3 The power of algorithms and keys of participation

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3.1 Introduction

We live in the era of algorithms. Some even called it a new economy, the algorithm economy. They are the building blocks of any software application. Every day we are increasingly exposed to algorithmically curated information. Algorithms dictate everything users see online. From news to search information, to entertainment (Netflix) and shopping (Amazon), algorithms increasingly impact how we make decisions, how we consume information and how we understand the world around us. Web users increasingly enjoy more access to information more speedily and in an accessible manner as the media landscape shifts more towards digital and mobile domains (Levordashka & Utz, 2016; Boczkowski et al., 2018). The general belief that algorithmic use has a significant impact on daily life in this digital world is reflected in the high level of interest in public and scholarly debates (Gillespie, 2014; Willson, 2017).

What is an algorithm? Essentially, algorithms are a step-by-step list of instructions that are executed, in a certain order, for solving a problem or performing a task (Gillespie, 2014; Introna, 2016). For example, a cake recipe is an algorithm for making a cake. We use algorithms every day. A computer program is an implemented set of algorithms. Furthermore, algorithms are used to run the Internet and all Web services, including Web searches.

The use of algorithms will continue to proliferate everywhere as huge amounts of data are being generated, collected, analysed and managed by companies, public administrations and governments. Additionally, the exponential growth of Internet users makes it impossible to manage certain tasks manually. There are just not enough moderators to thoroughly review each piece of content due to the volume of content submitted on a daily basis. Moreover, the complexity and subtleties of language present significant obstacles. Artificial Intelligence (AI) and techniques like Machine Learning (ML), Deep Learning (DL) and Natural Language Processing (NLP) are at the forefront of this new era of algorithms. Moreover, AI-based algorithms, particularly the ones based on deep learning, are challenging the notion of transparency and objectivity (Zerilli et al., 2018).

One of the Web services that uses intensive algorithms is social media. Social media (and the Web) has grown exponentially in the last decade, and it has forever changed the way we interact, work and do business (Sterrett et al., 2019). Social

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media is defined as "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of User Generated Content" (Kaplan & Haenlein, 2010, p. 61). It includes, among other tools, weblogs (e.g. TechCrunch, Gary Vaynerchuk Blog, and TMZ), microblogging (e.g. Twitter, Tumblr and Weibo), social networking platforms (e.g. LinkedIn and Xing), platforms for sharing videos and images (e.g. TikTok, YouTube, Dailymotion, Pinterest, and Instagram), instant messaging (e.g. WhatsApp, Snapchat, WeChat and QQ), news aggregators (e.g. Reddit, Hacker News and BizSugar) and social live streaming services (e.g. Socialive and Periscope).

All these social media services use algorithms to perform different tasks and different personalization mechanisms. The adoption of social media algorithmic tools serves as a helpful way to avoid becoming overwhelmed with the amount of information. For example, Facebook and Twitter show to the user posts from his/her closest friends and in the user feed because those are the people that the user interacts with most often. However, it transfers human decision-making power towards social media algorithms (Diakopoulos & Koliska, 2016). Often, users do not know how these algorithms make decisions for them. The control of advertising that appears on YouTube videos is an example. This is done automatically by algorithms that pick which advertisements the user will see during a YouTube video in real time. These decisions may have strong implications related to the risk of discriminating those affected (Coeckelbergh, 2020; Cowgill & Tucker, 2020). This content bias issue and the potential discrimination effect can occur intentionally (Speicher et al., 2018), or even unintentionally through their respective choice of criteria (Diakopoulos, 2013).

Yet, there has been scant attention to the different effects of the social, organizational, cultural and political dynamics related to the process of algorithm development and implementation (Diakopoulos, 2016; Ettlinger, 2018). One of the big issues is the potential risk of algorithmic bias and, in certain situations, ethical concerns (Tsamados et al., 2021). Although the term bias differs based on the context (Narayanan, 2018), in general, tt refers to errors that are systematic and repeats that result in unfair consequences, like favouring one arbitrary user community over another.

This chapter outlines the challenges of using algorithms in social media, in particular transparency and objectivity. First, I describe the main areas of algorithm usage in social media. Then, I discuss the challenges associated with that use.

3.2 Social media and algorithms

As mentioned before, social media services are the kings of algorithm usage. This section delves into the three most common uses of algorithms on social media: content curation, user data collecting and content production.

3.2.1 Content curation

Curation is the act of selecting, classifying, filtering, prioritizing and presenting content. Algorithmic curation and filtering is one of the most used tools on social media (and digital media in general), and it is a great challenge in

hyper-technological and digital society (Thurman et al., 2019; Jussupow et al., 2020). Essentially, filtering algorithms automatically select and filter data that the user sees based on the extrapolation of viewing or usage preference of the user's previous behaviour, or many other users, to predict what that user might like too (Messing & Westwood, 2014; Bakshy et al., 2015; Rader and Gray, 2015; Mothes & Ohme, 2019). Algorithmic filtering has the potential to improve users' experience (Bozdag, 2013; Ricci et al., 2015, Zarouali et al., 2021). Recommender algorithms which are quite common in online retailing platforms like Amazon or streaming platforms like Netflix are a type of curation algorithms.

A good example of algorithmic curation on social media is Facebook. In 2011, algorithms were incorporated in the news feed feature. One of the key goals was to decrease content hypersaturation on social media. Then, in 2018, the platform decided to prioritize posts from family members and friends over public content. According to Facebook, the company wants users to get the content they care about and from the friends they care about. Most of social media companies argue that the introduction of curation algorithms is to offer a user-centered solution for managing vast amounts of content, allowing the users to quickly "see what matters" on their social feeds.

The three most frequently used filtering algorithms are content-based filtering, demographic filtering and collaborative filtering (Ryngksai & Chameikho, 2014; Thorat, 2015). Content-based filtering analyzes user preferences related to similarities in products, services or content features to make recommendations for the user. The demographic filtering approach employs the social-demographic data (e.g. age, gender, job) of a user to select the content that might be suitable for recommendation. Finally, collaborative filtering algorithms make suggestions for an individual user by collecting data and preferences from many other users. This perspective relies on the premise that social media users who accepted specific content are likely to accept it again in the future.

There are different types of curation personalization approaches on social media. The most common differentiation is between explicit and implicit personalization (Thurman & Schifferes, 2012; Kaptein et al., 2015; Borgesius et al., 2016; Haim et al., 2017; Yeung, 2018; Reviglio & Agosti, 2020). Explicit personalization relies on data that the social media user proactively disclosed, and implicit personalization uses data that the social media user has not directly volunteered; in some cases, the user does not require a user to create an account. Basically, it tracks user behaviour. Some algorithms use a combination of both types of personalization. More recently, a new type of personalization is emerging – contextual personalization – which is based on the user's current location and time.

Although curation algorithms have the potential to increase user experience and satisfaction, this had not always been the result. In the last years, curation algorithms have been criticized for creating "filter bubbles" and other phenomena on social media (for a critical review see: Dahlgren, 2021; Cinelli et al., 2021). The term filter bubbles, also called echo chambers (Sunstein, 2009) was coined by Eli Pariser (2011), is related with the filtering algorithms mechanism that dictates the information and opinions that the user can see based on the user's own beliefs. Some studies suggest that filter bubble state limits diversity of content, and it can

increase user polarization (Flaxman et al., 2016; Dubois & Blank, 2018; Chitra & Musco, 2020). Some recent studies investigated whether the YouTube video recommendation system contributes to social media polarization by promoting sensitive content (e.g. Hussein et al., 2020; Roth et al., 2020). Hussein et al. (2020) discovered a filter bubble effect in top recommendations for all topics, excluding vaccine controversy, after examining more than 56,000 videos across five topics. They also found that for users with brand-new accounts, demographic factors like gender, age, and geolocation have no effect on amplifying disinformation in returned search results.

Despite the potential filter bubble risk, other studies do not support this viewpoint (e.g., Hosanagar et al., 2014; Bakshy et al., 2015; Borgesius et al., 2016; Fletcher and Nielsen, 2018; Boxell et al., 2020; Levy, 2021). A study conducted by Hosanagar et al. (2014) found that algorithm filtering can build commonality, not fragmentation, in online music preferences. Similar studies have found the YouTube recommendation algorithm may foster the creation of highly homophilous communities (e.g. Hussein et al., 2020; Kaiser & Rauchfleisch, 2020; Tang et al., 2021). A recent study by Boxell et al. (2020) found that although affective polarization has grown faster in the United States, it is decreasing in other countries with high Internet usage. Also, the authors found that U.S. polarization was highest for the older age groups (75+).

3.2.2 User data collection

Social media algorithms are also collecting vast amounts of data from social media users, and using that data for different purposes, such as advertising, promotions, business intelligence, data analytics, and personalization. As we mentioned before, one of the most relevant aspects is how data collection tools affect how users find social media content (Mittelstadt et al., 2016).

Social media firms collect enormous amounts of data about social media users, allowing them to create advanced psychometric profiles of users (Schirch, 2021). This data has proven to be immensely valuable for many social media firms because their business model based on advertising revenues depends on this sort of data. Social media data-centric business models focus on collecting as much data as possible and link it to individual users, and create psychometric profiles of those users which will let the firms better target their advertising strategies. This data-centric approach affects the design of social media profiles, which is continuously reviewed and updated.

Profile making has become omnipresent in social media platforms and digital world. Users are frequently invited (most of the times it is mandatory) to create profiles for using most of the Web services. Combining algorithms with profiling approaches might be troublesome since the profiling criteria can provide controversial categories and adverse effects, allowing discrimination or questionable user targeting. For example, some years ago, Facebook allowed to target "anti-Semites" (Angwin et al., 2017). Also, some social media platforms (e.g. Google, YouTube or Facebook) allegedly used racial profiling (Angwin & Parris Jr., 2016; Gardner, 2020).

The rise of data analytics and emerging technologies like machine learning and AI are expanding the ability of social media firms to contextualize data and draw on insights gained from this data analysis. Overall, social media platforms based their design, operations and business model on a datafication strategy. Social data collected by social media firms can be categorized into four main categories:

- Personal data. It includes data that can be used to identify a person. Beyond the common information like name, phone number, and addresses, it also includes data of national IDs, passport number, social security numbers, gender, photos, and financial data, as well as non-personally identifiable information (Non-PII) such as Web browser type, Web browser cookies, language preference, IP address, and device types and IDs.
- Engagement data. Also called interaction data, it includes data that describes how consumers interact with the social media platforms, mobile apps, text messages, emails, paid adverts.
- Behavioral data. It includes data generated or in response to the user experience with a social media platform and it encompasses the transactional details such as product usage, purchase history, and gathering qualitative data (e.g., click tracking, scrolling, and mouse movement).
- Attitudinal data. It helps to understand that social media users think about the platform and the content provided. Examples include online reviews, user satisfaction surveys and content desirability.

3.2.3 Content creation

New emerging technologies are allowing social media firms, businesses and certain users to create content automatically. Content creation automation is a growing area, especially in the digital marketing arena. Certain AI tools like NLP are quickly expanding content creation automation in social media (Farzindar &Inkpen, 2017; Khan et al., 2020).

NLP, sometimes referred to as computational linguistics, is a branch of computer science, AI and linguistics, that uses different machine learning techniques to build algorithms that process and analyze natural language data. NLP comprises two main areas: Natural Language Understanding (NLU) and Natural Language Generation (NLG). While NLU concentrates on machine reading comprehension through grammar and context, NLG concentrates on text generation.

The benefits of adopting NLP comprise the large volume of textual and speech data that can be managed, the velocity of analysis (tens of thousands of documents in seconds) and the capacity to detect tiny patterns that would be indecipherable to human analysts otherwise. Further are the large number of data sets (known as corpuses) and the time required to train some NLP models, and the challenge of converting the NLP model analysis outcomes into a human-readable format are all disadvantages.

Another example of algorithm application within content creation is the use of "chatbots", software programs based on AI to conduct online conversations via audio or text (Shevat, 2017). Essentially, chatbots are algorithmically automated

users that are programmed to establish a conversation with a human agent (Følstad & Brandtzæg, 2017; Prasetya et al., 2018). The main purposes for chatbots adoption include informational support, social-emotional support or entertainment (Gehl and Bakardjieva, 2017; Meng & Dai, 2021).

Also, chatbots have been investigated from several dimensions (Adamopoulou and Moussiades, 2020). The most investigated dimension is related to the technical aspects such as speech conversation systems (Masche & Le, 2018), and programming techniques for chatbots (Long et al., 2019). Another relevant dimension is related to human-chatbot interactions, for example chatbots and customer purchase intentions (Luo et al., 2019), customer service and satisfaction (Kang & Kim, 2017; Chung et al., 2020) and collaboration and interaction with chatbots (Araújo & Casais, 2020; De Cosmo et al., 2021; Li et al., 2021). The adoption of chatbots is growing rapidly in instant messaging platforms and social media sites (e.g. Kahiga, 2019; Assenmacher et al., 2020), and also some industries are at the forefront of chatbots adoption such as: healthcare (Safi et al., 2020), tourism (Melián-González et al., 2019; Calvaresi et al., 2021; Li et al., 2021) and finance (Hwang & Kim, 2021; Jang et al., 2021).

Social chatbots, also referred to as "emotional chatting machines" (Zhou et al., 2018), are becoming popular. They are designed to be humanlike, with the potential to perceive, integrate, understand and express emotions (Stieglitz et al., 2017; Zhou et al., 2018). Usually, users feel chatbots as friendly digital colleague (or even co-worker) and not just as basic digital assistants (Costa, 2018; Ciechanowski et al., 2019; Adamopoulou & Moussiades, 2020). Using an artificial conversational system on Twitter, Xu et al. (2017) discovered that over 40 percent of user requests are emotional rather than informative. Over time, chatbots have become more sophisticated and based on new AI features such as sentiment analysis, machine learning and deep learning, and they are able to detect emotional situations and respond to the emotions appropriately during the conversation (Xu et al., 2017).

A big issue in content creation is the problem of fake content (Di Domenico et al., 2021). Fake content is many times created and shared using social media algorithms. In the case of fake news, this is especially crucial (Zimmer et al., 2019; Abu Arqoub et al., 2020; Di Domenico & Visentin, 2020; Preston et al., 2021). Marx et al. (2020) discovered that social bots interfered with COVID conversations on social media, spread misinformation, and interspersed news from reputable sources.

The sharing habits of social media users are equally important. On Twitter, tweets that include images and videos are more likely to be retweeted than only text tweets (Goel et al., 2015; Vosoughi et al., 2018). Moreover, tweets with videos are six times more likely to be retweeted than images (Farkas, 2016). For example, during the 2016 United States Presidential election, tweets from Hillary Clinton and Donald Trump with photos or videos obtained more favourites and retweets than those without (Pancer & Poole, 2016; Lee & Xu, 2018). Vosoughi et al. (2018) mention that real Twitter users are still 70 percent more likely to retweet fake news than real news. In addition, the authors found that it is highly possible that human users fake content than social media bots.

The problem is just starting and it is getting worse with the evolution of deepfake technology (Westerlund, 2019). This term is a combination of the words

"deep learning" (AI technique) and "fake" (not real). Deepfakes are AI-generated content that are created by manipulating real-life images or videos of people to create fictitious circumstances. (Ferreira et al., 2021). Deepfake videos by Barack Obama and Mark Zuckerberg, for example, have gone viral on social media.

3.3 Algorithm challenges

If social media firms want to use algorithms in different tasks in social media, then then they must confront the present challenges of using algorithms. Below, we discuss some of the main challenges, particularly transparency and objectivity.

3.3.1 Transparency

The lack of transparency of social media algorithms is often cited by users (Burrell, 2016; Leetaru, 2018; Kim & Moon, 2021). Algorithmic solutions are becoming progressively complex and heterogeneous, and substantially opaque. One of the big concerns of social media algorithms is that they appear like a black box (Pasquale, 2015; Burrell, 2016; Buhmann et al., 2020). Basically, there is an input, something happens in the black box and an output comes out.

Some algorithms are designed to be deliberately opaque. In most of the cases (with the exception of open-source platforms), it is nearly impossible to view the internal algorithm operation. The reason is because most algorithms are proprietary in nature (Kitchin, 2017). Some online firms are built around algorithms such as online travel, search engines, social media and recommendation services, and most of them are protected under intellectual property and patent regulations. As more algorithm business models are emerging, more firms possess the incentive to protect their algorithms like trade secrets, releasing minimal details but never fully divulging the inner workings of their systems to the public. This opacity also affects researchers and the analysis of transparency in algorithmic environments. Some techniques like reverse-engineering help to study algorithms, but they are complex and time-consuming (Kitchin, 2017).

Social media firms are sometimes open about what helps users and businesses to understand how to improve their content rank and qualify as high-quality on these social platforms. Consider the recent adjustments to Facebook's algorithms: prioritize posts from friends that spark meaningful conversations and interactions over transactions, and post more authentic and genuine video content. Recently, some researchers have started proposing new mechanisms to improve algorithm awareness. For example, Fouquaert and Mechant (2021) created the "Instawareness" visual feedback tool to reduce illiteracy about the Instagram curation algorithm. As the usage of algorithms increases, so does algorithmic illiteracy. An increasing number of experts, researchers and institutions are requesting to teach algorithmic literacy to Web users, especially younger generations. Sometimes, even AI experts who build algorithms are unable to fully comprehend the machine learning techniques that allow decisions to be made (Rainie & Anderson, 2017).

Another critical issue with transparency is not alerting the user that he or she is communicating with a chatbot or that the information is being shared by a bot.

Bots created roughly 19 percent of all tweets connected to the 2016 United States elections, according to a study by Bessi and Ferrara (2016). The combination of technological advancement and usage of social cues bears the challenge for consumers to accurately differentiate between algorithmic or human conversational agents. This development is highlighted by an empirical study on Google's chatbot Meena, in which its conversation quality was rated nearly as highly as the quality of real human conversations, leaving previously appraised chatbots such as Cleverbot or Mitsuku far behind (Adiwardana et al., 2020)

3.3.2 Objectivity

Algorithm adoption has frequently been questioned due to concerns about algorithmic bias, objectivity and trustworthiness (Lee, 2018; Shin, 2021). To maintain various judgements and a democratic society, it is vital to keep the audience informed without persuading them toward a single viewpoint. Algorithms are more than just tools; they also act as trust builders and stabilizers, guaranteeing users that their judgments are fair and objective, unbiased, inaccurate, or showing skewed results (Gillespie, 2014). As mentioned by Gillespie (2014), the algorithm's technological nature is positioned as a guarantee of objectivity. Yet, because what we search for and read feeds directly into what algorithms play back to us, the objectivity and impartiality of information sources is constrained by our own preconceptions and pretensions. To put it another way, we develop our own filter bubbles, and algorithms assist us in staying within them.

According to Ward (2009), the real recording of an event defines objectivity, and it's critical to keep the public informed without swaying them toward a certain point of view in order to maintain a democratic society and a diverse range of judgments. An example of lack of objectivity is the Robert Mercer scandal that was highlighted in the documentary *Trumping Democracy*. Trump appointed Steve Bannon as his campaign manager and recruited Breitbart News, a data firm headed by Steve Bannon and funded by Robert Mercer. Using AI and data analytics, this firm analyzed data from Google, Facebook, banks and other sources to determine who would support Trump and who would not. Breitbart News also exploited a Facebook feature known as "dark post," which allowed them to send out persuasive and tailored messages to millions of individuals before they vanished. All these messages were managed using algorithms.

Another good example is the usage of social media bots during the United States presidential election campaign of 2016, which demonstrated how influential and persuasive social media bots can be in influencing political debate, distorting communication and raising doubts about their future role (Howard et al., 2018; Grinberg et al., 2019). Social media bots can increase the prominence of a topic or ruin people's reputations by flooding social media with fake news and manipulating social media's currency: likes, shares, follows, and retweets. Although some researchers (e.g. Yang et al., 2019; Pastor-Galindo et al., 2020; Schuchard & Crooks, 2021) have proposed metrics to detect social bots, spot a social bot is not a simple task. The number of social media bots has exploded in recent years, and their impact on online conversations is quickly becoming a major issue on social media.

On a positive side, some experts mention that social media have helped society overcome the bias in legacy media. It encourages the minority groups to have a voice and to interact with different types of communities. Nevertheless, algorithmic social media may be frightening for many users because it takes information and transforms it into another piece of information based on calculations. There is evidence that when social media platforms moderate user-posted content, they consider freedom of expression and press considerations (Klonick, 2018). However, there is evidence that they attempt to reconcile these decisions with their own corporate objectives, and that these objectives may be prioritized (Citron, 2014; Klonick, 2018).

The filter bubble perspective proposed by Pariser (2011) suggests that, rather than maintaining diversity, algorithms attempt to maximize economic advantage by increasing content consumption. In consonance with this viewpoint, social media algorithms remove content that is deemed to be irrelevant to specific users while supplying them with more social media content that they are more likely to consume. Additionally, when faced with scenarios with high polarization, misinformation can quickly spread (Vicario et al., 2019), like in the coronavirus health crisis (Cinelli et al., 2020). The COVID infodemic phenomenon – an oversupply of COVID information, including false or misleading information, and the quick diffusion of fake news, photos, and videos – is a current example of objectivity issues on social media. It is very contagious and grows exponentially, much like the virus. It also makes the COVID-19 pandemic response activities more difficult.

In addition, a study conducted by Puschmann (2017) shows that if users choose to read radical, bizarre or racist news, search engines will assist them locate it. However, there is no consensus about the effects of YouTube algorithm filtering on radicalization. While some studies suggest an increase on radicalization exposure (e.g. Faddoul et al., 2020; Ribeiro et al., 2020), other research, like Ledwich and Zaitsev's (2020), suggests that the YouTube recommendation algorithm does not increase radicalisation.

The most important social media firms (YouTube, Facebook, Instagram, Tiktok, and Twitter) have all recently launched active initiatives to combat the diffusion of disinformation and conspiracy theories on their platforms. Some social media firms are deleting accounts that share this type of content, as well as deleting posts, articles and images. However, many people think that social media firms are still too slow and hesitant to take action against groups benefitting from conspiracy theories.

A recent example of algorithmic bias is the spread of anti-vaccine videos on YouTube. Some research (e.g. Abul-Fottouh et al., 2020) suggests that pro-vaccine YouTube videos are more likely to promote other pro-vaccine YouTube videos than anti-vaccine YouTube videos, and vice-versa. Anti-vaccine YouTube videos may have been less visible due to YouTube's demonetization policy (also referred as "Adpocalypse") for sensitive topics. This YouTube policy refers to the practice in which YouTube video creators are denied paid adverts in their videos of sensitive topics, resulting in a financial loss.

It is important to highlight that sometimes algorithmic bias is not intentional and actually might be caused by the datasets used to train the algorithms. There are

two main data problems: insufficient training data and data bias. Algorithms in machine learning rely on datasets, also called training sets, to improve the learning predictions of algorithms. An algorithm learns a model from the training data that it can apply to other users or items and predict what the correct outputs should be for them. A technique known as supervised learning is used to do this.

Many times, in these AI algorithmic learning contexts, the training data is considered to be representative of the target group or population. But, in case some groups are less represented, the model's predictions for unrepresented or underrepresented groups may be imbalanced and biased. There is also the problem of social media users not representing the general population (Mellon & Prosser, 2017). Finally, the topics and views expressed on social media platforms might vary significantly over time and space (Mellon & Prosser, 2017; Migliaccio et al., 2019). As a result, algorithms must learn with new training sets on a regular basis.

Overall, researchers and social firms that use algorithms need to improve their rigor in terms of testing, executing, and managing the representativeness of training sets. Additionally, some studies (Turner Lee, 2018; Cowgill et al., 2020) suggest that lack of diversity in the algorithm developers creating the training set could lead to underrepresentation of specific groups. Oppositely, the overrepresentation of training sets (i.e. too much data) can skew the decision toward a certain direction.

In conclusion, the algorithms themselves do not hurt the main principle of objectivity. Yet, the way some platforms choose to use these algorithms may cause a problem. These platforms have the power to decide whether a story can be popular or not, depending on the database of each of the users. One solution is to control the term of privacy of these platforms and minimize the harm they cause. Another solution can be to warn users and educate them more about the topic of fake news and how to protect themselves from the harm that causes these algorithms (Edwards & Veale, 2018).

3.4 Discussion

With billons of users, social media platforms will continue using algorithm curation techniques. Social media just started using algorithmic curation and it is already posing some challenges that need to be addressed. From a critical approach, algorithmic curation is essentially about power – who controls what we see and how we perceive it. Social media platforms, in this view, are not neutral and often they serve as content curators.

One of the most significant drawbacks of utilizing algorithms in specific social media activities is that the process involves a significant amount of decision-making based on a set of human values. Moreover, these algorithms are designed and programmed by individuals with their own viewpoints, attitudes and even prejudices (Mager, 2012; Kitchin, 2017). This has implications for the dissemination of information (Gillespie, 2014) and how the public sphere uses it (Morozov, 2011; Crawford, 2013; Seaver, 2017). Also, it has implications in the social media user's perception of being well-informed (Weeks et al., 2017; Fletcher & Nielsen, 2018; Thurman et al., 2019; Feezell et al., 2021).

Another important debate is related to algorithmic services accountability (Diakopoulos, 2016; Kemper & Kolkman, 2019), that is, who is responsible for the outcome of a firm's algorithmic decisions (Fink, 2018; Lepri et al., 2018; Buhmann et al., 2020). Some researchers (e.g. Fox, 2007; Kim & Moon, 2021) argue that transparency must be a prerequisite for algorithm accountability.

In terms of objectivity, while algorithm representation can be enhanced, we must keep in mind that most real-world data is skewed by default. This indicates that algorithm designers can reduce data bias, but not completely eliminate it. Automatic procedures are human-made, and therefore do not eradicate, but rather reproduce, human bias. However, some algorithm design choices are better than others. The problem is getting worse with new data protection and privacy regulations being adopted. We need to work on both dataset representation and model design, if we wish to reduce algorithm bias.

There is also an important aspect related to social media education. In that regard, students have historically been taught how to critically assess content rather than how social media platforms might alter that content (D'Ignazio & Bhargava, 2015; Head et al., 2020; Mihailidis, 2018). Algorithm bias can be mitigated through social media education, which should be included in any strategy. Most of the users never check their social media platforms settings, particularly the privacy settings. Furthermore, some social media users struggle with online searching and only know how to conduct basic searches. There is a final aspect related with only checking the top search results. There is sometimes no argumentation for algorithmic bias just because the top result is not what the social media user expected. If the algorithm's filtering process is transparent, it is possible to justify why some results are not at the top of the list.

Finally, legislation plays a critical role in social media algorithm curation (Reviglio & Agosti, 2020; Zuiderveen Borgesius, 2020). Definitively, everyone agrees that regulation is needed to improve the deployment of social media algorithms. While some users advocate for tighter rules on social media algorithm management, others advocate for the abolition of social media censorship. Over the last few years, some people are proposing that social platforms should improve the social algorithms by removing AI to make decisions related to content curation (Morgese, 2020). Some governments have been actively analyzing and developing new legal systems in recent years in order to reduce algorithmic bias and promote transparency and impartiality. Since governments also use algorithms, they have significant market power and control over many key algorithmic use cases. For example, the United States government is introducing legislation to counteract algorithmic bias and establish a new online transparency environment, particularly in sectors such as education, healthcare and the financial sector.

3.5 Conclusion

This chapter discusses the challenges of using algorithms in social media. The scholarly literature reviewed backs up the idea that the algorithmic bias challenges posed by these technologies warrant a discussion from a socio-technical and regulatory standpoint. Because of a variety of factors, resolving the algorithmic bias

problem is difficult. The first reason is related to the definition of algorithmic bias, misinformation, disinformation and objectivity. The second reason is that it is not always obvious during the algorithm creation that the model may have a bias problem. The third major reason is that the data training set used may be biased. Finally, there is sometimes a lack of social context because algorithms are frequently designed to be used in different contexts, which may result in a lack of testing for specific contexts (Hao, 2019).

The first step in implementing effective algorithmic strategies is to understand the many origins of algorithm bias. It needs thinking beyond how they work, and why and where they are used. This is not only a request that social media firms reveal their internal way of working and reveal their undeclared criteria. It is a societal question that needs to be addressed by society in general (Olhede & Wolfe, 2018).

In terms of research, algorithm bias has been analyzed in the political arena but it needs to expand to other areas like healthcare. In general, there is a consensus about the need to understand algorithms and their impact on the public sphere. This debate needs to think beyond how algorithms work, where they are used and how they are funded. Rather than seeing algorithms as just lines of codes or sophisticated mathematical models, it requires analysing them from a socio-technical perspective (Kitchin, 2017; Shin, 2019; Selbst et al., 2019). A socio-technical approach to social media algorithms adoption should aim to reveal the intricate workings of social media algorithms, including both the process of filtering content and the social process of transforming it into a legitimate solution. These social media algorithms are supposed to function without the need for human participation, and there is some skepticism about the legitimacy of the process. As a result, it appears that algorithms are reproducing certain contemporary human-centric systems, which have some vulnerabilities related to bias issues. Therefore, algorithms can act as an amplifier of bias that exist in humans, and increase inequalities or discriminations (Karimi et al., 2018). Often, human bias is being mirrored by algorithms, and society needs to reflect on this. In some cases, algorithms reflect the skewed nature of our questions and data.

Algorithmic use, like any new technology advance, necessitates a thorough examination of its technical, social, regulatory and business implications. Technology is ushering in a new era in which machines are taking over human functions. We are seeing an increase in human-machine interactions, which will soon become the new normal. Technology is still in its infancy, and it lacks the technological advancements necessary to completely replace people in many decision-making processes. However, it is rapidly evolving, and characteristics such as AI consciousness will be a significant step forward in enhancing algorithm decision-making. Society and other different stakeholders must consider the best approach to use algorithms, rather than viewing them as a threat, but as an opportunity. Algorithmic processes will augment our intelligence by thoroughly examining data and content in ways that humans cannot. Overall, the deployment of algorithms will open up new possibilities and capacities for improving the human experience. Both humans and machines must progress together as part of this future voyage.

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