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Can the United States' Google Search Algorithm be Reflective of Implicit Racial Bias?

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ABSTRACT

Given the sociological consensus of systemic and implicit racial bias in many American institutions, the interactions of those systems and their sources with computer science and algorithms, specifically Google Search, are largely unknown. The current literature aiming to research the relationship between implicit bias and computer algorithms, such as “Algorithms of Oppression: How Search Engines Reinforce Racism” by Dr. Safiya Noble and “Race After Technology: Abolitionist Tools for the New Jim Code” by Professor Ruha Benjamin, seems to demonstrate that there is evidence or precedence of computer algorithms having implicit racial bias. Given the current state of the literature on this topic, this study aims to demonstrate whether the United States’ Google Search algorithm is reflective of implicit racial bias. With the hypothesis that the United States’ Google Search algorithm is reflective of implicit racial bias, in order to test this hypothesis, the method would require the collection of data, mean search times, the organization of data into normal distributions, and the use of statistical analysis, hypothesis testing, to determine an algorithmic bias. The results suggest that with specific occupational search queries, Google’s search algorithm seems to have faster mean search times for white occupational search queries than racial minority occupational search queries and tend to be significantly different from occupational search queries and White occupational search queries. Given the evidence performed by hypothesis testing, this research paper assertively concludes that the United States’ Google search algorithm is reflective of implicit racial bias.

Introduction

Pioneering the computer science industry, the web search engine Google Search, created by Google LLC, is the most used web search engine on the world wide web across all platforms, making up about 92.16% of the search engine worldwide market as of November 2020 and averaging 5.4 billion searches per day (Search Engine Market Share Worldwide, 2020; Google Search Statistics - Internet Live Stats, 2020). Google search is a prominent web search engine that has amassed an extensive index of the internet through unsupervised machine learning mining bots called web crawlers (Google, n.d.; Wu et al., 2012). When the user submits a query into the search engine, the query gets processed through several severs that search the index for matching results and uses the algorithm PageRank to determine the relevancy of results (Google, n.d.). After submitting a query, the time shown on the google search page is the time taken for the Google Query processor and PageRank algorithm to retrieve relevant results (Google, n.d.). However, recently, Google search has started to rely on artificial intelligence or machine learning to build more effective software that responds better to internet search queries (what you type in the search box) (Wu et al., 2012). Specifically, with a machine learning method known as deep neural networks; which are comprised of a series of layers of input and output, much of these inputs of information coming from the users or google employees who built these networks through machine learning (Noble, 2018; Wu et al., 2012).

This interaction of applied computer science and society in today’s age is unprecedented. So much so that few computer science pioneers could have foreseen the interaction of implicit racial bias and computer algorithms. Recently, academics such as Professors Ayanna Howard and Jason Borenstein have noticed an intensifying stanch occurrence of implicit bias influencing computer algorithms. Implicit racial bias or implicit bias, more broadly, is a concept held in social identity theory, in which an individual holds impulsive or pre-reflective characterizations of a quality to members of a social out-group or, in this context, another race or ethnicity (Greenwald & Banaji, 1995). These held implicit biases had been shown to influence behaviors even when individuals are unaware of their biases (Greenwald & Krieger, 2006). Implicit racism and google search algorithms inductively relate as there has been current evidence released in popular books such as "Algorithms of Oppression: How Search Engines Reinforce Racism" by Dr. Safiya Noble and "Race After Technology: Abolitionist Tools for the New Jim Code" by Professor Ruha Benjamin, giving relevance to the notion of machine learning algorithms carrying implicit bias through inputs from employees and users. Considering there are few studies on the interaction of implicit bias and computer algorithms, the literature on implicit racial bias and google search's algorithm is much more limited. To address this gap in the literature, the purpose of this research paper is to determine whether the United States' Google search algorithm reflects implicit racial bias through the use of partly similar search queries that each invokes a different race and to use the resulting speeds to determine whether the difference in speed between the search queries are statistically significant or different and thus indicative of implicit racial bias.

Literature Review

The literature on the interaction between implicit racial bias and computer algorithms is relatively novel. This is somewhat due to the interactions between two new late 20th century areas of study, implicit bias theory and computer algorithms. Nonetheless, the literature on the interaction between these two areas is sufficient enough to provide background information for this study. The purpose of this literature review is to provide a theoretical and background understanding behind general algorithmic bias, Google's search algorithm, implicit racial bias, and as well as a review of the recent literature on the interaction between implicit bias and computer algorithms. A brief review of the current literature suggests that there does seem to be clear evidence that computer algorithms are subject to and prone to bias (Thiem et al., 2020; Sun et al., 2020). According to Alrik Thiem and his colleagues in a meta-analysis titled "Algorithmic bias in social research: A meta-analysis," he states that one in three of these algorithms used in social and natural sciences are affected, and one in ten are severely affected by bias in some way. More specifically, according to cybersecurity expert Megan Garcia, author of "Racist in the Machine: The Disturbing Implications of Algorithm Bias," and Professor Ayanna Howard et al. in her paper titled "The Ugly Truth About Ourselves and Our Robot Creations: The Problem of Bias and Social Inequity" there has been several findings of racial and gender implicit bias that has been embedded into algorithms and their implications as well as solutions.

Primarily, the prevalence and evidence of algorithmic computer bias are ostensible and central to this research paper. As stated by university professors Thiem et al. and Friedman et al., there is evidence of algorithmic bias and its prevalence. The presupposition of algorithmic bias provides a fundamental premise to the argument that Google's Search Algorithm may or may not reflect implicit racial bias. To preface, an important question to answer is what is a computer algorithm? According to Sun and his colleagues in their research paper "Evolution and impact of bias in human and machine learning algorithm interaction," a computer algorithm is a set of procedures carried out by a computer's programming to solve a problem or complete a task. Algorithmic bias is when a computer algorithm produces errors systemically that unjustifiably privileges one arbitrary group over another (Friedman & Nissenbaum, 1996). These algorithms, specifically machine learning algorithms, are contingent on the programmer or creator for reliable labels to build efficacious predictions (Sun et al., 2020). The contingency of a computer algorithm to its creators or programmers is fundamental to the notion of computer bias as it suggests its subjectiveness to bias from humans. An example of algorithmic bias would be if a credit advisory algorithm systematically designates poor credit ratings to credit cardholders with ethnic surnames by neighborhoods or discriminates on other irrelevant traits to credit score assessment. According to Friedman et al., there are many different types of algorithmic bias; there are preexisting, technical, and emergent. Preexisting algorithmic bias is when an algorithm carries biases that are impartial and exist prior to the creation of the system. Technical bias is when the technical components or design of an algorithm lead to systematic errors either by technical constraints or considerations. An emergent algorithmic bias is when there is no preexisting or technical bias and seems to develop after some time as a result of perceived change in the users (Friedman & Nissenbaum, 1996). This is also consistent with what Professor Betsy Anne Williams et al. stated in her paper titled "How Algorithms Discriminate Based on Data They Lack," in which she elaborates on how algorithms, specifically machine learning algorithms, may discriminate or become bias based on data they lack by building latent patterns with incomplete data that are prejudice or bias, which is descriptive of an emergent algorithmic bias. The distinction in algorithmic bias is relevant to this study as it may provide information on what type of algorithmic bias Google's search algorithm may have and may influence the method of determining possible bias.

Google's search engine algorithm is comprised of different algorithms, programming, and processors that all work together to provide information it deems relevant to the user's search query. As stated by Google on its webpage titled "How Google Search Works," that there are thousands to millions of potential web pages that google deems are possibly relevant to the user's search query; in order for Google to show the most relevant sources, they use a multitude of different algorithms and processors to do so. To preface, Google search works by first organizing information on the web with its "web crawler" (Google, n.d.). Web crawlers are unsupervised machine learning mining bots that search the world wide web to find missing web pages for Google to collect into their extensive index of the internet (Google, n.d.; Friedman, 1998). To elaborate, if Google were to be missing web pages, then it would send more web crawlers as they are responsible for providing google with an extensive index. These web crawlers are responsible for Google having one of the largest web indexes as it contains hundreds of billions of web pages with one hundred million gigabytes in size (Google, n.d.). This index is important as it is what Google's search engine uses to find relevant information for a submitted search query (Google, n.d.). Apart from Google's web index, it then uses a convoluted network of algorithms to find the meaning of the user's search query, the relevancy of sources, and the quality of content. When the user enters a query into the search box, it is fundamental that the google search algorithm is able to understand the intent and meaning of the search query (Google, n.d.).

According to Google, it uses and built language models that effectively determine the intent and meaning behind a query. These language models involve understanding spelling mistakes, using appropriate synonyms, and using a "freshness" algorithm that determines the trendiness of a search query (Google, n.d.). As stated by Google research scientist Nicholas Carlini, Google's language models use machine learning to build algorithms that understand and most resemble user's search query tendencies. This is particularly relevant to this study as it is prone to algorithmic bias by building latent patterns based on lacking information as earlier stated by Professor Betsy Anne Williams et al. Regarding Google's search algorithm determining the relevance of webpages, it uses simple algorithms that analyze the contents of webpages. More specifically, to determine relevancy, it uses algorithms that search webpages for similar words called relevance signals in the search query (Google, n.d.). For example, if the user were to search "how to plant apple seeds?", Google's search algorithm would verify relevancy by searching indexed webpages for the words "how to plant apple seeds," "plant," "apple," or "apple seeds." Furthermore, for Google to verify the quality of content, it goes beyond using words in search queries but uses an algorithm that measures other variables to prioritize web pages. One of these algorithms is called page rank; it uses several variables to determine the quality of a webpage and uses ranking systems to rank specific pages higher than others (Google, n.d.). Generally, Google search relies on algorithms to work; however, more specifically, they use deep neural networks (Metz, 2017). Deep neural networks are a type of machine learning algorithm where there are several layers between the inputs and outputs to get progressively more nuanced features (Schmidhuber, 2015). Renowned computer scientist Jürgen Schmidhuber, in his paper "Deep learning in neural networks: An overview," stated that deep neural networks are susceptible to bias in some form; this is also supported by Professor Betsy Anne Williams et al. where she stated that machine learning algorithms are prone to bias. In all, when the user enters a search query, the results and speed shown are how many relevant indexed webpages there are and the speed of each process of Google's search algorithm (Google, n.d.). This data, expressly, is essential to this paper as it will be what is used to determine whether the algorithms are implicitly biased.

When reviewing the literature on implicitly bias algorithms, it would be prudent first to understand what implicit bias is. Implicit bias is a sociological concept in social identity theory in which an individual, who belongs to a social in-group, holds an impulsive unconscious thought or belief about an individual of a social out-group, which can often be negative or positive (Greenwald & Banaji, 1995). An example would be a white person who is an employer reading the application of a black person and discarding it because he unconsciously associated his name with his social group and holds a negative unconscious belief about that social out-group. According to the leading academics of social identity theory, Professor Anthony Greenwald and researcher Nick Bryd, the way implicit bias is determined is through inference or inductive reasoning, in which the premises of different outcomes can be used to infer a bias in controlled experiments or studies. The most consequential information is that implicit bias can influence an individual's behaviors; this information holds broad implications for society, such as discrimination in employment, social interaction, and even algorithms (Greenwald & Krieger, 2006). Primary to this paper, the interactions of implicit bias and computer algorithms are quintessentially one consequence of the broad implications of implicit bias influencing an individual's behaviors that this paper and many others intend to study. Other studies and books aiming to research the relationship between implicit bias and computer algorithms are "Algorithms of Oppression: How Search Engines Reinforce Racism" by Dr. Safiya Noble, "Race After Technology: Abolitionist Tools for the New Jim Code" by Professor Ruha Benjamin, "Dissecting racial bias in an algorithm used to manage the health of populations" by Ziad Obermeyer et al. and "Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice" by Rashida Richardson et al. All these studies and books listed are the latest and most notorious research available about the interaction between implicit racism and computer algorithms and all find a bias in algorithms against minorities. Like Dr. Greenwald stated, implicit bias can have far-reaching implications, and this has been represented in algorithms in many industries such as computer science, healthcare, and even the justice system.

The studies mentioned in this literature review have shaped and informed the ways in which this study will conduct itself. This literature review has informed the manner in which algorithms and, more specifically, Google's algorithms ought to be understood and studied as well as how implicit bias influences these algorithms. Although there have been books such as "Algorithms of Oppression: How Search Engines Reinforce Racism" by Dr. Safiya Noble that also study the interaction between Google's platform and racism, this paper seeks to statistically determine whether Google's search algorithm can be reflective of implicit racial bias through the use of the time given by Google's query processor.

Method

To determine whether Google's search algorithm reflects implicit racial bias, the methodical approach that would be most appropriate is a quantitative research design or, more specifically, a causal-comparative design. Although this method is relatively idiosyncratic, it is most familiar to a causal-comparative design as it is a research design that attempts to find a causal relationship between two or more variables while also comparing and contrasting correlational research (Salkind, 2010). This is because in determining whether there is an algorithmic bias in google search, it would require determining whether the independent variable affected the outcome or dependent variable while also being both correlational and experimental (Salkind, 2010). This method would, in short, require the collection of data, the organization of data into distributions, and the use of statistical analysis to determine an algorithmic bias. The independent variables are search queries, and the dependent variables are the mean search times.

The independent variables, search queries, are integral to determining whether there is an algorithmic bias. These search queries will be searched in google search using a separate incognito browser for each query during three parts of the day to control for filter bubbles; which is when google provides unique search results for different users (DuckDuckGo, 2018; Wall Street Journal, 2012). This will be performed in the first two weeks of March, from the 1st to the 13th. Since this paper is measuring the United States' google search algorithm, in the search settings of

google search, the region should be set to the United States, and the rest of the setting must be set to the default. A google account must be signed out to control for confounds, and the "Signed-out search activity" must be set off.
There will be two types of search queries for this study, occupational queries, and racial occupational queries. The occupational queries that would be used are the roles or occupations: doctor, student, criminal, athlete, and person. The racial occupational queries would have races or ethnicities that would be adjectives to occupational search queries; the races would be "White," "Black," "Asian," "Hispanic," and "Native American." Examples of a racial occupational search query would be "Asian athlete," "White person," or "Black student." This would result in a total search of 30 general search queries. The dependent variables would be search times given in the user interface after searching a query. This is important as this recorded data would determine if the algorithm is quicker with certain racial queries.

In determining an algorithmic bias, this study will use hypothesis testing, in which each search query will have a normal mean distribution, and they will be tested for a statistical difference between the normal distributions of an occupational query and each racial occupational search query. This method of hypothesis testing is justified by a study in 2010, published to Postgrad Med Journal, in which the doctors and professors, Thiele and colleagues used a method by which they took information from different search algorithms to evaluate speed, accuracy, and user confidence by performing hypothesis testing, which is similar to this method. Another reason for building a normal mean distribution is because when searching queries, the search times will vary, thus in order to test for statistical significance or difference, a mean search time must be made from a normal distribution (Google, n.d.). Hypothesis testing would allow for the statistical analysis of whether the particular racial occupational query such as "white doctor" is more or less statistically different than "doctor" and whether there is a statistical difference between white occupational queries and racial minority occupational queries. When searching the search queries, there should be a sample of 50 searches for each query, record the search times, and build a normal mean distribution for each occupational and racial occupational query. The normal distribution should be made first with the occupational queries without a racial adjective and then with racial occupational queries to compare mean search times. This determination of statistical difference would be with a 2-sample z test, as the sample is larger than 30 and is being used to determine a statistical difference between the mean search times of the occupational query and the racial occupational query. After calculating the standard deviation, the mean search time, and using a sample of 50 search times for each distribution, the null hypothesis should be set to $\mu_1 = \mu_2$, the p-value should at most be 0.05 to determine a statistical difference or implicit bias.

Results

Doctor

All the racial "doctor" queries are statistically different from the occupational query "doctor." However, between different racial doctor queries, all racial minority doctor queries are statistically different from the white doctor query, and "Hispanic doctor" is statistically different to all other racial queries as well but has a mean search time greater than white doctor's search time. All racial minority doctor queries besides Hispanic doctor show no statistical difference to each other.

Student

When performing the 2-sample z test, the only racial occupational queries that are not statistically significant to the occupational query "student" are "Black student" and "Hispanic student." When comparing the racial minority student queries to "White student," the only statistically significant queries were "Hispanic student" and "Native American student."

Criminal

When comparing the occupational query “Criminal” to all the racial criminal queries, the p-values were essentially zero, thus rejecting the null hypothesis that the query “Criminal” is not statistically significant to all the racial criminal queries. However, when comparing the racial occupational query “white criminal” to racial minority criminal queries, they all had extremely small p-values, which suggests a significant difference between “white criminal” to racial minority criminal queries.

Athlete

For the normal distribution of the occupational query “Athlete,” the only racial queries that were statistically different were “A Black Athlete,” Asian Athlete,” and “A Native American Athlete.” The racial occupational queries that were statistically different to “White Athlete” were “A Black Athlete” and “A Native American Athlete.”

Person

For the occupational query, “Person,” and racial occupational query, “White Person,” when performing the 2-sample z test, the p-value was essentially 1, suggesting no statistical difference of “White Person” to “Person.” However, when comparing the occupational query “Person” to racial minority “person” queries, they all resulted in a statistical difference. When using a 2-sample z test for the racial occupational query “White Person” and the racial minority “Person” queries, all the racial minority “Person” queries were statistically different to “White Person.”

Discussion

The results of this research study have led to a myriad of convoluted information that would merit ample discussion. This discussion section of this research paper would be utilized to summarize the information in the results section, interpretation of the key findings, discussion on the implication of the results, limitation of the results, and further recommendations for research. For the summarization and interpretation to be as comprehensive and succinct as possible, the discussion section will be relegated into five subsections based on the occupational queries: “Doctor,” “Student,” “Criminal,” “Athlete,” and “Person.” These subsections will have the discussion of racial occupational queries within each occupational query subsection. The discussion section will also be relegated into three additional general subsections: Implications, Limitations, and Recommendations.

Doctor

After obtaining information from 2 sample z test of the occupational query “Doctor” and racial “Doctor” queries, the determination of racial bias for the queries of “Doctor” became somewhat ambiguous. The occupational query “Doctor” has a longer mean search time than all other racial “Doctor” queries and is statistically different from all racial “Doctor” queries. This may be a result of the query “Doctor” being significantly broader than racial “Doctor” queries. This notion of the occupational query having larger mean search times and being statistically significant to the racial occupational queries has been shown to be a trend among other occupational queries.

However, when comparing the racial occupational query “White Doctor” to other racial minority “Doctor” queries, there does seem to be a statistical difference between them. The query “White Doctor” also seems to have a faster mean search time than the other racial minority “Doctor” queries. This empirical dissonance between “White Doctor” and racial minority “Doctor” queries gives credence to the argument or hypothesis that the U.S Google Search Algorithm reflects an implicit racial bias on the occupational query of “Doctor.”

Student

The statistical analysis for the occupational and racial occupational queries for “Student” led to a less statistically significant result between most of the races compared to the “Doctor” query. Primarily, as shown to be a trend, the occupational query “Student” had a longer mean search time than the other racial occupational queries. This may result from the query “Student” being broad enough to lead to a longer search time, as it is likely very numerous in Google’s index. Thus, when the racial “Student” queries were 2-sample z tested with “Student,” there was a statistical difference for all racial “Student” queries.

Furthermore, when tested with “White Student,” most racial minority queries led to no statistical difference, except for “Hispanic” and “Native American” student. It is not necessarily apparent as to why, yet one reason may be that there is not much searching for “Hispanic” and “Native American” students so that the algorithm may be reflective of that condition. It could also be that there is a latent bias against “Hispanic” and “Native American” students or that confounding factors in Google’s search algorithm led to a bias for these queries. The results under the overarching query of “Student” may be indicative of implicit racial bias for “Hispanic Student” and “Native American Student.”

Criminal

The data obtained for the occupational query “Criminal” has a longer mean search time than the racial occupational query. This may be a result of the occupational queries being broader than the racial occupational query. However, when the “Criminal” query was z-tested with racial “Criminal” queries, these results produced statistical significance for all racial “Criminal” queries.

When performing 2-sample z testing with “White Criminal” and racial minority “Criminal” queries, the results produce more significant results. The results that were produced states that a “White Criminal” is statistically different from all racial minority “Criminal” queries. This would suggest that the Google search algorithm is implicitly bias against racial minority “Criminal” queries. The most notable results from this section are that “Black Criminal” has the lowest mean search time and is statistically significant to all other racial “Criminal” queries. This may be indicative of an implicit racial bias where the algorithm more quickly finds results on “Black Criminal” because the general public carries such biases or that black overrepresentation in the criminal justice system may have impacted Google’s index. Either way, the results constitute an implicit racial bias against racial minority “Criminal” queries.

Athlete

Uniquely, for this section of data, the occupational query, “Athlete,” has a mean search time similar to that of the racial occupational queries’ mean search time. Thus, when performing a 2-sample z test, the only racial “Athlete” queries that were statistically different to “Athlete” were “Black Athlete,” “Asian Athlete,” and “Native American Athlete.” This is sufficient evidence to determine that there is a particular bias that explains why specific racial “Athlete” queries are statistically different to “Athlete” given other racial “Athlete” queries not being statistically different to “Athlete. This may be due to some bias within the algorithm or disparities in Google’s index.

When comparing racial minority “Athlete” queries to “White Athlete,” the racial minority “Athlete” queries that are statistically different to “White Athlete” were “Black Athlete” and “Native American Athlete.” What is peculiar in this section of data, much like the last section with the “Criminal” queries, is that “Black Athlete” has a very dissimilar mean search time to other racial queries concerning the mean search time and hypothesis testing. This may be a result of racial bias or disparities in the index.

Person

When performing a 2-sample z test, the occupational search query of "Person" is not statistically different from "White Person" but is statistically different from all other racial minority "Person" queries. The p-value was essentially 1, and the mean search times and sample standard deviations are almost identical, which would suggest a likely no statistical difference to the Google search algorithm "White Person" and "Person," yet a statistical difference between "Person" and all other racial minority "Person" queries. When comparing the query "White Person" to racial minority "Person" queries, the results were the same. There showed a statistical difference between "White Person" and racial minority "Person." This evidence would indicate an implicit racial bias in Google's algorithm. This may be due to implicit racial bias from the myriad of Google search users that has influenced its machine learning algorithm or disparities from Google's index.

Implications

The implications of the results of this study reach across several areas of academia such as sociology and computer science. The question of whether Google's search algorithm can be reflective of implicit racial bias is both a sociological and computer science question. The evidence in this study showing there to be evidence of implicit racial bias in Google's search algorithm can be reaffirming evidence that builds on the gap or existence of systemic racism in computer algorithms due to implicit racial bias. The pioneers of such an immerging sector such as Safiya Noble with "Algorithms of Oppression: How Search Engines Reinforce Racism," and Ruha Benjamin with "Race After Technology: Abolitionist Tools for the New Jim Code," has done research on Google's search and algorithmic technology's interactions with implicit racial bias and their racist outcomes, yet this research will provide more evidence to complement the literature mentioned for such an incomplete gap. This evidence will also influence how systemic racism could be view and the sociological analysis that may be included to analyze the significant effects of implicit racial bias. This evidence would also have broad implications for computer science as it may change how machine learning algorithms are built in order to withstand racial biases. This research could also lead to a new method of studying implicit racial bias in other algorithms.

Limitations

Although this research has produced noteworthy evidence, there were several limitations in this research paper regarding the method and analysis of the results. The method of this study is idiosyncratic and has not been used before for analysis of Google search times. The use of search time and the statistical difference between them as evidence of implicit bias is not necessarily substantiated by mainstream computer science, making this method and the statistical analysis of the research to be a limitation. Often in computer science, the dissection or analysis of complex machine learning computer algorithms by simply looking at inputs and outputs can be difficult to induce reasons about the process. An example would be with the trend of occupational queries having longer mean search times and being statistically different to racial occupational search queries; the reasonings proposed in the discussions as to why are tenuous as there is not enough sufficient technical evidence available to accurately induce a reason. Another limitation was with specific Google's search queries, where Google search's feature of a list being shown after the searching of a query can block or have the display of the query's search time to be missing. This would lead to the use of certain queries that include "A" at the beginning in order to evade Google's listing feature; this modification of the search query may have skewed the results or provided confounds. Overall, this study's method to determine implicit racial bias is somewhat limited to an extent; however, based on the evidence, it is sufficient to give a shrewd conclusion or insight.

Recommendations

The recommendations would be that further studies can have better, more established methods to determine implicit racial bias. As acknowledged in the limitations section, analyzing computer algorithms is difficult as the only evidence available are inputs and outputs. Thus, this paper would recommend a more sophisticated method that encompasses more knowledge of computer science to determine bias more efficiently. Ideally, there would also be more sharing of technical information from Google's database or index that would lead to more sophisticated statistical analysis and methods. This paper would also recommend using different types of queries that would either invoke race, gender, or religion. This would broaden the scope of the question from implicit racial bias to general prejudicial bias.

Conclusion

Ultimately, with the performance of causal comparative research, literature reviews, and statistical analysis, the purpose of this research paper was to determine whether the United States' Google search algorithm can be reflective of implicit racial bias. Given the evidence performed by hypothesis testing, this research paper assertively concludes that the United States' Google search algorithm is reflective of implicit racial bias. The results suggest that with specific occupational search queries, Google's search algorithm seems to have faster mean search times for White occupational search queries than racial minority occupational search queries. The results also suggest that certain racial minority occupational search queries tend to be significantly different from occupational search queries and White occupational search queries. A quintessential example was with "White Person" having faster mean search times and not being statistically different to "Person," but all racial minority "Person" queries were statistically different to "Person" and "White Person" and had similar mean search times longer than "White Person." With the evidence of algorithmic bias shown through hypothesis testing, it raises the question of whether the use of hypothesis testing was the most effective method for determining algorithmic bias. With this quandary, this paper would recommend future studies to account for that question and experiment with more sophisticated methods that invoke more complex computer science to more unequivocally prove implicit bias.

With the pioneers of the immerging sector of computer science and systemic racism, mentioned in the literature review, Safiya Noble and Ruha Benjamin have published literature on the relationship shown between Google, algorithmic technology, and implicit racism; however, this research paper will provide new causal-comparative research to the gap of the United States' Google's search engine algorithm as it relates to implicit racial bias demonstrated through hypothesis testing of the normal distribution of the mean search times of occupational and racial occupational search queries. The results obtained by the research provide new evidence to the gap previously mentioned that the United States' Google search algorithm is reflective of implicit racial bias.

References

Benjamin, R. (2019). *Race After Technology: Abolitionist Tools for the New Jim Code* (1st ed.). Polity.

Carlini, N. (2020, December 15). *Privacy Considerations in Large Language Models*. Google AI Blog. https://ai.googleblog.com/2020/12/privacy-considerations-in-large.html

DuckDuckGo. (2018). Measuring the "Filter Bubble": How Google is influencing what you click. *DuckDuckGo*. Published.

Friedman, B., & Nissenbaum, H. (1996). Bias in computer systems. *ACM Transactions on Information Systems*, *14*(3), 330–347. https://doi.org/10.1145/230538.230561

Friedman, J. H. (1998). Data Mining and Statistics: What's the Connection? *Stanford University*, 1–7.

Garcia, M. (2016). Racist in the Machine. *World Policy Journal*, *33*(4), 111–117. https://doi.org/10.1215/07402775-3813015

Google. (n.d.-a). *Google*. Google.com. Retrieved November 2020, from https://www.google.com/

Google. (n.d.-b). *How Google Search works*. https://www.google.com/search/howsearchworks/

Google Search Statistics - Internet Live Stats. (2020, November). Www.Internetlivestats.Com. https://www.internetlivestats.com/google-search-statistics/#share

Greenwald, A. G., & Banaji, M. R. (1995). Implicit social cognition: Attitudes, self-esteem, and stereotypes. *Psychological Review*, *102*(1), 4–27. https://doi.org/10.1037/0033-295x.102.1.4

Greenwald, A. G., & Krieger, L. H. (2006). Implicit Bias: Scientific Foundations. *California Law Review*, *94*(4), 945. https://doi.org/10.2307/20439056

Howard, A., & Borenstein, J. (2017). The Ugly Truth About Ourselves and Our Robot Creations: The Problem of Bias and Social Inequity. *Science and Engineering Ethics*, *24*(5), 1521–1536. https://doi.org/10.1007/s11948-017-9975-2

Metz, C. (2017, June 3). *AI Is Transforming Google Search. The Rest of the Web Is Next*. Wired. https://www.wired.com/2016/02/ai-is-changing-the-technology-behind-google-searches/

Noble, S. U. (2018). *Algorithms of Oppression: How Search Engines Reinforce Racism* (Illustrated ed.). NYU Press.

Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2020). Dissecting racial bias in an algorithm used to manage the health of populations. *Yearbook of Paediatric Endocrinology*. Published. https://doi.org/10.1530/ey.17.12.7

Richardson, R., Schultz, J., & Crawford, K. (2019). Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice. *94 N.Y.U. L. REV. ONLINE 192*. Published.

Salkind, N. J. (2010). Causal-Comparative Design. *Encyclopedia of Research Design*. Published. https://doi.org/10.4135/9781412961288.n42

Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural Networks*, *61*, 85–117. https://doi.org/10.1016/j.neunet.2014.09.003

Search Engine Market Share Worldwide. (2020, November). StatCounter Global Stats. https://gs.statcounter.com/search-engine-market-share

Sun, W., Nasraoui, O., & Shafto, P. (2020). Evolution and impact of bias in human and machine learning algorithm interaction. *PLOS ONE*, *15*(8), e0235502. https://doi.org/10.1371/journal.pone.0235502

Thiele, R. H., Poiro, N. C., Scalzo, D. C., & Nemergut, E. C. (2010). Speed, accuracy, and confidence in Google, Ovid, PubMed, and UpToDate: results of a randomised trial. *Postgraduate Medical Journal*, *86*(1018), 459–465. https://doi.org/10.1136/pgmj.2010.098053

Thiem, A., Mkrtchyan, L., Haesebrouck, T., & Sanchez, D. (2020). Algorithmic bias in social research: A meta-analysis. *PLOS ONE*, *15*(6), e0233625. https://doi.org/10.1371/journal.pone.0233625

Wall Street Journal. (2012). On Google, a Political Mystery That's All Numbers. *Wall Street Journal*. Published.

Williams, Brooks, & Shmargad. (2018). How Algorithms Discriminate Based on Data They Lack: Challenges, Solutions, and Policy Implications. *Journal of Information Policy*, *8*, 78. https://doi.org/10.5325/jinfopoli.8.2018.0078