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Faculty of Business Economics

Master of Management

Master's thesis

Reporting biases in innovation

Dipanti Ghosh

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Business Process Management

SUPERVISOR :

Prof. dr. Stephan BRUNS

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Preface

Before you lies the dissertation on Algorithmic biases in social media: The case of decisions on Covid-19 vaccines. In order to complete the criteria for the University of Hasselt's Masters in Business Process Modelling programme, this paper was created. For the whole of 2022, from January to August, I worked on this dissertation.

It was my personal initiative to pursue this investigation. Together with my advisor, Stephan Bruns, I developed the research question. Although it was challenging to do the research, I was able to successfully address the topic we had framed by reading widely throughout the relevant literature and studies.

Fortunately, Stephan Bruns was always available and willing to answer my queries.Thus, I would like to thank my supervisors Stephan Bruns for all the help and support he's given me during this ordeal.

I hope you enjoy your reading.

Dipanti Ghosh

Leuven, August 19th, 2022

Abstract

1.Research Purpose

The COVID-19 epidemic made it necessary to use social media as it was the only way for governments and people to disseminate information. Regardless of whether the social media algorithms serve a beneficial or bad purpose, it has an impact on how its users views the content they are directed to and behave accordingly and follow the requirements imposed by the governments.

2.**Research Method**

As a first step to the approach, the research question analysed was -How do biased social media algorithms impact people's decisions for covid 19 vaccinations? To answer the question,a study of the general literature of algorithmic bias and its related prior research was conducted. Thereafter, the main research question was split into two sub questions namely 1)How do social media algorithms affect people's decisions? 2)Its relevance to the Covid-19 vaccine decisions and were researched in the results section. Likewise, the literature review was used and analysed in the context of decisions of covid 19 vaccines and then the conclusion was discussed which included main takeaways, limitations, and future recommendations. Additionally, a broad range of research papers were understood and analysed due to the lack of existence of similar research.In short, first, theoretical data was gathered , and then that data was applied to the research question to get the results.

3.Findings

This results suggests that social media sites and its biased algorithms have the potential to mislead the public about the vaccine decisions .Thus, it is disclosed that the biased social media algorithms impact people's decisions for covid 19 vaccinations by creating non transparent, revenue and engagement centric algorithms that further create echo chambers and filter bubblers.Likewise,due to humans inherent biasness which results in information overload and social herding this leads to the polarized of its users that are distrustful of organizations and governments. The research revealed that most big health organizations don't even consider the algorithm in social media being a problem due to the inherent belief that machines are not biased.Thus lack of research discussing the impact of social media algorithms in regards to vaccine decision was noticed while doing the research.

4.Value of the Study

Since this research topic has never been undertaken before the value of the study is high and would help understand governments,users and businesses on how to manage risk situations.Similarly, big health organizations don't even consider the algorithm in social media being a problem due to the inherent belief that machines are not biased, thus this study helps to understand the value of algorithms in the context of social media vaccinations. Likewise,the impact of social media algorithms and its bias is vital in understanding the vaccine hesitancy as vaccination is a very important part of human disease prevention and evolution.Additionally,content such as misinformation impact those who already hold some preconceived biases, but they had had the opposite effect on those who were sceptical or unwilling to be vaccinated.Thus, the value of this study lies in the fact that it found that the governments are responsible for making sure that social media platforms are not manipulating their users as well as responsible for protecting the rights of its citizens.Likewise,governments are also responsible for handling the spread of information regarding vital matters like the covid-19.

5.**Critical considerations**

Lastly, some critical considerations to take in mind when analysing the research paper are that with any research, limit exist. In this study , understanding and application of existing literature and studies were done which left out the possibility of finding new results and contributing to the data at large. Again, the amount of literature data was relatively restricted as most of the research conducted in analysing the decisions of users due to social media algorithm were in business context and not in health context.Similarly,data about social media bias is quite non transparent and requires immense support financially and technically to be analysed.Likewise,the covid pandemic is still ongoing and many in third world countries have not received their vaccines , and maybe wont.Thus , the study is biased as research was mainly focussed in the users decisions regarding vaccines in the first world countries where the governments made it a priority to make their citizens vaccinated. The study did not factor what people in poor third world countries do regarding their decisions on the luxury vaccination of covid-19.Lastly,these limitations leave scope for future research. It is recommended to research the topic further.For future research, it can be recommended to work with some big companies or social media analysing companies to exclusively look at the new literature that is inaccessible or not published yet and do an online study regarding the perception of the people, since this topic is not really researched and would need many resources.

Keywords-Algorithm,Bias,Socialmedia,Covid-19,Vaccine,Decisions

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Algorithmic biases in social media: The case of decisions in Covid-19 vaccines

1. Introduction

Historically, pandemics and epidemics have harbored bias and prejudice (Shinoda et al., 2021). It was the situation with illnesses like HIV and Ebola and is the situation now with COVID-19 (Cao et al., 2020). However, the day when only explicit and implicit human bias impacted our daily lives is long gone (Falck, 2021). Nowadays, most of our biases have crept into the digital world of social media in the form of data, which has developed into algorithms that support crucial operational and strategic activities globally (Bai et al., 2021).

These algorithms have traditionally been assumed to reflect the racial, cultural, gender, age, regional, or socioeconomic variety of human society in the systems (Köchling et al., 2020).

However, only recently have there been concerns that algorithm systems in practice are prone to making mistakes and can introduce bias on a massive structural scale, much like humans (Newman et al. 2019). For example, Amazon, an online retailer with 60% male worldwide employees and 74% male executive staff, recently stopped using a recruitment algorithm after learning that it was biased against women (Aumüller-Wagner, 2019). The information that programmers utilized to develop the algorithm came from applications primarily submitted by white males for ten years and sent to Amazon (Aumüller-Wagner, 2019). The data was compared to the company's predominately male engineers. The computer was trained to discern particular words in the applications rather than pertinent skill sets to ascertain an individual's match (Alfons, 2020). Due to gender bias, the Algorithm program devalued resumes of women who attended women's colleges and any CV that mentioned "women" in the content (Aumüller-Wagner, 2019).

The example mentioned above in the context of this research is called an "algorithmic bias," a phrase from the realm of artificial intelligence that references algorithms that regularly make inaccurate and biased conclusions (Londoño et al., 2022). Learning algorithms rely on significant data input (Londoño et al., 2022). The program improves as more data is collected (Guttag et al., 2019). Based on the facts they collect as input, ALGORITHM systems start making predictions (Holstein et al., 2019). They then attempt to identify patterns in it. However, some of the primary reasons for algorithmic bias are incomplete, inaccurate data, and biased human habits. (Hosio et al., 2021).

To view the algorithm bias from a different context, according to newly published statistics on how people retrieved information and news about the coronavirus global epidemic, more than a quarter of 18-to 24-year-olds in the United States used Instagram to obtain news stories. At the same time, 19% utilized Snapchat, and 6% utilized TikTok (Volkmer, 2021). In contrast, only 17% used newspapers to gather information. In other countries, data exceeded even greater levels: in Germany, 38 percent of 18-through 24-year-olds utilized Instagram on its own to receive news, while in Argentina, the exact figure exceeded 49% (Rasmus et al., 2020).

Thus, this raises the concerns regarding biased algorithms to a higher level as people rely heavily on social media to build their perceptions, get news and information, and decide their actions regarding critical topics (Johnson, 2020). The importance of understanding social media bias is vital because social media is used as the primary tool of communication these days and is a tool that connects families, friends, and communities (Chalfin et al., 2016). For example, the COVID-19 outbreak scenario illustrates the crucial influence of this emerging digital landscape (Volkmer, 2021). The transmission of knowledge significantly impacts how individuals behave and can change how people make decisions (Hütter et al., 2020). Likewise, social media sites like Twitter, Instagram, Facebook, etc. provide people with immediate access to an unparalleled variety of data regarding all issues, including the COVID 19, but also potentially propagate rumors and dubious data due to the biased algorithms that are used by the companies (Rasmus et al., 2020). Recent research has looked at how information about COVID-19 affects public views of the pandemic, the propensity of some socio- Political groups accept false information, and adherence to public health recommendations, including the ability to consider a COVID-19 vaccine, is higher (Volkmer, 2021).

However, to our knowledge, no study has been undertaken relating to the algorithmic bias inherent in social media and its effects on vaccination decisions during COVID-19. Henceforth, the literature on algorithmic bias is reviewed in this study to close this knowledge gap. Finally, it is essential to grasp how much data from social media algorithms influences user behavior and decision-making. This research aims to uncover how users' exposure to the material selected by social media algorithms fuels hostility and polarisation on these platforms.

2. RESEARCH APPROACH

Overview

This research sets out to examine the research question - How do biased social media algorithms impact people's decisions for covid 19 vaccinations?

Similarly, in the given research, the literature review will be addressed by discussing the prior studies and literature on the implications of algorithmic bias on social media platforms and its effect. Followed by the results section, the main research question will break down into two sub-questions. Of them, the first will be,

A. How do social media algorithms affect people's decisions?
B. Its relevance to the Covid-19 vaccine decisions.

Furthermore, an application section discussing the literature study conducted during the initial part of the research earlier in the report will apply in the context of Covid 19. Lastly, the paper's conclusion will answer the study's primary research question and suggest avenues for further investigation.

Data sources

In this research, finding possibly pertinent articles was the first step. A wide variety of data, notably from Scopus, the IEEE Xplore Digital Library, Web of Science, JSTOR, ScienceDirect, and research gate, as well as scientific articles published in academic journals and conferences, were taken into account. Since algorithmic bias is a new idea that has just recently begun to seek recognition and algorithms' inept focus on changing dynamically, an emphasis on making sure the articles are between the year (2015- 2022). Additionally, since the direction of the research is also applying previous studies, thus it is essential to take the year into account, as taking old examinations into account can lead to errors explaining current algorithms. Additionally, the search results, which contain articles that are not often peer-reviewed but might have a significant theoretical and practical influence, are considered. Likewise, the search strings used to identify the relevant paper based on the research question are displayed below.

Search Strings
Algorithm <u>AND</u> Bias <u>And</u> social media
Algorithm <u>AND</u> Bias
Algorithm <u>AND</u> social media
Social Media <u>AND</u> Algorithm
Algorithm <u>AND</u> social media <u>AND</u> Decision Making

Social Media AND Descion Making
Social Media AND Decision Making AND Bias
Social Media AND Ddecision Making AND Bias AND Covid-19
Social Media AND decision Making AND Bias AND Vaccine

The examples above show that the search strings are based on the research question. Thus, the literature and understanding were obtained by in-depth examination and comparing the many previous research. However, it is noteworthy that no papers had previously analyzed the influence of social media algorithms in the context of covid-19 vaccine consumption decisions, so there is a significant dependence on comprehending a lot of individual studies and then collecting them to solve the research issue.

Screening procedure

This second step required removing theoretically or contextually unrelated publications by screening the article names, keywords, and abstracts. An article would qualify as relevant if 1) it primarily focused on algorithmic bias in social media and 2) its conceptualization was in line with the impact of social media algorithms and decision-making in the context of covid-19.

Given the magnitude of the issue and the lack of prior analysis, the procedure centers on gathering theoretical data via preliminary study and applying it to the context of covid vaccines at hand.

3. Literature review

3.1 Bias

The term "bias" is tricky and used differently across many fields of study (Danks, 2017). The given term is used to describe unequal treatment amongst different social groups. However, despite its usefulness in various contexts, this definition is too broad to be useful in many areas.

Therefore, bias is increasingly segmented across academic fields. For instance, implicit bias (beliefs, actions, and decisions influenced by underlying unconscious prejudices) and explicit bias (conscious biases and discrimination towards others) exist in the cognitive sciences. Then there are cognitive biases (how people react to new information and make choices) and machine biases(repercussions of a misguided presumption in machine learning) in philosophy. Statistical bias (a persistent pattern that generates disparities across results and facts) and machine bias in computer science(Amodio, 2010).

However, bias in diverse disciplines leads to the same outcome, namely discrimination. For instance, in employment, as an example, Swedish researchers performed a field study and found that overweight candidates were viewed less positively throughout the job process (Agerström, 2011). In the experiment, participants submitted made-up applications for many actual positions (Agerström, 2011). All the applicants had included photographs and identical resumes; however, in the pictures attached, some were overweight while others were not (Agerström, 2011). Thus, it found that the number of calls received by the non-overweight applicants was higher than the overweight applicants (Agerström, 2011).

Similarly, another well-known instance of bias in science is Andrew Wakefield's 1998 study, which linked MMR vaccination to autism (Rao et al., 2011). Wakefield was proven to have been affected by confirmation bias in 2010. Thus the paper was retracted from the British Medical Journal since he overlooked and modified a great deal of the research data (Rao et al ., 2011).

Thus, in this research, we explore the role of cognitive bias in answering the research topic at hand, as most social media relies on this bias. In addition, an explanation of how this bias connects to social media algorithms and artificial intelligence will be discussed. Likewise, details on how these systems all work together to affect human behavior and create serious negative repercussions for our society will be discussed below.

3.2 Bias in human cognition

The brain employs a classifier known as a cognitive bias to make sense of the world (Rosso, 2018). Considering the focus of the study, where the aim is to understand the bias present in algorithms, it is essential to stress the pervasive nature of cognitive bias in the human mind.

People's inherent biases are an advantage in a world where making decisions may be difficult (Amodio, 2010). The term "confirmation bias" refers to the human tendency to conform to the opinions and actions of everyone else around them instead of relying on one's own rationality (Potapov, 2014). Neuropsychological research suggests that confirmation biases are so fundamental to human thought that they are difficult to change (Johnson, 2018). For instance, during election campaigns, people seek anything that supports their candidate's beliefs and reject everything else. Such a subjective manner of acquiring information may alter voters' faith in a candidate and their capacity to perceive or overlook key facts, influencing the election outcomes and the country's future (Allahverdyan, 2014). Thus, understanding the existing cognitive biases in algorithms is vital. (Nadella, 2018).

Algorithms: what exactly are they?

According to recent definitions, "algorithms are simply detailed explanations of the sequence of operations that must be performed to get the desired result (T.K. et al., 2021). One of the most prevalent ways information disseminates is using such tools" (Shu, 2022). Thus, only those in computer fields worked with algorithms for a while (Shu, 2022).

Many would argue that humankind has entered a new era—the Age of the Algorithm (Dalby, 2017). However, that has changed, and algorithms have become a widespread part of daily life (Napoli, 2015). The term "algorithm" is in common parlance (Deranty, 2022). In recent years, words like algorithmic bias, social media algorithms, marketing algorithms, etc., have been used commonly (Dourish, 2016). However, algorithms themselves are seldom new. Unknowingly, humans have been using them for centuries (Robert, 2019). An example, the earliest known algorithm was found on clay tablets from Babylonia, dating back between 1600 and 1800 B.C (Knuth, 2014). The Babylonians used to record their computations on tablets for future use to count numbers, thus proving humans have unknowingly used algorithms for a very long time (Knuth, 2014).

However, the origin of the word algorithm was not in Babylonia, despite its first recorded use (Mehri, 2017). The word algorithm derives from the name of the Persian mathematician living in the ninth century named, Muhammad ibn Mūsā al'Khwārizmī (Knuth, 1972). It was induced by the mathematician's Latinized name "Algoritmi," which meant the decimal number system (Knuth, 1972).

However, the algorithm as we know it now appeared in England in the nineteenth century, but its widespread application did not begin until the 1950s, when the first widely accessible computers were utilized (Bullynck, 2016). Since then, algorithms have progressed to be tremendously complicated (Bullynck, 2016).

Likewise, today, more than ever, sophisticated algorithms are required to manage the deluge of data and find the most relevant information to a given situation (Robert, 2019). These complex algorithms have proven successful at novel, difficult tasks and are now invading domains historically reserved for human judgment (Yeomans et al., 2019). For instance, one of the most significant influences on people's choices is the opinions of their peers, and social media is one avenue via which these algorithms are beginning to exert their sway (Becker et al., 2017). Thus, in this context, it is critical to learn about algorithms and their significance in social media.

3.3 What is social media?

Social media is defined as a range of Web-based apps that leverage the human and technical underpinnings of Web 2.0 (applications using information sharing, user-centered design, and cooperation), which permits the production and sharing of user-generated content (Kaplan et al., 2010). However, this definition is quite broad, and debates persist about its precise meaning and use. The contributing factor is the rapid pace at which material may be updated on social media platforms (Kaplan et al., 2010). Likewise, "social media" is often used as a catch-all word for a wide range of online communication that combines technical means with the sharing of thoughts, posts, pictures, etc. (Kaplan et al., 2010).

Various resources are available online that classify the many kinds of social media. For instance, the categorization of the Social Media Environment into ten distinct areas (Power & Phillips-Wren, 2011).

- Wikipedia for publishing
- Tumblr, Pinterest, and YouTube for sharing
- Phpbb and Skype for discussion
- Facebook, LinkedIn, and Instagram for networking
- Twitter for microblogging
- Friendster for livestreaming
- Justin. tv for live broadcasting
- Second Life and Habbo for virtual reality.
- Pogo and Doof for social gaming.

- World of Warcraft and Happy Farm for multi-player online gaming.

Since sharing and networking-oriented social media platforms are the most widespread, we limit our analysis to only those platforms. Instances include social media platforms such as Facebook, Instagram, and YouTube.

3.4 Biased Algorithms

It is very important to know that the idea of algorithmic bias stems from societal issues like systemic inequality, discrimination, and prejudice as its foundations (Lee et al., 2019). As a result, different social systems and philosophical perspectives define algorithmic bias differently (Saxena et al., 2018). For an entire society to be regarded as equal and impartial, everybody should be treated equally, especially in societal, legal, and economic problems (Tisdell, 2020). But there is disagreement on what should be equalized (Mcknight et al., 2016). Several philosophers contend that the eventual goal of equity and justice is to equalize advantages such as well-being (in other words, happiness or preferred fulfillment), wealth (i.e., money and possessions), capacities (i.e., skill and materials necessary to execute responsibilities), and obligations(Egbekpalu, 2021).

According to other thinkers, disparities in well-being, wealth, and capacity are okay if they are the consequence of individual choices, decisions, and responsible risk-taking rather than their innate traits, aptitude, or fate (Ayton et al., 2020). According to this theory, algorithmic bias occurs when rewards and costs are distributed inequitably across various people or groups (Lee et al., 2019). As a result, if an algorithm allocates rewards and costs in an inequitable manner and the inequitable distribution results from variations in people's innate traits, skills, or luck, it is called biased(Ayton et al., 2020).

Likewise, when looking at algorithmic bias from a different perspective, it is found that, in a just social structure, people's likelihood of succeeding in the employment search, as well as other status groups, must rely more on their innate skills and desire to develop those skills than on their social status or background. However, it is morally acceptable to give disadvantaged groups multiple advantages (Rawls, 2001).

Under the previous interpretation of justice, it is appropriate for an algorithm to favor underserved populations more than other groups, and this cannot be regarded as an instance of algorithmic prejudice(Kordzadeh et al., 2021). Therefore, when algorithmic bias is theorized and quantified using a philosophical paradigm, it can be expressed differently depending on the philosophy it refers to (Kordzadeh et al., 2021). Similarly, perceptions of bias might differ between businesses, judicial systems, countries, and faiths (Sen et al., 2019).

Considering the variances in algorithmic bias definitions caused by differences in philosophical, political, and cultural viewpoints on fairness, most interpretations have two key characteristics:

1) A biased algorithmic system's outputs show a departure from the concept of equality, and

2) the divergence happens consistently and repeatedly rather than randomly (Mehrabi et al., 2022).

Hence, an overall definition of algorithmic bias is "a persistent departure from equality that appears in an algorithm's results" (Lee et al., 2019).

3.5 Bias in Social Media Algorithms

Bias in social media algorithms means they tend to make decisions that unfairly benefit or penalize one set of content, people, news, or businesses over another(Cascini et al., 2022). Algorithms rely heavily on information produced by humans (such as user-generated content) and information gathered using tools developed by humans(Cascini et al., 2022). Human confirmation bias has thus spread across the systems and is further strengthened by high-tech socio-technical systems such as the Internet. So, algorithms may reflect (or even amplify) pre-existing inequalities or prejudices (Karimi et al., 2018). Therefore, this is not always the result of prejudice, but of the norm being generally followed(Chandler et al., 2011). Since algorithms tend to favor observable events and traits of human nature over those that are harder to quantify, they may amplify or add bias to existing (biased) processes(Chandler et al., 2011). For instance, overestimating Twitter's importance for many social happenings is a symptom of this problem, which is exacerbated by the fact that certain data is easier to gather and analyze than others (Tufekci, 2014).

However, algorithms are important. Implementing algorithms encourages the development of highly specialized data collection infrastructures and rules, such as monitoring and surveillance (Introna & Wood, 2004), which in turn impact or strengthen the algorithms themselves. Thus, another study implies that the structures of society and the solutions that might apply to problems are affected and influenced by algorithms (Diakopoulos, 2015).

- **Artificial intelligence:** Everything that is concerned with giving social media intelligence is categorized under artificial intelligence (AI) (Kaplan, 2022). AI can share information in social media platforms but can also keep it from people (Kaplan, 2022). Similarly, it can create and distribute targeted social media advertisements and propaganda (Ghouri et al., 2022). Recent research on how an algorithm distributed STEM job advertising in social media found that males were more inclined to see them, not due to their higher probable to click, but rather because it is more expensive to market to women (Lambrecht & E, 2019).

- **Machine learning:** Artificial intelligence (AI) and machine learning (ML) are often used interchangeably although they are not the same (Kim et al., 2013). As a branch of artificial intelligence, ML is one of many applications (Ullah et al., 2021). ML describes autonomously learning computer programs that rely on human data (Hodorog et al., 2022).For example, an attempt by Microsoft to connect with millennials in 2016 resulted in a racist chatbot that praised Nazis and made sexist comments after initially declaring, "humans are great" (Buckels et al., 2018).Thus proving, the single rule of machine learning: models always learn exactly what they were programmed to (Buckels et al., 2018).

- **Natural Language Processing:** A wide variety of methods and strategies have been developed for ML, one such method is called "natural language processing" (Belfin et al., 2020). Natural language processing (NLP) is the processing of texts to extract meaning in social media(Hu & Liu, 2015). Powerful computational processing of human language is required to provide correct outputs due to the fact that people talk using idioms and abbreviation thus leaving scope for biases(Molyneux, 2019).For instance, a study indicated that twitter posts published in the kind of English used by African Americans were twice as likely to be reported as inappropriate as those posted in other forms of English (Sap et al., 2019).Likewise, another research, this one using a sample of 155,800 tweets, demonstrated the same pervasive racial prejudice against this form of English (Davidson et al., 2019).

Some other related research done in algorithmic bias is detailed below.

- A study conducted at MIT discovered that three popular commercial biometric technology systems' algorithms misidentified people with darker skin tones (Hardesty, 2018). In a study of facial analysis software, the error rate was 0.8% for men with light skin and 34.7% for women with dark skin (Hardesty, 2018).
- According to the paper Xenophobic Machines, the algorithmic system used to decide whether applications for childcare assistance were identified as wrong and possibly fraudulent had racial discrimination integrated into its design from the start(Amnesty International,2021). Consequently, the Dutch tax authorities erroneously charged tens of thousands of parents and caregivers from poor households. This disproportionately affected people of color. (Amnesty International, 2021).
- In healthcare, skin lesion categorization accuracy is educated using white patient images(Norori et al., 2021). The efficiency of diagnosing black patients is 50%(Norori et al., 2021). Because black lesions differ from white lesions, computer algorithms are less likely to accurately detect black patients(Norori et al., 2021). Misdiagnosis and lack of financial means may delay skin cancer diagnosis and treatment for African American patients, thus resulting in African Americans having the lowest 5-year survival rate for melanoma, at 70% compared to 94% for white people(Norori et al., 2021).Thus the development and upkeep of biased social media algorithms is a function of machine learning, NLP, and AI, which raises the question of how these algorithms are used on different social media sites.

3.6 Biased social media algorithms in practice.

It is worth noting in this part that, traditionally, algorithms have been geared more toward teaching people how to solve a problem than towards comprehending how something works (Casey & Brayton, 2018). Since most social media sites are for-profit businesses and different websites employ different sets of input data, it is not easy to understand precisely how algorithms are used in social media (Harambam et al., 2018). However, a general idea and outlook are common knowledge as all the algorithms used result today from careful consideration of several factors(Harambam et al., 2018).

Primarily, many of these factors are based on user data, which means that the algorithms attempt to match a user's preferences, as determined by their profile, with content that he/she would engage or react to(Shin et al., 2022). For instance, when users express interest in specific hashtags or materials, Instagram directs them to similar pictures in related categories (Shin et al., 2022). When algorithms work collaboratively, individuals are paired with others with similar tastes. In this manner, users are shown content that they may find interesting since another individual previously sought it out with a similar profile, but this can restrict their ability to read other topics outside of their tastes (Shin et al., 2022). For instance, an algorithm may consider a user's specific geolocation as part of the algorithmic process because of the algorithm's ability to recognize and process this data as unique(Shin et al., 2022). For example, Reddit restricted the users of the Russian subreddit to prevent the dissemination of propaganda due to the Ukraine war (Zhu et al., 2022).

Relevance ranking is, and always has been, subjective on the assumption that the relevant algorithm can determine the requirements of a given system user (Kapoor et al., 2017). Additionally, one of the algorithm's core concepts is relevance, which is crucial to the algorithm's functioning (Sarker, 2021). Consequently, social media platforms organize their findings using relevance rankings since users expect an algorithm to present them with relevant information (Beer, 2016). For example, statistics show that over 70% of Twitter users in the US read the news on Twitter (Mitchell et al., 2021). Most of these people also rely on Twitter to provide them with news, as they find the quantity and quality of the news satisfactory (Mitchell et al., 2021). However, another survey reveals that less than 10% of Twitter users have doubted the authenticity of the news they are exposed to (Wang & Zhuang, 2018). Additionally, if a person can understand the words, pictures, or moving images in a post, they are shown and can put the information to good use. For example, if they can react or watch, the post is relevant to the algorithm for the user, which means that the user can be shown that information repeatedly (Wang & Zhuang, 2018).

Furthermore, to get a deeper insight and understanding of how the relevance system in the algorithm works, the focus has been directed to the world's most popular social media website, Facebook (Statista, 2022). Facebook's algorithms, which power the world's most popular social network, use a classic example of a ranking system. Facebook's relevance ranking algorithm considers likes(how many people have found it positive or negative), weight(how valuable content is), and time(how recent the content is) to determine the order in which users' posts appear (Pdxscholar & Morgan, 2019). Posts on a user's Facebook feed will be shown in descending order of retrieval status based on many factors (Zuckerberg et al., 2006). Affinities are focused effectively on the user's earlier interactions on the site, despite various activities having varied weights. (Zimmer, 2019). For instance, if user X often watches user B's (for instance) stories and posts and then interacts with them (by liking, commenting, and sharing), then future postings from user B will give user X a more significant weight (based on the number of likes, shares, and comments) than they would otherwise (Zimmer, 2019). Facebook also considers the post's subject matter (image, video, or simply text) and the author's reputation (how frequently their posts are seen by others, commented on, etc.)vital. (Zimmer, 2019). Likewise, the age of a post increases in value as it ages since it sheds information on users' habits, thus helping algorithms to understand user behavior (Zuckerberg et al., 2006).

However, despite all this information, it must be noted that Facebook or any other social media algorithm is very complex and continuously updating, and new factors are introduced frequently(Davenport et al., 2019). For example, how the algorithm adds variety avoids repeating the same order of previously given ranked lists (i.e., the sorting criteria are different each time) (Pdxscholar & Morgan, 2019). Furthermore, increased weight is given to postings from people rather than from corporations, and the location between the poster and the reader is essential (Pdxscholar & Morgan, 2019). This feature directs users to the most popular resource in their geolocation (Pdxscholar & Morgan, 2019).

Additionally, Facebook's ranking is always unique to each user and considers their shared interests and data consumption habits as well as their network of friends and family (Lee et al., 2019). As a user reads a particular user's content more often, that user's content rises to the top of the Feed and stays there (Guo et al., 2017). Therefore, after a short period of intense usage, the algorithm is biased as it prioritizes content from the user's preferred posters (Guo et al., 2017). Consequently, it assumes that the form above of personalized content and algorithm influences user conduct and routine as the bias maintains both the system and the user and results in a polarized media landscape(Bruns, 2016).

3.7 The effects of biased algorithms on social media landscapes

Concerns regarding social networking and blogging sites' influence on making decisions trace back to the 1980s (Power & Phillips-Wren, 2011). For example, a novel called Ender's Game, released in 1985, had a pivotal subplot about a set of brothers and sisters (Power & Phillips-Wren, 2011). These brothers and sisters were internet bloggers who used the pseudonyms "Locke" and "Demosthenes" to discuss politics, diplomacy, and wars (Power & Phillips-Wren, 2011). The kids in the novel were regarded as prodigies (Power & Phillips-Wren, 2011). Hence, both siblings eventually amassed a following, which led to distorted occurrences which affected attitudes, all of which contributed to worldwide unrest, thus reaching the highest ranks of government (Power & Phillips-Wren, 2011). Although algorithms are not explored in this story, it could be inferred that people fear cognitive biases that cause undesired social behaviors (Power & Phillips-Wren, 2011).

For example, some early research suggests that social media algorithms affect both personal and group decision-making when it comes to decision-making (Kirkpatrick, 2011). According to researchers, social media algorithms played a key part in the Arab spring. Likewise, social media made referendums in the US simpler (Kirkpatrick, 2011). Using social media and its algorithms, Akron attorney Warner Mendenhall gathered more than twice the 3,200 signatures needed for a recall election (Kirkpatrick, 2011). Similarly, London's riots were facilitated by social media and their user-generated algorithms, as well as the planning of the cleaning initiatives (BBC News, 2011).

Therefore, it's not a stretch to acknowledge that from board games to shopping to ordering food, problems with fewer constraints have all been solved by algorithms (MAIEI, 2021). Because of this proficiency, humans now significantly depend on algorithms (Mittelstadt, 2016). People depend on Facebook so much that they use it as a calendar to remember people's birthdays. People are now so used to algorithms that they would sleep in self-driving cars, go out on outings with partners suggested by algorithms, and let algorithms manage their pension accounts (Rader & Gray, 2015).

Thus, using algorithms with varying levels of complexity to understand habits is not always easy (Shin et al., 2022). By default, algorithms with machine learning consider user locations; for instance, this process might control the distribution of a certain kind of news or knowledge to a given region (Morstatter & Liu, 2017). For example, Facebook developed a "marked safe campaign" for individuals affected by the Nepal earthquake to let their friends and family members know they were okay(Meta, 2015). This resulted in a unified feed for those living in the affected area(Meta, 2015). This also helped raise donations and awareness of the disaster(Meta, 2015). Thus, algorithmic design may have both beneficial and detrimental results (Shin et al., 2022). Likewise, many people could see a spike in postings related to food and health, international movies, or geopolitics in their feeds because of the algorithm designed to direct its users to content created by social media platforms (Siles et al., 2020). For example, an increase in content about Russia-Ukraine has been happening in social media so far that battle has been nicknamed "the world's first TikTok war" because users share information in real-time on a user profile called "WarTok" (Needleman & Seetharaman, 2022). However, another research found that a user in TikTok is exposed to misinformation about the Russia-Ukraine conflict within 40 minutes of joining the social media site (Sloan, 2022), which led to the white house informing its influencers about the significance of the war (Lorenz, 2022).

Thus, it is not a stretch to claim that well-known websites with devoted users, like Facebook, TikTok, and Instagram, are aware of what can spike users' interests and know their clients better than their friends etc. (Schwartz et al., 2022). These algorithms, with their collected data, affect human behavior by getting humans to rely on them and creating phenomena like those discussed below.

3.7.1 Filter bubbles

The term "filter bubble" describes a situation unique to the Internet in which users access to objective information is restricted by social media and search engines that use algorithms to show users only those results most likely to be of interest to them(Casey & Brayton, 2018).

Many social media algorithms give customized content recommendations based on various factors, like frequency of use, age, gender, geography, and other information (Swart, 2021). As a result, a deluge of content confirms someone's present viewpoints and ideas, ensuring that users see what they like(Kapoor et al., 2017). Likewise, in humans, there is a tendency to follow other humans whose opinions are similar to their own, so the algorithm takes advantage of this fact and

It only shares content that aligns with a user's preference, irrespective of whether the data is biased or not.

Social media platforms are not the only source limited by filter bubbles (Casey & Brayton, 2018). The area someone lives in and their social circle filter bubbles in significant ways (Rodgers & Nguyen, 2022). For instance, if someone resides in a gated neighborhood, it can be assumed that the only kinds of vehicles available are BMWs, Teslas, and Mercedes. Likewise, someone's work and neighborhood also serve as a filter bubble (MAIEI, 2021).

The inclination of humans to believe what they see is high without recognizing what's in front of them. Thus, the gets truth filtered, and that's one of the major issues with such partial blindness; the frequency of use of social media doesn't help this cause either(Ferre et al., 2021). Such disintermediation brings out users' propensities to a) choose material that supports their worldview—i.e., confirmation bias—and b) gather like-minded individuals who polarise their opinions—i.e., echo chambers(Zimmer, 2019). For instance, this bias was also supported by a field experiment with 727 online news consumers (Garett,2009). People were more interested in reading online news items that they saw as supporting their current perspective, and they were less interested in consuming opinion pieces that differed from their own(Garett,2009).

For example, just like in real-world friendships, individuals spend the most time communicating with people who share their interests and values while using social networking sites. More than 80% of friends on Facebook had the same political party, according to the research of 10.1 million Facebook users in the United States who had declared their political leanings (Bakshy et al., 2015).

In ways like this, communities become polarised around disparate and heterogeneous narratives, which frequently express utter disagreement with mainstream views and best practices (Xu et al., 2021). Viewpoint variety has long been seen as a crucial aspect of democratic societies, but the rise of polarization due to social media algorithms is making it weaker (Volkmer, 2021).

3.7.2 Echo chambers

It's common parlance to use the terms "echo chamber" and "filter bubble" interchangeably (Pippin et al., 2022). However, the idea of an echo chamber takes on a different meaning in the academic world (Pippin et al., 2022). When people are purposefully ignored and dismissed from a conversation, it is said to be occurring in an echo chamber (Pippin et al., 2022). It systematically undermines the credibility of those outside the chamber to manipulate people's faith in them, thus creating polarization (Pippin et al., 2022).

For instance, people in their echo chambers may have prevented voters from hearing conflicting viewpoints, which some argue led to the outcomes of the 2016 American election and the Brexit referendum (Bruns, 2019). In a similar vein, research has demonstrated that individuals, on average, lean more toward supporting evidence (leading to confirmation bias) than contradictory evidence (Hart et al., 2009; Smith et al., 2008).

Again, insular populations are more susceptible to radicalism, says another study (Spohr, 2017). Many internet extremist groups adopt a similar tactic by translating true and factual content into emotionally driven, politically biased media via social media platforms (Rehm, 2017). This is how an angry or curious citizen becomes an extremist(Rehm, 2017). White nationalist groups accountable for the Christchurch atrocity followed this tactic(Purtill, 2019). Again, dwelling in an echo chamber may lead to decreased user trust in governments, limited access to information, and create social fragmentation of communities (Möller et al., 2018). Likewise, echo chambers magnify content in social media, from real, factual reporting to highly emotional, deliberately biased news, thus contributing to the creation of filter bubbles in society (Bhatt et al., 2018).

3.7.3 Information Overload

Two types of activities affect and create bias in the human brain due to algorithms, mainly Information Overload and Social Herding (Swart, 2021).

The first situation of information overload is made worse because search engines and social networking websites provide customized suggestions based on the large quantities of information about users' historical preferences they have access to (Roetzel, 2018). However, additional research has shown that using social networking sites may also increase one's knowledge base (Abyre et al., 2021). By facilitating the identification of new information resources, social media may increase the range of perspectives, arguments, and facts to which users have access. To provide one example, one can discover data favoring both opposing sides of the argument if they are curious. (Flaxman et al.,2016)

Nonetheless, it can't be ignored that social media sites give more priority to content in their customer's feeds that customers are most likely to know or agree with, regardless of how extreme, and they keep their customers away from anything that could cause them to reconsider their thoughts and leave the page (Roetzel, 2018). For example, research demonstrated that American conservatives are more susceptible to false information than liberals(Grinberg et al. 2019). However, more investigation into how people use low-quality information on Twitter reveals that no one is completely immune to this weakness, which affects people on both political extremes (Zheng et al., 2022), thus reinforcing that biased algorithms affect all.

3.7.4 Social Herding

The next situation that algorithms create by manipulating our feeds is social herding. For example, in August 2019, in New York City, sounds that sounded like gunshots caused many to flee(Gajanan, 2019). However, the sounds were not of the gun but a dirt bike(Gajanan, 2019). People around the incident yelled "shooter" before fleeing. They didn't discover the source of the explosions but just followed (Gajanan, 2019). Therefore, based on this instance, it can be assumed that it's wise to ask first and act afterward (Gajanan, 2019). However, things are the opposite in real life(Baddeley, 2010). Human brains utilize knowledge about the group to deduce the proper course of action in the absence of explicit signals, similar to how schooling fish and flocks of birds function(Baddeley, 2010).

This kind of social conformity is prevalent (Baddeley, 2010). When individuals can see what music other people share on social media, they end up downloading similar tracks, according to intriguing research of 14,000 Web-based volunteers (Salganik, 2006). Furthermore, when individuals were segregated into "social" groups where they could only see the preferences of those in their immediate vicinity and had no knowledge of people outside of their group, the preferences of various groups quickly diverged (Filippo Menczer, Thomas Hills, 2020). However, in "non-social" groups, where members were unaware of others' preferences, preferences remained mostly constant (Mencze et al., 2020). To put it another way, social groupings provide a demand for conformity that is so strong that it may override personal preferences, and by magnifying chance early variations, it can drive severe divergence within separated groups (Menczer et al., 2020).

Similar dynamics apply to social media (Roetzel, 2018). People mistakenly equate popularity with excellence and imitate the actions they see. According to researchers, information spreads via "complex contagion" (Mønsted et al., 2017). When users are exposed to an idea repeatedly, usually from various sources, they are more likely to adopt and reshare it (Mønsted et al., 2017). The "mere exposure" effect, which occurs when individuals are subjected to similar signals, such as specific individuals, makes them prefer that stimulation over others they have met less often, amplifying this social prejudice even more (Mønsted et al., 2017).

These biases manifest in an insatiable need to pay attention to content that becomes viral because people assume that it must be important since everyone else is discussing it(Bogert et al., 2021). Websites such as Instagram, Facebook, and Pinterest display popular material at the front of the devices and inform their customers of how many individuals have loved and liked a certain issue and display stuff that aligns with their beliefs (Roetzel, 2018). Few of their users are aware that these indicators cannot provide impartial evaluations of quality; thus, people end up doing the wrong thing in big numbers (Roetzel, 2018).

4 Results

This section, an understanding of the answers to the research questions, which have been broken down into two groups. The questions are: 1)To what extent do social media-biased algorithms influence user's decision-making? 2)Explain how this relates to the decisions regarding COVID-19 vaccinations.

To tackle the first question about the extent to which decision-making is biased in social media algorithms, it can be first highlighted that the number of people logging into Facebook, Twitter, and other social networks continues to rise, thus targeting more people and their ability to make decisions(Yahaya et al., 2019). The Pew Research Centre released their most recent social media fact sheet, which found that 7 out of 10 people use social media to communicate, interact with news content, exchange information, make decisions, and enjoy themselves. Similarly, it is important to understand that 76% of Facebook users log in daily, and 71% of the American population has a Facebook account(Auxier & Anderson, 2021).

However, these social media users commonly have no notion about who or what impacts the information in the news feeds(González-Padilla et al., 2020). It is believed that somewhere between 27% and 62% of consumers are uninformed that algorithms are employed to customize their feeds(Auxier et al., 2021). Those who are acquainted with the notion of algorithms often have an inaccurate understanding of what it comprises (Auxier et al., 2021). According to a Pew Research survey (Auxier & Anderson, 2021), 74% of Americans remain uninformed that Facebook saves information on their interests and personality traits, according to a Pew Research survey(Auxier & Anderson, 2021). Similarly, the same study found that many voters are uncomfortable with the concept of personalized political campaigns and oppose the collection of personal data to influence their decisions(Auxier & Anderson, 2021).

Research on several decisions influenced by social media algorithms is discussed below in the context of this investigation.

Initial research implies that social media influences decision-making by increasing the channels via which people may get relevant information and perspectives(Karafillakis et al., 2021). For instance, Instagram was bought by Facebook, so linking people's Instagram accounts with their Facebook accounts is quite common. This linking creates a sharing of data between two channels and thus influences people and their decisions from multiple platforms. Likewise, since these platforms are commercially focused, they share the same data with other channels. For instance, Instagram, Facebook, and LinkedIn share over 50% of user data with third-party firms(PCloud, 2018).

Studies claim harmful behavior can be incited through social media algorithms. Moreover, when people are pushed toward certain content by social media algorithms, they may become very polarized and take action based on it, which can have serious consequences in many areas of life(Abyre et al., 2021). As an example, in a survey with 30 participants, 29 (or 99%) indicated they had never considered the Earth may be flat until watching conspiracy films on YouTube(Urman et al., 2022). In any case, the aforementioned study's authors argue that this phenomenon is the result of YouTube's innate algorithm, which sustains a "rabbit hole" (a sequence of steps that leads the visitor to YouTube to view or read more unorthodox linked information) to increase watch time and increase revenue(Urman et al., 2022). Similarly, research finds that in cases like this, mistrust in organizations and the government is promoted, thus leading to higher chances of wrong decisions being made by people in collective numbers(Urman et al., 2022).

Similarly, studies claim people's behaviors and motivations change, and they may become less self-aware while in a large group of online spaces (Levy, 1989). However, some other research suggests that people bring their own pre-existing attitudes and beliefs into a crowd, rather than the algorithm generating biases (Convergence theory) (Yahaya & Ayodeji, 2019). Thus, proponents of the first argument state that algorithms inspire certain behaviors in their members, while others advocate that groups of individuals with shared goals voluntarily assemble to establish such movements made more accessible by social media echo chambers(Yahaya & Ayodeji, 2019). Thus, social media's ability to create large groups and exert influence in decision-making and behavior is a key feature (Yahaya & Ayodeji, 2019).

Trust in social media algorithms has been presented as an essential driving component of impacting social media users and consequences of behaviors shared and distributed among consumers, according to Yahaya & Ayodeji, 2019). For instance, studies have shown that consumers' faith in their social media feeds substantially affects their choices and actions (De Bruyn,2008). Another instance that has been influenced by the YouTube algorithm is in Brazil, where a politician on the extreme right, Jair Bolsonaro, became a surprising YouTube sensation and ultimately became president(New York Times, 2022). This is among the most prominent examples of the algorithm's political influence(New York Times, 2022). The New York Times discovered in 2019 that YouTube's discovery and suggestion engine had consistently led visitors to extremist and conspiracy channels in Brazil(New York Times, 2022). Even Bolsonaro's supporters give YouTube to credit for his victory. Thus, impacting the decision of common Brazilians regarding their human right of voting(New York Times, 2022).

Furthermore, studies have shown that social media users are unaware of biased algorithms(Shearer & Gottfried, 2017). For instance, people rarely ask for content to be shown to them. They are limited in their filter bubbles, which show them misleading information based on their past habits and user data.Thus shortening the process of decision-making in social media compared to real life without the internet, which involves first asking, afterward acquiring information, next analyzing the information, but only after applying the information, then deciding, and finally assessing(Shearer & Gottfried, 2017). For example, an internal Facebook analysis claims Facebook's algorithms enabled misinformation operations headquartered in Eastern Europe to reach almost half of all Americans before the U.S. presidential elections in 2020 (Meta,2020). The campaigns garnered 140 million monthly U.S. visits and created content for the religious, Christian, and black communities. Likewise, 75% of people who were shown those campaigns were not following or looking for such content; instead, Facebook's algorithm pushed the story onto users' feeds(Meta,2020). This creates ramifications for the lives of millions of Americans since the right to vote for president is widely regarded as a cornerstone of democracy(Meta,2020). Such impacts on decision-making have been observed in U.S. presidential elections and health and safety(Meta,2020). For example, those interested in healthy cooking, for instance, would be shown anorexia-related material, while those interested in conservatism might be directed to extremist blogs(Meta,2020).

Likewise, algorithms of social networking sites have a considerable influence on people's daily lives, which has ramifications for a variety of fields, including healthcare, education, politics, entertainment, law, knowledge, and the news, among others, according to various research(Roetzel, 2018). These decisions by social media users had an impact on geopolitics, businesses, economies, consumer behavior, etc. For example, the herd mentality induced by social media algorithms in South Korea about not using Japanese products impacted the 2019 revenues of famous car brands like Nissan, Honda, and Toyota(Lee et al., 2022). Similarly, the boycotting of French wine throughout 2003 in response to its geo-political stance against a lack of support for the U.S. invasion of Iraq resulted in a decline in sales of 13%(Ashenfelter et al., 2007).

Another research suggests that the Role of Social Media algorithms in Promoting Health and Well-Being-Related Policy and Social Change should also be discussed (Yeung, 2018). For example, the volume of posts (for example, the number of Twitter posts) on good nutrition, sports exercise, and stress reduction indicates the extent to which individuals consider their well-being or engage in healthy activities (Yeung, 2018). Similarly, Social networking sites typically allow users to do check-ins, where individuals broadcast their presence at a particular place (for example, at a gym). This leads to algorithms suggesting meal plans or certain foods etc., to the user resulting in them making better decisions for their health (Yeung, 2018).

Similarly, good decisions can be made due to social media and its biased algorithms (Delgado et al., 2022). For instance, commercial businesses all over the globe have launched initiatives to increase the use of varied, realistic models in advertising after the body positivity movement took off because of the flawed artificial intelligence in algorithms that identified the most popular search phrases (Jarman et al., 2022). This action marked a departure from the common practice of firms hiring just one sort of model to advertise their products (Jarman et al., 2022).

Therefore, several factors in the present day are affecting the exponential increase in social media users' decision-making. The weight of social media decisions is exceptionally high and essential, which leads us to understand the role of biased algorithms in influencing the covid 19 vaccine decisions.

The decisions in this context greatly impacted all of humanity as many people were told to remain indoors and follow stringent controls(quarantined). In response, most people stayed inside, businesses were closed, children were kept indoors, and the roads were quiet. This quarantine resulted in a meteoric rise in the prevalence of digital technology worldwide. Covid forced users of all ages to become more dependent on the internet, creating more scope to influence their decisions. Everything done in real life—school, purchasing, working, meetings, parties, and socializing—had suddenly moved online. Social media proved to be a savior by facilitating people's ability to maintain meaningful bonds despite physical isolation. Throughout 2020, social media use accounted for 50–70% of the time spent online due to the COVID-19 outbreak (Beech, 2020). To reiterate, it is not easy to differentiate between good and harmful levels of social impact through social media. Nonetheless, the detrimental consequences of social media in decision-making during the COVID-19 pandemic are evident and discussed below.

During the epidemic, several studies allege that decisions made by users of social media platforms due to biased algorithms incited dangerous behavior (Pandya & Lodha, 2021). In addition, social media algorithms lead users to see biased material and act on that bias, which creates grave repercussions (Pandya & Lodha, 2021). For instance, A viral message purportedly written by a German noble laureate is only one example (Nyilasy,2019). The post described how taking the vaccine would result in death in two years(Gisondi et al., 2022). Due to the inclination of social media algorithms to promote material with more engagement, the post became viral. Such misinformation pushed by Algorithms resulted in anti-vaccination sentiments in Kolkata, India(one of the worst-hit regions during the covid pandemic) (Gisondi et al., 2022).

Similar research found that big online echo chambers changed people's goals and behaviors (Jennings et al., 2021). For instance, due to YouTube's well-known echo chamber-esque algorithm, anti-vaccine sentiment is more prevalent on the platform, according to research (Jennings et al., 2021). Similarly, the vaccination acceptance rate among YouTubers recorded was low at 45% (Jennings et al., 2021). Analysis of vaccine-related videos on YouTube found that 65% of people were critical of vaccines (Jennings et al., 2021). Vaccine-related issues, including autism, undisclosed adverse effects, etc., were common topics in these videos (Jennings et al., 2021).

An examination published by BMJ Global Health provides compelling evidence that vaccination requirements and the failure of health officials to adequately communicate the rationale for such laws significantly harmed the public's faith in vaccines (Bardosh et al., 2022). According to studies, consumers' trust in social media algorithms had a significant bearing on the decisions made by users and which resulted in the ripple effects during the covid 19 pandemic (Schippers, 2020). For instance, the adult vaccination rate in the United States is at roughly 65%, whereas in Brazil, the Effective COVID Vaccination Initiative by the government resulted in a 100% vaccination rate among adults in Rio and Sao Paulo compared to 78.2 in New York (Adriana, 2022).

In addition, research has revealed that social media users are not conscious of the biased algorithms. Therefore they don't realize their decisions are influenced due to the algorithms(Shearer & Gottfried, 2017). For example, UNICEF found that in India, concerns about the vaccination's potential adverse effects and the belief that others need vaccine more were the two most common explanations for vaccine reluctance (UNICEF, 2021). The study's inconclusive results emphasise the need to investigate the potential contribution of biased social media algorithms on vaccine scepticism.

During the epidemic, the algorithms of social media sites had far-reaching effects on people's everyday life, with consequences for a wide range of sectors, nations, etc(Roetzel, 2018). For example, the Bolivian Senate legalised the manufacture, sale, and usage of chlorine dioxide after the spread of the U.S. government's recommendation to use of bleach to combat covid spread like wildfire in social media even for English speaking countries(The New York Times,2022). In nations where drugs are not strictly controlled, the popularity element in social media algorithms allowed this knowledge to propagate (The New York Times,2022).

Likewise, an increasing amount of data suggests that the algorithmic expansion of social media platforms influenced people's decision making during the covid-19 epidemic by flooding them with conflicting information and perspectives(Yahaya & Ayodeji, 2019).For instance, Continued spread of false information, as shown by the fact that tweets flagged as fraud get more likes and retweets than non-misinformation tweets, even when the content of both is the same implies that the algorithm in social media has a tendency to opt for sensualized content (Zannettou, 2021).

During covid 19, major study highlights the Role of Social Media Algorithms in Fostering Health-Related Policy and Social Change regards to vaccine (Liew & Lee, 2021). For instance, constant understanding and listening of social media users in social media platforms and use of artificial intelligent based algorithms helped to identify trends which lead to change of policies regarding vaccine intake by governments worldwide (Liew & Lee, 2021).

Equally, during the CoV19 outbreak, research suggests beneficial decisions were made due to the popularity-driven biases of social media algorithms (Alfatease et al., 2021). For example, in the Aseer area of Saudi Arabia, 613 people voluntarily participated in research that reported

37% of respondents strongly believed that sharing information about the COVID-19 vaccine on social networks has enhanced their interest in becoming vaccinated (Alfatease et al., 2021).

Misinformation concerning the effectiveness of the COVID-19 vaccine spreads rapidly on social media (Gabarron et al., 2021). The effectiveness of the vaccination or the presence of adverse effects are not the only factors that should be considered when determining the veracity of the vaccine hesitancy (Gabarron et al., 2021).The role of social media and its algorithms are quite potent and vital to be explored in this regard.

5 Applications

The widespread spread of the coronavirus outbreak constituted an immediate threat to public health (Liu, 2022). Since the virus's first outbreak in China, it has travelled to every continent, killing countless people along the way. Given the virus's extreme infectiousness, the World Health Organization (WHO,2020) recommended a wide range of measures to stop its development (Gunasekeran et al., 2022). One such recommendation is to limit social interactions among individuals to lessen the likelihood of the spread of disease (Bao et al., 2020). Following these guidelines, several countries, such as Denmark, the Great Britain, India, and Australia, enacted stringent laws of social isolation (Wong et al., 2020). People were required to stay home and to refrain from physical interaction with those who were not members of their immediate family, all consequences of the quarantine rules (Wang et al., 2021). Any person infected with the virus or in touch with an infected person was required to remain in quarantine (Rita, 2021). Every level of education from kindergarten to university was cancelled(Rita, 2021). All this led to the emergence in the use of social media and other forms of digital spaces where the sole means of maintaining relationships with distant relatives, acquaintances, and colleagues was via the internet(Abbas et al., 2021). During the peak of the epidemic, social media's role as a platform for communication and news dissemination reached new heights (Abbas et al., 2021). People's actions in terms of seeking up-to-date knowledge about the virus and taking a stand on the vaccination issue were profoundly influenced by social media and its algorithms(Abbas et al., 2021).

5.1 What Biased social media algorithms effected the covid 19 pandemic

As it has already been discussed that the idea of algorithmic bias stems from societal issues like systemic inequality, discrimination, and prejudice as its foundations (Lee et al., 2019). Thus, as a result ,the tendency to make decisions that unfairly benefit or penalize one set of content, people, news or businesses over another is potent in the case of covid19 pandemic.

Due to increased use of social media and quarantine during the pandemic people heavily relied on information produced by social media, which had a tendency to direct users towards content similar to the one they read prior(Tsao et al., 2021). Similarly, human confirmation bias helped spread biases like anti trustees of the government and organizations and further reduced the people willing to take vaccines(Tsao et al., 2021).

Likewise, as it is true that algorithms reflect (or even amplify) pre-existing inequalities or prejudices (Karimi et al, 2018).However, a lot of times prejudices didn't play a role in the opinions of vaccines within social media users but rather the fact that a new vaccine was made super-fast was going to be inside humans and thus created fear(UNICEF,2020). This, combined with the ocean of misleading content on all social media channels and biasness of social media algorithms favouring popular content led to the info emic discussed by WHO(WHO,2020).

Algorithms are crucial because they promote the growth of specialised data gathering infrastructures and regulations, which are used for things like formulating health policies and notifying individuals about the new covid 19 measures, their immunizations, and travel limitations (Yeung, 2018). Due to the high demand for up-to-date information during the epidemic, social media platforms fell prey to the practice of algorithms that leads to boosting popular content, which spread a wave of misleading information. All of these points to the role that algorithms played in not only raising covid vaccine uptake but also in influencing vaccination aversion (Cinelli et al., 2020).

The sheer volume of material created during the peak of covid made it impossible for any algorithm to monitor all of the user-generated content posted in it (Gisondi et al., 2022). In addition, as discussed in the literature, confirmation bias hinders the ability of algorithms to mitigate the damage caused by people's inherent prejudices (Gisondi et al., 2022). Users were aided in their vaccination decisions in social media by their own bias as well as social media algorithms in combination with the artificial intelligence, machine learning, and natural language processing (Gisondi et al., 2022).

- Artificial intelligence: To provide just one example, Artificial intelligent -enhanced social media algorithms have been discovered to facilitate the reporting of potentially fake information.
- Machine learning: For instance, machine learning has allowed governments, organisations, users, etc., to connect numerous sources of reliable/unreliable information in their sites, which, depending on the content, has either increased or decreased vaccination hesitancy.
- Natural Language Processing: For example, authorities were able to reach out to certain subsets of social media users with pertinent information thanks to the incorporation of natural language processing systems into social media algorithms.

Similarly, social media sites like Facebook, Instagram, etc. having trouble containing a wave of false information as their user bases swelled to record levels owing to quarantine restrictions. Due to a shortage of human reviewers (due to workers working from home too or being unwell), platforms have largely assigned the job of content moderation to automated algorithms, many of which are very prejudiced. Thus, resulting in lower moderation of content in social media and thus higher differences in public opinion on the position on vaccines .

5.2 Effects of human behaviour due to poor algorithmic management during Covid-19

5.2.1 Filter Bubbles

To prevent spreading the disease, many remained inside. A wide range of social and cultural variables impact this shift in behaviour, but for the sake of this study, we will only focus on those that influence vaccination uptake.

Since most individuals were confined to their homes, the only means by which they could be heard or seen was via social media, thus considerations like approval or acknowledgment had a disproportionately large effect on people's behaviour. Twitter and TikTok trends affected policy in many Latin American nations, leading to potentially dangerous responses to the epidemic. Medicines like hydroxychloroquine have been used, along with several unproven home cures and unfounded health claims(The New York Times,2022).

The result of all this was a growing political divide between countries. Through the duration of the epidemic, polarisation caused individuals to reach divergent conclusions about the severity of the threat and the best way to respond to it. Algorithms that decide which posts appear in a user's feed might be blamed for reinforcing pre-existing ideological divides by limiting their exposure to information that could challenge their worldview. Face-to-face political interactions may have facilitated dialogue between the polarised parties, but the absence of such meetings reduced the flow of information, which in turn fuelled biased behaviour among social media users during the epidemic.

5.2.2 Echo chambers

Since echo chamber takes on a different meaning than filter bubbles in the academic world, it can be assumed that echo chambers are responsible for undermining the credibility of those outside the chamber thus creating polarization(Pippin et al., 2022).

For instance , people in their echo chambers prevented others from hearing conflicting viewpoints, which lead to toxic home remedies being followed in poor countries as a cure for covid(The New York Times,2022).

Similarly, it is also well-known that isolated communities are more prone to radicalism , and the quarantine during covid period makes them even more isolated. Therefore, implying that the consequences of people from these communities not administering vaccinations would be worse because increased they are being secluded from the society and its important decisions. Similarly, staying in anti-vaccine "Echo chambers" may reduce user faith in governments, which in turn reduces access to crucial information and puts the whole society in danger as her immunity won't be achieved if people don't vaccinate(Europe PMC, 2016).

5.2.3 Information Overload

The World Health Organization has previously recognised the serious info emic that is covid 19 in terms of information overload(WHO,2020).Therefore, based on the literature research in the earlier section, it has been established that users' ability to exercise judgement is impaired by the proliferation of information and the pressure to make content-based decisions(Roetzel, 2018).

Social media platforms rely on algorithms to censor material; thus, they can't always filter out false or misleading claims as algorithms are not yet capable of monitoring everything correctly(Roetzel, 2018). This creates the likelihood that users may make recommend or share erroneous judgments based on the covid 19 vaccine in their social media feeds, resulting in their acquaintances being exposed to such misleading content(Roetzel, 2018). Thus , social media and its rippling algorithm has made 75 % of people aware of the presence of misinformation in the platforms, according to a study(Alfatease et al., 2021).

5.2.4 Social Herding

In a good example of social herding, individuals were more likely to get the covid 19 vaccinations because of the role played by social media algorithms in promoting material from the most popular and frequently viewed sites. The global population is slowly but gradually being immunised and learning about the vaccine's effectiveness. Vaccine scepticism fell from 28.5% to 24.8% globally, although there was an increase in of vaccine hesitancy in several countries, including 20% in South Africa, 8.8% in the U.S, as well as 8.2% in Nigeria (8.2%), and 3.3% in Russia. Vaccine reluctance was recorded at its highest rate in June 2021 in 48.5% in Russia 49%, 43% in Nigeria , as well as 40% in Poland , and at its lowest rate 2,4% in China , 18,8% in the UK (18.8%), and 20% in Canada (Lazarus et al., 2022). Thus, social herding within misinformed echo chambers and filter bubbles still holds a vital place in influencing users in deciding about their Covid 19 vaccines.

6. Conclusion

To conclude, and answer the main research question it can be said that the to establish community on social networks, algorithms (and their methods to construct filter bubbles, echo chambers etc) are responsible for amplifying users information-gathering habits on deciding about the intake of covid vaccine .Similarly, the reliability of big social media platforms on leaving content moderation on algorithms is worrisome as algorithms follow and use users past behaviour to provide them with information. This focus on past behaviour doesn't let the user explore new and conflicting ideas leading to many serious effects on themselves and those around them. Similarly, the reward of social media algorithms to keep on feeding users with biased content results in longer

Likewise, this research suggests that social media sites and its biased algorithms have the potential to mislead the public about the vaccine decisions .Thus,to answer the main research question , it can be said that biased social media algorithms impact people's decisions for covid 19 vaccinations by creating non transparent,revenue focussed algorithms that further create echo chambers and filter bubblers due to humans inherent biasness which results in information overload and social herding. Thus, paving the way to a polarized society that is distrustful of organizations and governments.Additionally some key points that the research concludes is:

a) Firstly,most big health organizations don't even consider the algorithm in social media being a problem due to the inherent belief that machines are not biased.Thus lack of research discussing the impact of social media algorithms in regards to vaccine decision was noticed while doing the research.

b) Secondly,the impact of social media algorithms and its bias is vital in understanding its impact in vaccine hesitancy however, it can't be ignored that the social media algorithms also helped in spread the right information and policies to the people during the quarantine thus keeping the information flow between the people and their governments.
c) Thirdly, content such as misinformation impact those who already hold some preconceived biases, but they had had the opposite effect on those who were sceptical or unwilling to be vaccinated.Thus, it can be concluded that despite existence of misinformation, people who believe what they believe are more inclined to ignore the social media algorithms direction towards misinformation.
d) Fourthly, it can be noticed that the issue lies amongst humans and their confirmation bias but it cannot be ignored that social media platforms and their algorithms are responsible to quite some extent as they provide no transparency to its users and are often caught in various scandals.
e) Fifthly, it can be concluded that governments are responsible for making sure that social media platforms are not manipulating their users as well as responsible for protecting the rights of its citizens.Likewise,governments are also responsible for handling the spread of information regarding vital matters like the covid-19.
f) Lastly,it can be concluded that the problems of algorithmic bias in social media can be fixed by better AI development by humans however, the inherent bias within humans will wont be easy to rectify. Thus Humans are indeed the solution and the problem.

6.1 Limitations

Furthermore, as with any research, limit exist. In this study , understanding and application of existing literature and studies were done which left out the possibility of finding new results and contributing to the data at large. Again, the amount of literature data was relatively restricted as most of the research conducted in analysing the decisions of users due to social media algorithm were in business context and not in health context.Similarly,data about social media bias is quite non transparent and requires immense support financially and technically to be analysed.Likewise,the covid pandemic is still ongoing and many in third world countries have not received their vaccines , and maybe wont.Thus , the study is biased as research was mainly focussed in the users decisions regarding vaccines in the first world countries where the governments made it a priority to make their citizens vaccinated. The study did not factor what people in poor third world countries do regarding their decisions on the luxury vaccination of covid-19.

Lastly,these limitations leave scope for future research.

6.2 Future research

It is recommened to research the topic further.For future research, it can be recommended to work with some big companies or social media analysing companies to exclusively look at the new literature that is inaccessible or not published yet and do an online study regarding the perception of the people, since this topic is not really researched and would need many resources.

Likewise,since the topic has never been researched before , it leaves the scope of researching it in many ways. For example, comparing findings from different nations, regions, races, or cultures might lead to new study ideas like descriptive studies or anticipating public feelings or public responses about the influence of covid 19 vaccine on users decisions would help the users,businesses and governments to understand how to handle such emergency situations etc

Lastly,when it comes to what did this research achieve , it can be said that this research is the only research so far that takes the existing literature about social media bias in the context of algorithm (which is a very limited topic) and applies it to a relatively new topic- covid 19. This research created a link between the human bias and their decisions, the social media algorithms and the covid-19 pandemic.

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