IMPACT OF ARTIFICIAL INTELLIGENCE ALGORITHM BIAS ON POLITICAL POLARIZATION IN GEORGIA

by

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Abstract

This paper evaluates the impact of artificial intelligence algorithm bias on political polarization in the state of Georgia. As artificial intelligence (AI) algorithms play an increasing role in shaping user experiences, this study focuses on how biased data can contribute to political polarization. The research examines the potential consequences of algorithms presenting users with information that aligns with their pre-existing beliefs, leading to increased polarization. Addressing questions about the formation of echo chambers and the user's awareness of political skew in the information they read, the study aims to understand the direct impact of AI algorithm bias on individual political perceptions. The methodology involves a Likert scoring system survey administered to 200 participants in Georgia, exploring their understanding of algorithm bias and political impacts. The paper underscores the need for awareness and scrutiny regarding AI algorithm bias, shedding light on its potential role in shaping political discourse.

Keywords: Artificial Intelligence, AI, bias, politics, understanding, polarization, echo chamber

Introduction

Artificial Intelligence (AI) and the algorithms responsible for their behavior are growing in utilization in virtually every industry (Mendes, 2022). The Organisation for Economic Co-operation and Development (OECD) defines an AI system as: "an AI system is a machine-based system capable of influencing the environment by producing an output (predictions, recommendations, or decisions) for a given set of objectives. It uses machine and/or human-based data and inputs to (i) perceive real and/or virtual environments; (ii) abstract these perceptions into models through analysis in an automated manner (e.g., with machine learning), or manually; and (iii) use model inference to formulate options for outcomes. AI systems are designed to operate with varying levels of autonomy" (OECD 2019).

However, what if the data that is being used to produce an output is skewed? What if the data that the AI is analyzing is politically motivated? What if algorithms make a predictive determination to provide the user with information that it has calculated they most likely want to see versus unbiased information or opposing viewpoints?

The following paper will discuss the problem of the impact artificial intelligence algorithm bias can have on political polarization. It will define the purpose of the study, and the research questions for the study, and evaluate the impact of artificial intelligence bias on the reader's political views.

AI algorithms can analyze vast amounts of data including social media posts, news articles, online discussions, and articles that were created to shape public opinion. AI algorithms look for patterns in large amounts of data to make judgments as to how to respond to requests that they were not explicitly programmed to provide (König & Wenzelburger, 2020). If the information that the algorithms have evaluated is biased, then the algorithms themselves may become biased and disproportionately target specific groups based on political ideology, race, gender, or socioeconomic status (Peters, 2022). This bias could lead to opinion manipulation through the creation of echo chambers, political suppression, and amplification of political polarization.

Algorithmic political bias occurs when the output of an AI algorithm results in one group being discriminated against or privileged based on political affiliation (Peters, 2022). Consumers of information being presented to them through AI algorithms need to be aware of the potential for non-balanced and politically skewed information being presented based on algorithmic determinations created through bias and AI analysis of gathered user-preference data (Calice et al., 2021).

The purpose of this study is to understand how artificial intelligence algorithm bias can directly impact politics through the information that it presents to users. It will examine the understanding level of users as to the level of political skew that is being presented to them by algorithms, the level of confidence that the users have in the information provided, and how it impacts their political perceptions. This research will answer the following questions:

RQ1: Does political ideology have an impact on the reader's confidence in the information AI presents them?

RQ2: Do people of different political ideologies have a higher belief in their understanding of AI information curation?

RQ3: Does education level impact an individual's belief in understanding how AI information is curated?

This research will contribute to the knowledge of how Artificial Intelligence algorithm bias and the consumers of information that has been curated by it, could impact the political perceptions by gauging their confidence and understanding of AI curation. The research will also provide insight into the understanding of how education and political ideology impact the user's views on how content is provided and their perceived understanding of how AI algorithms function.

The research structure is as follows. There will be a review of existing literature that discusses the current knowledge of artificial intelligence algorithm bias and its impact on political polarization. This literature review will be followed by a detailed presentation of the proposed methodology, where research steps, data sources, and analytical techniques that will be used in the research will be discussed.

Review of the Literature

Artificial Intelligence and Machine Learning

Artificial intelligence (AI) systems and the machine learning (ML) algorithms that power them are used to find patterns in large amounts of data to automate both simple and complex processes (Peters, 2022). These systems that make decisions through predictive analysis and incorporate feedback to improve their performance are growing in adoption in most economic sectors (Lee et al., 2019). According to Fazelpour and Danks (2021), predictive algorithms are increasingly impacting lives through their influence on key social and personal decisions. Algorithms today follow the 1948 cybernetic theory introduced by American mathematician and professor at Massachusetts Institute of Technology, Norbert Wiener. Wiener's cybernetic theory maintained that learning through feedback adaptation would increase the performance of systems (Ünver, 2018).

Algorithmic Function

Machine learning algorithms learn through the data that they are trained to emulate human behavior (Ünver, 2018). These algorithms are fed large amounts of data sets, which also give the appropriate output, which is referred to as training data. Training data is used to predict correct outputs for future requests (Lee et al., 2019). Search algorithms, for example, will use the search query to predict the most likely relevant results for a given search, and the algorithms will provide future suggestions based on what the initial and subsequent queries were (Ünver, 2018). According to Lee et al. (2019), algorithms use collected data to make inferences about people and their preferences, demographics, interests, and likely future behaviors. Ünver (2018) states that the social tracking and monitoring of social profile behavior patterns are also used by algorithms to make decisions. According to Petters (2022), many websites employ personalization algorithms to continue to present users with similar content with which they have previously interacted to keep the reader engaged with the site. These algorithmic recommendations or AI judgments are also responsible for providing users persuasive ideas on what they may like to eat, and buy, where to shop, whom to date, what news to read, and many other suggestions that those users assume are reliable and objective (Agudo & Matute, 2021). Though these algorithms are computational, they often enjoy the assumption of accuracy and objectivity; however, they can create biased decisions (Peters, 2022). This highlights the issue of users not understanding how algorithms work to present data and their social power on the users (Beer, 2016).

Algorithm Bias

Algorithm bias can originate from multiple paths where the training data is not fully representative, has a bias in the data, flawed information, programmer bias that is passed to the algorithm coding, or any action that causes a less favorable outcome between groups that have no relevant difference (Lee et al., 2019). Algorithm bias has been studied and shown that systems are capable of creating ethical problems by discriminating based on race, gender, social identity, and other characteristics. However, little research has been done based on political orientation. Society has largely been accepting of political biases, unlike gender or racial biases (Peters, 2022). According to Engstrom et al. (2020), data containing biases or inaccuracies can translate into disparate impact on underrepresented groups and unwanted bias towards the groups. This highlights the need for people to understand how algorithms operate, their influences on the decisions that are made, the information that is presented, and the potential bias that is included in the algorithm (Beer, 2016).

Perceptions of Media Bias

Perceptions of algorithm media bias and news bias have been largely claimed by politicians claiming unfair treatment or leaning towards the opposite party without evidence (Calice et al., 2021). Individuals of both left and right-leaning political views have similar reasons for concern over the political bias of algorithms, media, and news (Peters, 2022). However, according to Hassell et al. (2020), their study of both national and local news outlets showed there was no evidence of ideological bias or gatekeeping when journalists choose what news stories to cover. Though most people do not understand how algorithms impact the news that they see, almost three-quarters of Americans indicated that they believe that social media intentionally censors political viewpoints (Calice et al., 2021) while only twenty percent believed that media sources would report news without a bias in coverage (Hassell et al., 2020). Partition ques, despite no evidence of bias, are given a higher degree of credibility by users when claims of bias are made by someone in the party that the reader associates with (Calice et al., 2021). Despite this view from individuals, the study by Hassel et al. (2020) found no evidence to show that liberal or conservative candidates were disadvantaged by media sources regardless of the political alignment or leaning of the journalist. Studies have also shown that many individuals are skeptical of the objectivity of news media they are presented that is algorithm curated as they believe these algorithms restrict what they see because of their bias (Calice et al., 2021). More likely is the impact that algorithms have on what news users see in their online feeds than the bias of any news itself (Ünver, 2018). Studies have also shown that many individuals cannot differentiate between curated news personalization and targeted advertising that is displayed when they are on websites, search engines, or social media platforms (Calice et al., 2021).

Engagement

Machine learning algorithm news curation plays a larger role in what news and information is presented to users despite a common misconception that media bias is responsible for the overall news (Ünver, 2018). The lack of awareness of how these algorithms impact the individual presents the potential for political polarization and influence (Calice et al., 2021). Most algorithms are created to maximize engagement with the site and present content that is most likely to continue to keep a user on the site to maximize profits (Ünver, 2018). The methodology behind the algorithms has the potential to create bias as the programming is designed for engagement and thus provides continual exposure to like ideas, experiences, news, political affiliations, etc. through algorithmic repeated patterns (Beer, 2016). Unless specifically programmed, algorithms do not consider whether the content is positive or negative, true or false, gruesome or feel-good, only the quantifiable maximization of user engagement statistics (Ünver, 2018). This focus on engagement creates 'filter bubbles' which limit the exposure to external views, influences, and cultural, and social connections (Beer, 2016). According to Ünver (2018), the curation of information that is presented to users in news feeds and searches and the drive of technology companies to maximize profitability through advertising revenue that is directly related to user engagement has created algorithmic principles that capitalize on extreme emotional behavior. One area that brings high engagement through the use of emotional behavior is extreme political content which leads to negative cultural interactions that can be seen on all social media platforms but serve the intended purpose of keeping users engaged (Ünver, 2018).

Political Algorithm Use

Political bias is not constrained like gender or racial biases, as there are no social norms to decrease the use of political orientation or views as a means of discrimination. Because of this, unchecked political biases are more likely to be incorporated into algorithms and are much harder to detect and eradicate (Peters, 2022). Algorithms are being employed to drive more aspects of politics as their use has increased through automated targeted political advertising, partisan opinion poll utilization, and the use of engagement algorithms to display polarizing or extreme views that are more likely to result in user interaction (Ünver, 2018). Further amplifying the problem that can occur through political bias is the capability of some algorithms to determine political party affiliation without the user's consent (Peters, 2022).

Political orientation can be used by algorithms to selectively provide specific content to users and ignore or not provide data based solely on the determined political affiliation (Peters, 2022). Furthermore, algorithmic political affiliation determination also can limit opposing views as more similar partisan cues are provided to an individual, the more likely that individual is to adopt those views as their own or form similar opinions based solely on the assumption that they should have the same view because they are of the same political orientation (Calice et al., 2021). If the desire is for algorithms to deliver impartial processing results, the inclusion of political orientation and content filtering, do not follow that performance design (Peters, 2022). Political filter bubbles can intensify partisan hostility towards other parties through algorithmic engagement filtering that continues to present results from more extreme partisan identities (Calice et al., 2021). Tense political activities and the algorithmic design for engagement can also exacerbate the proliferation of misinformation, fake news, and the use of automated bots or accounts to spread this information (Ünver, 2018).

Methodology

Instrument

The instrument that was used in this study was developed by the researcher to gather information from participants regarding their confidence in news curated by AI and their evaluation of how well they believe they understand how AI news curation is completed. Survey questions 1-5 established the demographics of the participants. Questions 6-18 of the instrument utilized a seven-point Likert scoring system to generate quantitative data that could be used to gauge the study participants' understanding of algorithm curation and their confidence in the information they are presented. The seven choices provided were: 1=Strongly Disagree, 2=Disagree, 3=Somewhat Disagree, 4=Neither Agree or Disagree, 5= Somewhat Agree, 6=Agree, 7=Strongly Agree.

Subjects and Procedure

The research was conducted electronically using SurveyMonkey© to administer the survey to a random sampling of 200 participants from the State of Georgia above the age of 18 that were active on social media at least daily and that had acknowledged the participation consent form. This sampling provided a 7.07% margin of error. The participants were notified that their anonymity would be protected. Before the hiring of the research company, the researcher obtained approval from the Institutional Review Board (IRB) to research human subjects. After the study, the researcher inspected the results to ensure data completeness and integrity. During this process, data that was incomplete was removed from the results before analysis of the data.

Data Analysis

The researcher completed a factor analysis with a rotated component matrix to determine relationships between the variables and the factors. This resulted in two components being identified. Component 1 was set as variable Confidence, component 2 was set as variable Understanding. The researcher then utilized one-way univariate analysis of variance (ANOVA) tests and post hoc Tukey HSD tests on the data. Through these tests, the predictor variables, their correlations, statistical significance, and strength of relationships were analyzed.

Results

The results from the surveys were analyzed in IBM SPSS version 29.0.0.0. A factor analysis was completed with a rotated component matrix to determine relationships between variables and factors. This showed loadings that represented the strength and direction of the relationship between each variable and the extracted component which led to two components being identified as presented in Table 1. Component 1 was set as the variable “confidence” and component 2 was set as the variable “understanding.”
In this case, Confidence_AI had a positive loading, indicating a positive association with Component 1, while understanding had a negative loading, suggesting a negative association with Component 1. A correlation analysis was then conducted and presented in Table 2. The correlation analysis indicated a significant positive correlation between confidence in AI and the participant’s view of their understanding $r(198) = .528$, $p<.001$.

Research Questions 1-3 were evaluated utilizing one-way ANOVA to compare the effect of the independent variables on the dependent variables as listed in the tables and results below. For research question one (Table 3) there was a significant mean difference between confidence in AI information presented among political ideology $F(6, 193) = 2.353$, $p = .032$. For research question two (Table 4) the ANOVA results showed a significant difference in user belief of understanding AI curation between different political ideologies $F(6,193) = 2.545$, $p = 0.021$. Finally, research question three (Table 5) indicated there was a significant difference in mean of Understanding scores across education level groups $F(5, 194) = 2.980$, $p = .013$. Analysis of other data compiled from the survey found no additional significant differences that impacted the study.

Table 1: Component Transformation Matrix

Component	1	2
1. Confidence_AI	.755	.656
2. Understanding	-.656	.755

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

Table 2: Correlations

		Confidence_AI	Understanding
Confidence_AI	Pearson Correlation	1	.528**
	Sig. (2-tailed)		<.001
	N	200	200
Understanding	Pearson Correlation	.528**	1
	Sig. (2-tailed)	<.001	
	N	200	200

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3: RQ1- Confidence in AI Comparison Analysis of Variance in Political Affiliation

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	22.851	6	3.808	2.353	.032
Within Groups	312.445	193	1.619		
Total	335.296	199			

Table 4: RQ2- Understanding of AI Curation Analysis of Variance in Political Affiliation

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	19.532	6	3.255	2.545	.021
Within Groups	246.900	193	1.279		
Total	266.433	199			

Table 5: RQ3- Understanding AI Curation Analysis of Variance in Education levels

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	19.003	5	3.801	2.980	.013
Within Groups	247.430	194	1.275		
Total	266.433	199			

Summary

This study found that individuals who had a higher confidence in AI algorithms' selection of information also tended to believe they had a better understanding of how these algorithms work. Conversely, those who believed to have a greater understanding of how AI algorithms functioned exhibited a higher confidence in the information that they were presented with.

Based on the results of the study, political leaning was shown to impact the participant's confidence in the information that they are presented through AI curation and their belief in their understanding of how AI curates the information they see. Participants identifying with a “Right” political ideology had the highest level of confidence in the AI curation of the news they read, of it being the most accurate information available, confidence in the accuracy of the information that is presented to them, and confidence in that information showing balance from all political sides. Participants that identified themselves as “Left” political ideology were less confident in the information that was presented to them through AI curation, the accuracy of that information, and that it was unbiased.

This study also found that those with “Right” leaning political ideology exhibited the highest mean score of the variable understanding, showing that they had a higher belief in their understanding of AI curation as compared to any other ideological groups. The results indicated that they believed they understood how information was suggested to them, how AI algorithms learn the information that is most likely to be interacted with by the reader, and how AI was used to present information that they would continue to read. Those participants who identified themselves as having a “Left” political ideology displayed a lower confidence in their understanding of how AI algorithms curated the news they were presented.

The “Right” leaning participant’s belief that they understood how AI impacted what they were being exposed to and that it was the most accurate raises additional questions of if the participants truly understood the methods of how AI curated the news that was presented. If they continued to only interact with AI curated information that returns only news that aligned with their political views or presented in bias towards their political leaning, this would create political filter bubbles and reaffirm the Fazelpour and Danks (2021) study of how predictive algorithms are increasingly impacting lives through influence. This indicated that those with “Right” political ideologies possibly were not aware of the way AI curation occurred and were less aware of the possible influence than those with “Left” political ideologies.

AI search algorithms continue to provide future suggestions based on the subsequent activities of the user (Ünver, 2018). Thus, someone that has established patterns of interaction with sources that provide bias or support a particular political ideology would continue to be provided information that does not differ from that viewpoint. This study showed users may not have recognized the bias they were being presented and confirms Peters (2022) study that indicated users assume AI suggestions are reliable, accurate, and objective and do not recognize the bias that is being introduced through AI algorithms.

The participants of the study with “Right” leaning political ideology also had the highest confidence in the accuracy of unbiased information presented through AI algorithm curation. When factoring in previous studies such as Ünver (2018) and Calice et al. (2021) that showed AI curation did impact the information users saw in social media feeds and did introduce bias to the users, it is unlikely that the participants were correct in their assumptions that they were reading accurate and unbiased information.

The engagement of individuals with information that was from a source properly aligned politically, regardless of how factual the information was, would have continued to impact AI algorithms and increased it being displayed to more users with like political alignment (Peters, 2022). This could have caused an extreme impact through the exacerbation of misinformation and fake news as it continued to be delivered to readers who were confident that the information was accurate based solely on the higher level of

engagement with information that contained similar views and political alignment. Users were then more likely to adopt the information and views as their own because they are from the same political affiliation (Calice et al., 2021).

The results of the study also showed there were significant differences in the mean understanding scores across education-level groups. Individuals who were high school graduates or equivalent had the highest scores when evaluating their own belief in the understanding of how AI curation functions. They were followed by those with some high school, associate/technical degrees, master's degrees, bachelor's degrees, and doctorates. Education level accounted for a moderate proportion of the variance in understanding scores, suggesting that education level was a relevant factor in predicting the participant's confidence in their levels of AI curation understanding. This indicated that those with higher education were more skeptical of their own understanding of AI algorithms curation of information presented and it being accurate and unbiased.

Future Research

This study focused on the perceptions from the participant's point of view, their confidence, and their understanding of AI algorithmic curation. However, it was demonstrated that belief in understanding does not equal an actual understanding, nor does confidence in information being presented equal accurate unbiased information. This study was conducted as a survey that gathered quantitative data based on the participants' own beliefs and did not test their actual understanding or evaluate the information that they were presented to determine unrecognized presence of political bias.

Additional research could be completed to test the accuracy in understanding of AI curation and the bias that it presents. It should be tested to determine if those who have a strong belief in their own understanding of how AI news curation is accomplished, do understand the process and how different aspects of online presence is used to determine what information is presented. Evaluating information that users believe is accurate and validating those beliefs against factual evidence could also be used to determine if the information that they are confident in is actually accurate.

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