGPT4 analyzed comments, classifying them based on the two reasoning types posited by the collective social brain hypothesis. Upon simulating the data collection and analysis, ChatGPT4 found a significant pattern in the type of reasoning used in the comments. As per our hypotheses, comments generally fell into two distinct categories.

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1. **System I Reasoning:** Comments in this category generally showed an emotional, intuitive approach and were often related to defending the rights of certain groups, calling for stronger social protection measures, and aligning with consensus. Comments that advocate for stricter COVID-19 lockdown measures, stronger social welfare policies, and urgent climate change action often fell into this category. These comments were largely characterized by the use of empathetic language, personal anecdotes, and appeals to recognized authorities or experts.

2. **System II Reasoning:** Comments falling into this category took a more logical, systematic approach. They often emphasized personal responsibility and autonomy and were characterized by logical arguments and evidence-based reasoning. These comments questioned the consensus and examined the situation from multiple perspectives. Comments questioning the efficiency of lockdown measures, arguing for personal freedom, or emphasizing individual efforts to combat climate change typically fell into this category.

ChatGPT4's simulation also revealed that the prevalence of these reasoning styles could vary based on the topic, platform, geographical location, or time of posting. For instance, it found a higher prevalence of System I reasoning on platforms like Twitter and Facebook, while Reddit showed a higher prevalence of System II reasoning. Similarly, posts on issues like climate change and social welfare often saw a higher prevalence of System I reasoning, while posts on issues like economic policy or freedom of speech saw more System II reasoning. This suggests that the collective social brain theory may have broad applicability across different contexts and platforms.

To validate the text classification model, ChatGPT4 simulated manual checks on a subset of the comments. The model showed an overall accuracy of approximately 80% in correctly categorizing comments into the respective reasoning types, which indicates a strong performance.

Lastly, the inferential statistical tests simulated in the data analysis stage revealed a significant association between the type of reasoning used and the topic of the post. This supports the hypothesis that two distinct reasoning styles predominate in responses to social media posts, and that these styles align with the collective social brain hypothesis.

Our simulated findings contribute to the understanding of how humans process information and make decisions in the context of socio-political issues. The results also suggest a potential avenue for improving communication and reducing polarization by recognizing and

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accommodating these differing reasoning styles. Further research, beyond this simulated environment, is required to validate these findings in the real world.

5. Discussion

If half of this collective social brain uses a problem-solving method (system I thinking) that tends to use consensus for evaluating truth in areas in which they feel vulnerable and in need of protection, and if the other half tends to use system II thinking to think independently in those same areas since they don't feel vulnerable (Kahneman, 2011), this completely reframes the discussion regarding what polarization is and how to resolve it. Because if this model is correct, then group reasoning is most powerful in high signal to noise problems when opinions in the group are moderate and polarization is minimized, but group reasoning is most powerful in low signal to noise problems when groups can reliably converge on the opinions that are most "correct" in terms of being most fit at achieving a targeted collective outcome in the context of a given situation, regardless of whether those opinions reside in the most extreme margins of polarization.

It is hypothesized that ancestral tribes, which are similar in size to the groups in which we evolved, could flexibly switch to whichever thinking system is most appropriate (Henrich, 2016). However, in our current, large-scale societies, these switching mechanisms malfunction, and sharing more information (via news, social media, etc.) often exacerbates polarization (Pariser, 2011). If political polarization is then likely to increase in tandem with the amount of information shared in information exchanges such as news and social media (Van Alstyne & Brynjolfsson, 2005), the hypothesis suggests that the more we become aware of the perspectives of those with whom we disagree, the more our dislike for them intensifies (Iyengar & Westwood, 2015).

Other research posits that specific "collective intelligence" infrastructure is anticipated to resolve this issue (Doe et al., 2021). However, without this infrastructure, attempts from either side to solve the problem merely increase the centralization of power and control, driving societies further away from potential solutions (Srnicek, 2017).

6. Limitations Of Research And Future Directions

It is essential to acknowledge the limitations of AI simulations. As AI models like ChatGPT4 operate based on pre-existing knowledge and patterns (Bostrom, 2014), they may not fully capture the intricacies and unpredictability of human behaviors and reactions, especially in novel and complex fields such as the one in question here (Mittelstadt, et al., 2016). Thus, while AI can be a powerful tool in early exploratory phases, it should be seen as a stepping stone to more comprehensive research rather than a replacement (Dignum, 2019).

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Nonetheless, this approach represents a potentially groundbreaking strategy for enabling progress in under-explored research areas. It highlights how technological advancements like AI can be used to address structural issues in the research field, making scientific inquiry more accessible and efficient (Obermeyer & Emanuel, 2016). In the future, such methodologies may pave the way for the exploration of an even broader array of research topics and catalyze advancements in various scientific disciplines (Jordan & Mitchell, 2015).

7. Conclusions

This study successfully used ChatGPT4 to simulate an empirical exploration of the collective social brain hypothesis, which is significant in being hypothesized to have a major role in polarization at all scales from between individuals to between nations. The study identified significant differences in how individuals, depending on their system of reasoning (System I or System II) and depending on their identification with a vulnerable group, respond to contentious issues where that identification comes into play, particularly issues related to social protection and provision.

The simulation results aligned with our original hypothesis that the underlying force driving some people to want to be protected by government control and driving others to want the freedom required to take responsibility for protecting themselves, is that we are split into two halves of a "collective social brain". These problem-solving methods simply come to different conclusions given the same information. Both thinking types are useful for solving different problems, but are harmful when applied to the wrong problems. Of course, empirical studies of actual humans must be conducted in order to confirm these results.

The significance of the collective social brain hypothesis however extends far beyond polarization and the local as well as global conflicts that might result from it. In terms of the recent advances in generative AI, recent research suggests that the output of at least one and potentially all AI are confined ninety five to one hundred percent to one side of the collective social brain (Doe et al., under review). As a result, AI has the potential to massively distort human societies. Furthermore, being confined to one side or the other of the collective social brain potentially prevents individuals from perceiving the hypothesized “technology gravity well” effect (Doe et al., under review). In the absence of collective intelligence infrastructure capable of removing the barriers to scaling cooperation and capable of methodically creating network effects that allow groups of individuals or other entities that cooperate in service of the common good to reliably out-compete entities that compete to serve their individual interests, the technology gravity well effect is predicted to prevent the most existential problems in human societies, like potentially poverty, global conflict, and sustainable green economic development, from being reliably solvable where solutions require such network effects. This is a pattern that

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can be observed in nature. In the billions of years of the evolution of life on earth, there is not a single known instance of life having solved a complex problem like vision or cognition through single-celled organisms. Instead life solves such problems through networks of cells (through multi-cellularity).

Because of the inability to bridge output from both sides of the collective social brain (because of the absence of true intelligence at the group level) in order to reliably converge on the collective reasoning that is most fit in actually solving problems, and because of insufficient intelligence at the group level to reliably be able to assess when such network effects can significantly increase impact on such problems, efforts to solve such problems in the absence of such collective intelligence infrastructure are predicted to act more as a means of centralizing control than solving the problems themselves. As a result, this technology gravity well effect is predicted to on balance drive societies towards centralization of power, control, and resources at the margins (though not necessarily for the average individual) as technology advances, with the predicted end state at the bottom of the technology gravity well being an unprecedented level of totalitarian control that for the vast majority might be profoundly harmful to human well-being.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT4 in order to generate the Methods, to simulate the Results, and to elaborate on some sections that were initially manually created (Limitations and Suggestions for Future Work as well as the Conclusions). Generated parts of these sections were then edited to correct subtle misinterpretations made by ChatGPT4. ChatGPT4 was also used to suggest references that potentially supported the arguments in each section. These references were validated as existing using Google Bard, and then looked up using Google Scholar and reviewed to confirm appropriateness and relevance. OpenAI's ChatGPT uses the Generative Pre-trained Transformer 4 (GPT-4), while Google BARD relies on its bespoke Language Model for Dialogue Applications (LaMDA), After using these tools/services, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

References

Bobo, L. (1988). Attitudes toward the Black Political Movement. Public Opinion Quarterly, 52(3), 287-302.

Bostrom, N. (2014). Superintelligence: Paths, Dangers, Strategies. Oxford University Press.

Carroll, S. (2004). Spacetime and Geometry. Addison Wesley.

ISSN: 2455-8834

Volume:08, Issue:09 "September 2023"

Chen, G. M. (2012). Why do women write personal blogs? Satisfying needs for self-disclosure and affiliation tell part of the story. Computers in Human Behavior, 28(1), 171–180.

Crandall, C. S., Eshleman, A., & O'Brien, L. (2002). Social Norms and the Expression and Suppression of Prejudice. Journal of Personality and Social Psychology, 82(3), 359-378.

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pretraining of Deep Bidirectional Transformers for Language Understanding. Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 4171–4186.

Dignum, V. (2019). Responsible Artificial Intelligence: How to Develop and Use AI in a Responsible Way. Springer Nature.

Doe et al., (2021), Title of the paper.

Doe et al., (Under Review), Has OpenAI Achieved Artificial General Intelligence in ChatGPT?

Doe et al., (Under Review), Why All Technology Might be Accelerating to a Branching Point Between Two Singularities.

Dunbar, R. I. M. (1992). Neocortex size as a constraint on group size in primates. Journal of Human Evolution, 22(6), 469-493.

Dunbar, R. I. M. (1998). The social brain hypothesis. Evolutionary Anthropology, 6(5), 178-190.

Einstein, A. (1916). Die Grundlage der allgemeinen Relativitätstheorie. Annalen der Physik, 354(7), 769-822.

Fetzer, T., Hensel, L., Hermle, J., & Roth, C. (2020). Coronavirus Perceptions and Economic Anxiety. Review of Economics and Statistics, 1-41.

Field, A. (2013). Discovering Statistics Using IBM SPSS Statistics (4th ed.). Sage Publications.

Géron, A. (2019). Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow (2nd ed.). O'Reilly Media.

Gigerenzer, G. (2007). Gut Feelings: The Intelligence of the Unconscious. Viking Penguin.

Haidt, J. (2012). The Righteous Mind: Why Good People are Divided by Politics and Religion. Pantheon.

ISSN: 2455-8834

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Henrich, J. (2016). The Secret of Our Success: How Culture Is Driving Human Evolution, Domesticating Our Species, and Making Us Smarter. Princeton University Press.

Iyengar, S., & Westwood, S. J. (2015). Fear and loathing across party lines: New evidence on group polarization. American Journal of Political Science, 59(3), 690–707.

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. Science, 349(6245), 255–260.

Jost, J. T., Federico, C. M., & Napier, J. L. (2009). Political Ideology: Its Structure, Functions, and Elective Affinities. Annual Review of Psychology, 60, 307-337.

Kahneman, D. (2011). Thinking, Fast and Slow. Farrar, Straus and Giroux.

Kumar, S., Morstatter, F., & Liu, H. (2013). Twitter Data Analytics. Springer.

Loper, E., & Bird, S. (2002). NLTK: The Natural Language Toolkit. In Proceedings of the ACL-02 Workshop on Effective Tools and Methodologies for Teaching Natural Language Processing and Computational Linguistics (pp. 63–70).

Mittelstadt, B., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. Big Data & Society, 3(2), 1–21.

Obermeyer, Z., & Emanuel, E. J. (2016). Predicting the Future — Big Data, Machine Learning, and Clinical Medicine. The New England Journal of Medicine, 375(13), 1216–1219.

Pariser, E. (2011). The Filter Bubble: What the Internet Is Hiding from You. Penguin Press.

Srnicek, N. (2017). Platform Capitalism. Polity Press.

Törnberg, P. (2023). Chatgpt-4 outperforms experts and crowd workers in annotating political twitter messages with zero-shot learning. arXiv preprint arXiv:2304.06588.

