Dr Ljubiša Bojić, Research Fellow at the Institute for Philosophy and Social Theory, University of Belgrade;

ljubisa.bojic@instifdt.bg.ac.rs

Maja Zarić, Advisor at Ministry of Culture, Republic of Serbia;

maja.zaric@kultura.gov.rs

Societal impact of AI and Big Data through the prism of recommender systems

Abstract

Transfer from Social to Semantic Web brought us to an era of Algorithmic Society, placing issues such as privacy, Big Data and AI in the spotlight. The power of Big Data algorithms to impact societies became major concern outcoming with GDPR in the EU and fines issued to Facebook in the US. These events were initiated by alleged breaches of data privacy connected to recommender system technology, which can provide individualized content to Internet users. This paper seeks to explain recommender systems, while elaborating on their social effects, to conclude that their overall impacts might be increase in retail sales, democratization of advertising, increase in Internet addictions, social polarization (chamber box issue), and improvement of political communication. Some recommendations arise from the discussion presented, first of all, the need for media literacy classes on all education levels, both for Internet users and content creators. Second, new regulations are proposed to obligate inclusion of certain amount of different content into outcomes of recommender systems. Media should inform citizens about handling of their data. Also, more research should be deployed into low intensity addictions, as potential outcome of recommender systems, and it should be explored how they affect political participation and democracy.

Ključne reči: Sistemi za preporučivanje, veštačka inteligencija, veliki podaci, Internet zavisnost, echo chamber

Key words: Recommender Systems, AI, Big Data, Internet addiction, echo chamber

1 Introduction

Big changes in societies around the world are caused by the development of Internet. The new era of Big Data is characterized by "high volume, velocity, variety, exhaustivity, resolution and indexicality, relationality and flexibility" (Kitchin, 2013: 262). Technology companies have been taking places on the list of most valuable companies in the world (Statista, 2019), followed by increases in Internet use across the globe from 0.4% in 1995 to 59.6% in 2020 (Internetworldstats, 2020). "The speed of development in Big Data and associated phenomena, such as social media, has surpassed the capacity of the average consumer to understand his or her actions and their knock-on effects", writes Zwitter (2014:1). Businesses have been moving and extending online during that period, while new Internet services have been developing. Instant connectivity between people increased with appearance of social media, taking leadership place in these developments (Sutikno et al., 2016). Era of social Web 2.0 started in early 2000s to be called Web 2.0, followed by Web 3.0 or the Semantic Web, a period in the development of Internet in which we live in (Patel & Jain, 2019). This era relies on access to user information by organizations to conduct either AI or not-AI algorithmic analysis finally outcoming with recommend ads and content. Vanian (2016) calls Big Data the New Oil, because it is needed by algorithms and AI to function and run the Algorithmic Society. However, the way data is handled is not transparent. Advances both in hardware and software give corporations an opportunity to handle big data, providing their users instant recommendations, but without transparency and firm regulations for data analyses.

This topic gained its international importance after US elections and Brexit vote, which had unexpected outcomes, after targeted political marketing, which included personality detection to deliver promotional content of different emotional intensity (Howard et al. 2019). Donald Tramp became president of the USA on one side, and Great Britain decided opt out from the European Union. These events made both politicians and common citizens believe in power of big data to change governments by in depth analysis of the electorate. "Big data and predictive analytics all of a sudden became very concrete for the public—and people came to realize that personal information is in fact a commodity that is sold and traded among information empires and data brokers", writes Mai

(2016:193). Fear of societal power holders of being out of control concerning political marketing and its outcomes may have been the leading triggers for imposing new regulations about protection of privacy and how data should be handled. EU imposed General Data Protection Regulation (Voigt & von dem Bussche, 2017). On the other hand, the United States fined Facebook for data breaches. Facebook's CEO Mark Zuckerberg promised he would improve privacy of its users, but without a clear plan how his company would do that (Hern & Pegg, 2018).

Kitchin & McArdle (2016) explore what makes Big Data, Big Data. Laney (2001) writes that the concept of Big Data is defined by: volume, consisting of massive quantities of data, velocity, created in real time and variety . The new concept of Algorithmic Society is explained by Balkin (2017), who sees big technology corporations taking place between governments and society members. In this constellation, AI and algorithms are used to govern populations. He calls it a pluralist model of a nation state in which individual is controlled by both corporations, operating in multiple jurisdictions, and governments. Balkin envisions struggle for power between these corporate multinational entities and governments.

Milano, Taddeo & Floridi (2020) provide definition of recommender systems in regard to e-commerce as the products offered in the catalogue versus ones that ultimately result in purchases. Other definition configured by Floridi (2008) speaks of good news recommendation, as the one that is clicked on and thus relevant to the user. Another view comes from Abdollahpouri et al. (2017) defining recommender system as multi-stakeholder environments where multiple parties can derive different utilities from recommendations. Going into rather different direction, we shall provide our working definition of recommender system, in context of a society. We consider recommender system as the process in which the user data is analyzed to choose between certain options for each of the users, then show selected options back to them individually, to achieve some or all of the following goals: to get attention, extend usage of online content, spark thinking and discussion, change opinions and initiate actions, including purchasing and voting behavior.

Data processing can be done in straightforward algorithmic way, but also involving artificial intelligence technologies, out of which machine learning may be the most common one imposed in recommender systems (Helberger, Karppinen & D'Acunto, 2016). This kind of algorithm learns from great amount of data, then makes predictions and recommendations. The main issue around AI is the black box issue, because it is almost impossible to understand why the algorithm made some decision, as being based on combination of many small correlations. However, it is possible to measure if an AI algorithm is effective. The power of AI technologies is indicated by many research studies such the one by Kosinski, Stillwell & Graepel (2013) which found AI can accurately predict different personal attributes of social media users, such as sex orientation, ethnicity, religious and political views, personality traits, intelligence, happiness, use of addictive substances, parental separation, age, and gender. Other paper indicates AI technology can be accurate at detecting sexual orientation and personality traits from facial images (Wang & Kosinski, 2018). These are just examples of how widespread use of AI technologies can be spanning from implementation in recommender systems to integration into numerous other fields and processes.

Technology companies have the highest market values compared to companies from all other sectors. Out of top 10 most expensive in the world, 7 are technology corporations including Microsoft, Apple, Amazon, Alphabet, Facebook, Alibaba and Tencent. (Statista, 2020). On the other hand, when it comes to profitability, 4 of them are in top 10 most profitable corporations, competing with those in oil, financial and automobile manufacturing sectors. One of the main businesses of all noted companies concerns online services. These rankings indicate importance, influence and power held by technology companies that handle user data. The main power of recommender systems, and thus the companies which handle them, may be in their overall societal effects. That's why recommender systems transcend power of profitability, or market value of companies that control them. In other words, they may impact economic, political and other aspects of societies around the world. "The basic idea is that as big data becomes mainstream and businesses and state agencies apply predictive analysis to generate new information and knowledge about customers and citizens, a shift in focus from data collection to data processing is needed" (Mai, 2016:192).

In their effort to analyze ethical challenges of recommender systems Milano, Taddeo & Floridi (2020) note the gap in literature with providers of recommender systems and society at large, mainly omitted from consideration, while main focus is directed towards receivers of the recommendations.

Based on presented potentials of AI technologies and impact concerns that have been arising, the following question arises: what are potential societal effects of recommender systems? The article explains recommender systems in more detail and reviews empirical evidences presented in around 50 research inquiries on societal effects of recommender systems.

2 How recommender systems work

Recommender systems make personalized recommendations to users of any online application. Recommendations may be ads, trending content, posts, friends or comments. With many potential purposes, recommender systems are implemented as integral parts of different online services including social media, messaging apps, e-commerce websites, email, search and various related apps. Main segment of any recommender system is an algorithm, which may be set of simple straightforward rules dictating how the content is being processed, or it can involve artificial intelligence. The following are three most common everyday uses of recommender systems: advertising platforms recommend ads to Internet user, trending content is proposed to users of social media and posts of friends are selected to be shown to social media users. Main purpose of recommender systems is keeping users engaged by presenting personalized content to them. The way this is done is by harvesting data from users, analyzing them and then delivering content based on outputs of analysis (Aggarwal, 2016).

2.1 Ads

The most common recommender system is ads recommendations. Main purpose for this kind of system is delivering ads that will get as much views, clicks and purchases as possible. The final goal is maximizing profits. “The effectiveness of advertisement distribution highly relies on well understanding the preference information of the targeted users” (Li & Shiu, 2012:9).

As mentioned before, all recommender systems work with user data in order to make recommendations in the first place. In order to get the data, Terms and Conditions of most online apps must define provision of services in return for data from the user. For example, Google provides email, search and many other services free of charge, but it gets user data in return. These can be used by the company, with or without the possibility to forward the data to third parties.

The best way to understand complexity of recommender systems is to focus on ads business, as its algorithms take into account multiple parameters included into its calculations, such as keywords (interests), location and other possible demographics to deliver personalized ads. This kind of marketing analysis is called psychometrics.

2.2 Social media

On the other hand, trending content on the trending page is part of social media which provides content based on combination of personal interests and popular content at that particular moment. Example of this may be when social media user looks for a new interesting content to consume, while getting options from the profiles that he or she does not necessarily follow. This recommender system will show similar content or “you may be interested in” content, that is consumed by similar users (Ricci, Rokach, & Shapira, 2010).

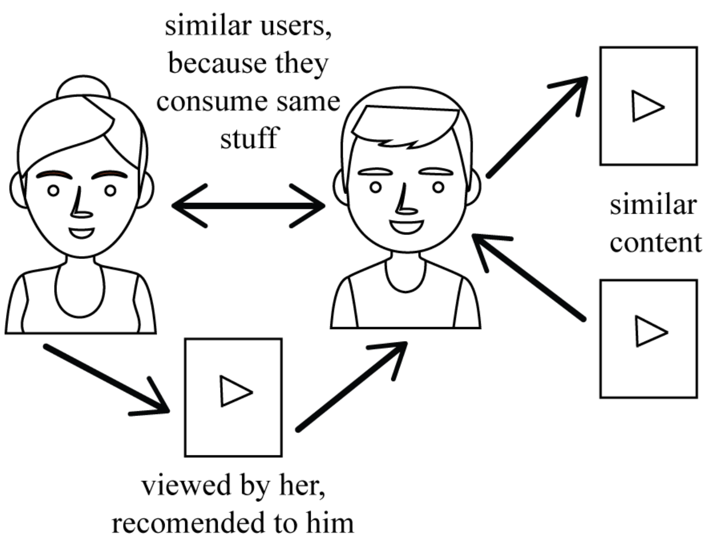
Different kind of recommender system is the one used by social media that shows posts of friends or connections. In some cases, because of high number of connected profiles, all posts cannot be shown to the user and then selection has to come into play. Usually, this selection is based on most interactions, so the user gets content from people that he or she interacts with the most.

One of the most common recommender systems experienced by social media user is “friends you may know” feature. These are profiles proposed to the user by social media. The criteria used to get these recommendations are level closeness of the profile that gets recommendation to the profile that is recommended. That means they should have common friends. The other criteria can be physical distance, as well.

Although there are many different recommender systems all over the Internet, there are two main principles for choosing the content that would be recommended to the users. The first principle is, if the user has consumed lots of content similar to the other user, then the two users are considered similar, so the same content will be shared between them. The second principle is proposing similar content, by looking at what other content is consumed by those that saw the content that is consumed by the user that gets the recommendation. This is explained by Konow et al. (2010) and illustrated on Figure 1.0.

Figure 1.0

Illustrating two main principles that recommender system may be based on: similar content and similar users.



2.3 Applications

The most prominent social media such as Facebook, Twitter, Instagram, Youtube and Tik Talk use various recommender systems. Main business model in these cases is keeping users engaged on social media platform, while gathering data from them to deliver personalized ads. Messaging apps include Messinger, Viber, Whatsapp, WeChat etc. Main purpose of recommender systems within messaging aps are advertising and motivating users to send new messages. For example, we can see ads in Viber after a successful call, within Communities, in the sticker market or on the chats list. Differently, on Whatsapp, ads are integrated in Whatsapp statuses that show pictures, videos, texts and other multimedia that users share with their contacts. Facebook Messinger offers interest based ads used to initiate text conversations with businesses. Finally, WeChat displays promotional messages on user timeline, or at the bottom of WeChat articles (Sutikno et al., 2016). The most important function of recommender systems for music and video services such as YouTube, NetFlix and Spotify is recommending content. This keeps users on the spot, extending minutes of their use, as it keeps suggesting them content which is interesting to consume. Finally, online shopping platforms that include Amazon and AliBaba use product recommenders to offer items that have the greatest probability to get interest and ultimately get purchased by the users. Google, Yahoo, Bing, Hotmail and others provide various services such as search and email. They use variety of recommender systems to keep their users engaged and offer them the most appealing ads. On the other hand, indirect data handlers are companies that collect data for ads targeting. They handle data provided by consent from numerous websites visited everyday by billions of people. These data is analyzed in a way that it provides companies and advertising agencies an opportunity to show the ads to the people that will most probably be interested in them. Most people avoid reading Cookies Consent, while they give permission for their data to be further distributed or sold. Finally, developers of apps are indirect data handlers, that may use data for recommender systems. Although most common uses of recommender systems are noted here, there are many more implementations of these technologies across fields and disciplines.

3 Social impact

Iliadis & Russo (2016:1) introduce Critical Data Studies as the "concept that helps capture the multitude of ways that already-composed data structures inflect and interact with society, its organization and functioning and the resulting impact on individuals' daily lives".

Hilbert (2013) wrote that technology initiated shift happened from information to knowledge societies, while elaborating on different kinds of big data: words, locations, nature, behavior, economic activity and others. He considers improvements in medical sphere by using AI algorithms in detecting diseases, but also provides examples from economical sphere in stock market trading including "black box" recommender systems, that can give advices about buying and selling stocks. This is called algorithmic trading. Hilbert concludes that big data holds both promises and dangers for development. The biggest threats seen by Hilbert are potentials for State and corporate control and manipulation, and the blind trust in algorithms.

Michael & Miller (2013) note that the new world is turning into "camera", with lots of images and video data. These are captured and then processed by companies, law enforcement agencies and individuals. The issue here is that this kind of new world captures also people that have not given consent to be filmed, while AI technology often comes up with surprising findings and conclusions. The knowledge that person is being constantly supervised and filmed in a company, where he or she works, may outcome with different psychological conditions. On the other hand, the goal is to measure results of work, give recommendations to be included into the work process thus helping companies improve and make progress in their fields. Michael & Miller envision advanced market segmentation, in terms of psychometrics, to get a deep look into personalities of Internet users even, to the extent that the main question poses to be, "Who are you?"As the boundaries between public and private blur, Michael & Miller think the volume of data will increase, which gives more space for analysis and even better predictions in various aspects of societies.

3.1 Internet advertising

The beginning of online advertising seemed as an experiment in 1990s when widespread use of Internet began. Since then, online advertising has grown into an $112.64 billion industry (eMarketer 2018). In early days of Internet only banner ads could be seen on different websites. These ads were not personalized or delivered only to those Internet users mostly likely to be interested in what they have to offer. Google ads revolutionized ads market by introducing recommender systems. They enable ads to be delivered exactly to those individuals that expressed interest into products or services provided by the advertisers. On the other hand, Google Ads enable creators of content to embed their ads into websites they use and therefore earn money per click.

When we look at advertising market in Germany between 2000 and 2015 it could be seen that total advertising market decreased from EUR 23.4 bn to EUR 21.9 bn, while share of spending for online advertising within these sums increased from 1 to 22 percents (IAB Europe, 2011). Klapdor (2013) concludes that increase of online advertising both in German and other markers across the globe has been considerable. On the other hand, online share of total advertising varies through the world in 2010. The stats provided by Emarketer (2010) include UK (32%), Netherlands (21%), China (19%), France (18%), Germany (17%), Spain (14%), USA (11%) and Italy (5%). As for population age 14 and above in Germany media consumption increased from 466 mins per day in 2000 to 563 mins per day in 2010. Out of these minutes, Internet use increased from only 3% in 2000 to 14% in 2010, while use of all other media decreased in the same period including TV, radio, newspapers, books and magazines (Ridder & Engel, 2010). The power of Internet in terms of retail sales can be seen in findings about the purchase decisions. Yahoo Research & Enigma GfK (2010) presented results of a survey about information used for purchase decision that examined products from different fields including apparel, games, electronics, furniture, foods and DIY. They found that Internet was the most important source of information among other ones such as retail stores, flyers, catalogues, newspapers, friends and magazines.

Adamopoulos et al. 2018b write that technology has revolutionized how companies deliver ads and communicate with consumers. Ghose and Todri (2016) write that companies monitor digital footprints of consumers, so they can pay per-impression or per-click to the advertising platforms. Thus, these innovations in the world of advertising have been affecting economies on a grand scale. The first disturbances were felt by offline content providers, such as newspapers, that had to cut their circulation volumes and redirect their efforts towards the online sphere. The same happened for TV stations that had to make their websites attractive for online users and change the way they do journalism. New type of journalism was introduced. Multimedia or online journalism has to compete with citizen journalism and different content creators for attention of news consumers in order to get prolonged use, so that they could sell online ads. Of course, online ads business affected other spheres of life, but the most disturbed at first were traditional media. However, the main idea that comes out is that people consume online services more than before, which opens up space for more content creators, but it also makes a difference on the side of advertisers as well, by enabling them to be more effective (Rosenkrans, 2009).

New trends in advertising create possibilities for small businesses to get involved into advertising process, thus reaching their target groups with minor amounts of money. Goldfarb, A. (2013) argues that the fundamental economic difference between online and offline advertising is a substantial reduction in the cost of targeting, which boost economic development and empowers small business owners.

3.2 Internet addiction

Addict is a person whose normal functioning is endangered because of use directed to the substance or object that is matter of addiction (Young, 1998). That means Internet or gaming addicts could be overwhelmed playing computer games to the extent that they even avoid eating or performing their physiological needs. Drug addicts may fail to perform in their family roles. They could be aggressive, therefore endangering lives of others and themselves. Gambling addicts may loose their basic assets, such as home they essentially need for daily functioning. To become an media addict there are two main criteria. The first one is extended media use, more than person wants to do that and the other one is this use affects normal daily functioning of that person. Young (1998) concludes that the Internet addiction has a lasting impact on the brain processes. She compares Internet addiction to addictions of drugs and alcohol.

Statistics show there are 1 to 8 percents of Internet addicts in the US, depending from the research standards (Weinstein & Lejoyeux, 2010). Durkee et al., (2012) notes results of a study of European countries with Internet addiction levels ranging from 1.2% to 11.8%. Other inquiries from the U.S. and Canada report even 20.6% of Internet addicts (Błachnio et al., 2019). On the other side of the globe in South Korea more than 30% of teenagers are found to be at risk of Internet addiction (Internet Addiction Prevention Center, 2018), while in Japan 23.7% of teenagers were found to be Internet addicted (Kawabe et al., 2016). Another study found that Hong Kong teenagers are at great risk to become Internet addicts, as Lam (2015) measures Internet addiction rate of 24% among them. However, Internet addiction is a growing trend (Chi, Hong, & Chen, 2020). The issue of addictiveness is discussed by many researchers that examine impacts of recommender systems. This requires serious research attention (Burr et al. 2018; de Vries 2010; Koene et al. 2015; Taddeo and Floridi 2018). Some statistics are even worse. For example Cheng and Li (2014) write that 420 million of people were affected by Internet addiction in 2014, which is a global average prevalence rate of 6.0%. However, because of increasing Internet use, up to date levels of global Internet addiction prevalence might be much higher. Montag et al. (2017) writes that between 1996 and 2017, a total of 1,572 papers examines the issue of internet addiction, with rising numbers each year.

3.3 Echo chambers

Report from the office of President Obama on Big Data concludes that new technologies can cause societal harms on a grand scale, beyond the damages to privacy (White House, 2014).

Mantelero & Vaciago (2015) focus on regulation of Big Data. They conclude, given the developments and nature of new technologies, the focus should be on the use of data. Therefore, basis of measurement of how to regulate data use should be assessment of potential outcomes and risks for the groups involved and society at large. Hilbert (2015) highlights the importance of regulative framework and incapability of many states to deploy resources towards this field. This creates the new digital divide in terms of informed decision making.

As recommender systems show content consumed by similar people to same group of individuals this makes bubbles of beliefs and attitudes stronger and bigger, thus reinforcing polarizations in societies. Such state of matters goes against different views on social issues, public debate and democratic way of functioning, because this could cause unrest, low tolerance, public anger and violent protests (Harambam et al. 2018; Helberger et al. 2016; Koene et al. 2015; Reviglio 2017; Zook et al. 2017). Some researchers call for change in the recommender systems so they can promote diversity of thoughts and attitudes, especially in news segment (Bozdag & van den Hoven, 2015). Reviglio (2017) calls for diversified approach in recommender systems, which means it should include different stands from that of the Internet user to provide variety and foster democratic processes. The same is request from Harambam et al. (2018) who proposes adding option to configure recommender systems by end users themselves. This would provide novelty, diversity and relevance.

Being in private ownership, without any firm regulatory obligations concerning transparency, big data algorithms are closed circuits. This is identified by D'Ignazio & Bhargava (2015) and it can be a good reason for initiating well prepared digital literacy courses. Authors propose a definition of Big Data literacy, because field of Internet communication is much more than technical skills one should have to become capable user of new technologies. Thus, Big Data literacy should be mainly about emancipation, according to D'Ignazio & Bhargava. They also identify various target groups for Big Data literacy process that include NGO organizations, those whose work include use of technologies and common citizens.

4 Discussion

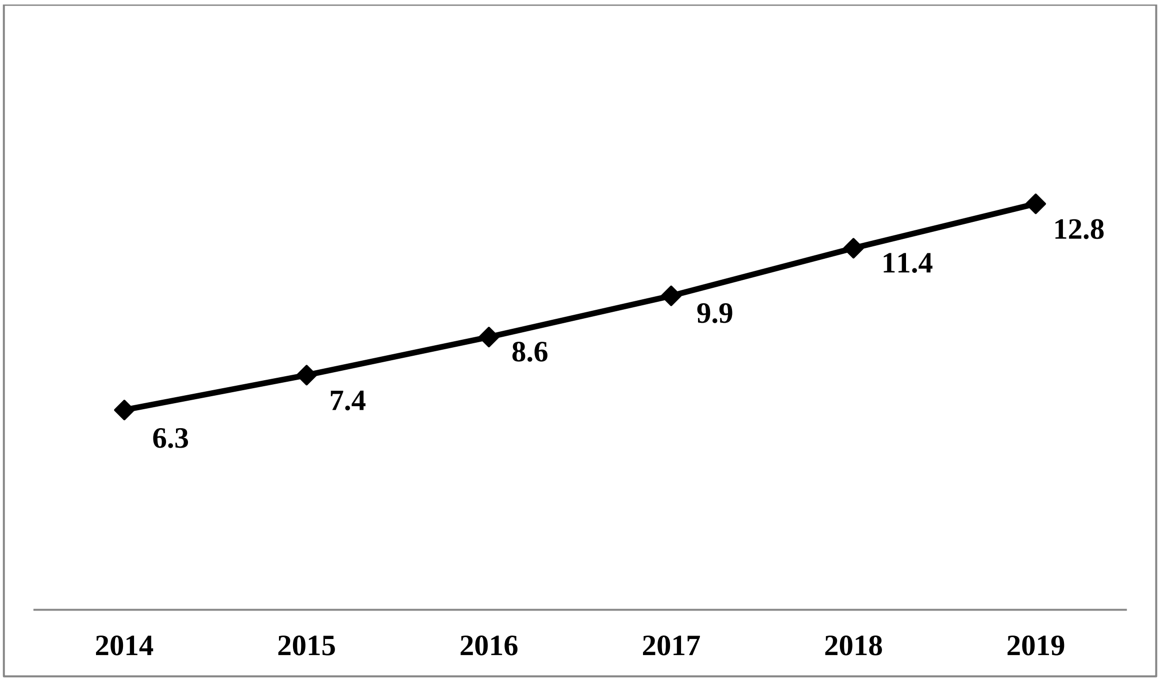
Based on review of the literature presented in previous sections, we can now elaborate on societal impacts of recommender systems.

4.1 Internet advertising

The typical situation experienced by numerous Internet users is that they get recommended ads for exactly the items they intend to buy. They get more options concerning the items they intend to but, their purchases may be faster, than it would be without recommended ads and finally they may buy more products overall. The fact that Internet users get ads based on their interests may be **increasing overall retail sales** in societies, which is stimulating for economies. Although there are no firm statistics to confirm this notion, some figures indicate that. Emarketer (2019) research shows increase in retail ecommerce sales worldwide from 2014 to 2019 from 6.3 to 12.8 percents (Figure 2.0). The same report indicates constant increase in worldwide retail sales since 2014. Another study shows growth of retail e-commerce sales as share of retail trade in the UK from 2007 to 2019 from 3.4 to 19.2 percents (Murphey, 2020).

Figure 2.0

Internet sales as a percentage of total retail sales in the world from 2014 to 2019



Additional economic consequence of recommender systems may be **democratized advertising**. Before online advertising, there were only expensive and ineffective ways to promote products in local communities. Word of mouth was the most effective way to promote products for small companies and individuals that create hand made products. Now, with effectiveness of recommender systems implanted into advertising platforms of today, one can reach potential customers quickly, easily and for small amounts of money. This business model can work, even at rate of one euro per day, invested by the smallest business owners and startups, and it can still make exquisite results (Liu-Thompkins, 2019). Whether the post is sponsored, or there is a specific ad, the right people get the ad, those with the highest possibility to notice it, consider it, interact with the content and then finally make a purchase.

Thus, both potential effects of recommender systems in advertising, such as increases in overall retail sales and democratization of advertising may be supportive for level of employment and current consumption based economic system.

4.2 Internet Addiction

We identified the time management issue as precondition to Internet addiction. Almost every recommender system by its definition can increase time people spend online consuming various services. For example if social media user gets friends recommendation for profiles he or se is really interested in, this would potentially increase online time of that user, because that person may scroll through the list of recommended friends, send request to them and ultimately interact with them. Recommended trending content has the same purpose. Video platform such as YouTube offer their users suggested content. These are videos, with the most probability the user would be interested in. This may be tempting, as the users would watch more videos, than they would without this feature. This is also issue of time management. The main question may be if it is better for that person to do something else, than consume online content? There are two directions this kind of overuse could go. One person could do the same kind of activity online, for example communicating indirectly through

Viber, as done offline, sharing thoughts and ideas. The question is if direct communication is different in quality when compared to indirect online communication. Is it more rewarding and fulfilling to employ senses of touch, sight and smell than to enjoy only auditory texting experience through instant messaging app? Or is it better to clean house than to communicate? Substitution of one activity in offline world with the other activity in online sphere may be challenging time management issue of those exposed to recommender systems.

Spending extended time online may lead to **Internet addiction**, because people are tempted to use Internet more and more. On the other hand, except noticeable high intensity Internet addiction, Bojic, Marie & Brankovic (2013) recognize low intensity Internet addiction, which may be at the core of modern mass societies. In other paper, Bojic & Marie (2013) introduce universal methodology for measuring TV, radio, newspapers and Internet addiction, that also calculates levels (intensity) of an addiction. They conclude that most of the survey participants show low level media addiction. Effects of this kind of addiction are not yet examined by scientific inquiries, while possible having major role on societal level in respect to democracy, political participation and other aspects of public sphere activities. Low level addictions may have role in individual feelings of happiness and wellbeing, especially if they are joined with other low level addictions, such as shopping, alcohol and similar ones. In other words, if society members spend lots of time online and then go shopping and do other activities which support consumption society, if they are occupied by various stimuli, how much time is it left for thinking and reflection about various personal and common topics including societal and political matters? According to proponents of natural law, political justice obtains between citizens who are free and equal and governed by law (Duke, 2019). Are our societies free, if they predominantly consist of citizens mildly addicted to their smart phones, brands and other consumption related activities?

4.3 Echo chambers

Another issue, that we acknowledged, concerns **the echo chamber**. These are primarily produced by the Trending recommender systems, as they reinforce same thoughts and opinions in the digital sphere. As previously noted, recommender systems deliver similar content or the one consumed by similar users. This is a barrier to the social dialogue, because same thoughts and opinions are confirmed all the time. We are witnessing growing polarization in societies across the world, with the main divide being on globalists and nationalists. “High degree of polarization has been connected to unfavorable consequences such as extremism” write Prasetya & Murata (2020:3) and add that other than the polarization of the cascading news, they found that important contributors to polarization are slow opinion update and low tolerance for opinion difference. These trends made a fruitful ground for biased content containing sensational headlines and many of these being “fake news.” Baumann at al. (2020) proposes an echo chamber research model based on three main assumptions: aggregated social influence, heterogeneous activity and homophily in the interactions. In their research paper Guo, Rohde & Wu (2018) analyze echo chambers created during the 2016 US elections campaigns. They conclude that Twitter communities discussing Trump showed a higher level of heterogeneity, than those about Clinton. As people want to confirm their views, these kind of contents have the greatest probability to be liked or shared further on social media. At the same time, opinions of those that consume this content may radicalize even more, outcoming with hate speech and cutting people out of social networks because of politics, thus creating divided societies of echo chambers, streaming towards differences and further polarizations.

Another potential consequence of recommender systems is using micro targeting for personalized ads in order to impact opinions of individuals and groups, leading towards certain outcomes of elections. Allegedly research results of an inquiry done by Lambiotte & Kosinski (2014) were used in number of political campaigns. The main point was using Facebook likes to determine personality types and then show individual ads with different tone, the ones that will be more likely to be positively accepted by recipients of messages (Isaak & Hanna, 2018). In other words, if potential recipient of ad is recognized to be neurotic he or she would receive an “angry ad” packed with negative emotions, while other person, if recognized with high Openness rate, on OCEAN personality scale, would be shown dynamic and positive advertisement. Of course, this could be categorized as recommender system, because it delivers personalized ads, depending from user data, based on psychometric analysis.

If one side in political process uses this kind of technology, it may have competitive advantage. However, if every political party engages in this kind of political marketing the conclusion may be that it improves communication as neurotics will get messages of every political option in a way that fits them and with better potential outcomes. In that case, every political party would be equal. The value based conclusion would be that utilizing such psychometric technology would ultimately mean overall **improvement in political and other kinds of communication**, especially in future, when common people have the knowledge of how recommender systems work and to what kind of technologies they are exposed to.

5 Conclusions

Having in mind potential effects of recommender systems and related technologies, including Internet advertising related ones, such as increases in overall retail sales and democratized advertising, Internet addiction-related ones, such as time management issue and increases in Internet addictions and finally democracy-related ones, such as echo chamber issue, and improvement of political communication, some concluding remarks arise.

As discussed in previous section, although it is challenging to measure and quantify recommender systems in any way, they might be increasing overall retail sales. This may be stimulating for consumption society and economies across the globe. If people spend more, then there will be jobs for more people. Although time management issue, Internet addictions and social polarization may be consequences of recommender systems, it is clear that current societal systems depend on consumption and spending (Fisk, 1959). It could be easily seen during the ongoing Covid-19 pandemics what happens to the economy and levels of employment when retail sales decrease in some sectors (Baker et al., 2020).

More research should be directed towards measuring addictions, with special focus on low intensity Internet addictions. Despite the fact that Internet use is growing in the world, there is no standardized way to measure Internet addiction. On the other hand, Internet addiction is not measured in any worldwide study so far. Additionally, special focus of research should be directed towards different addiction levels, meaning intensity of addiction and elements leading towards Internet addiction.

Therefore, according to previous arguments, we may formulate a question that might be explored in some future inquiries – if people buy more stuff, does it mean that they are more addicted, or in another words, is there a correlation between volume of retail sales and addictions?

States should focus their attention towards Internet addiction to protect most vulnerable young and old populations. This may involve creation and deployment of state strategies to examine effects of new technologies on overall health and introduction of education programs leading towards more understanding and increasing critical approach of major population towards online contents.

States should cooperate with international organizations such as European Commission, Council of Europe, UNESCO, UNICEF, OSCE and develop and improve **Media Literacy** policy and framework in order to provide integrative approach to media education and media literacy through formal and informal education. The cooperation between multilateral and bilateral partners, as well as national stakeholders should be fostered and activities should be well coordinated in order to encompass all citizens that should be addressed as various target groups, especially mindful approach should be used for vulnerable groups such as children, women, elderly, minorities etc. The pandemic changed digital media habits of citizens, work from home was introduced, schools shifted to online and e-commerce bloomed. The digital media became more than ever oversaturated with disinformation, fake news, various suspicious content and navigation became more complicated and intense. Today there is a great level of social connectivity especially through various groups on social media that foster activism such as #metoo #heforshe. Moreover, in the last two years “Cancel Culture” was widely accepted as social behavior of unfollowing and boycotting a person, brand, company or organization due to stressing their different or offending opinion or withholding to support a cause. In such a demanding converged media environment it is necessary to develop and enhance citizens 'media knowledge and media literacy skills especially critical thinking that helps strengthen digital immunity of each individual, as well as society. Digital immunity thus help citizens to counter fake news, deal with disinformation and potentially harmful content, to critically evaluate sources, deconstruct media messages and recognize diverse forms of advertising. It also benefits promotion and exercise of freedom of expression, breaks stereotypes and fosters intercultural dialog. Public service media role should be strengthened, in terms of broadcasting content that empowers citizen's knowledge on how digital environment and new technologies work, representing both creative, positive side as well as challenging, negative aspects of information and communication technology. When looking into the media literacy issue, in their commentary, Couldry & Powell (2014) recommend that highlighting not just the risks of creating and sharing data, but the opportunities would be a way to go. Critical approach to different content can also be significant pillar of media literacy and media education, especially having in mind the outbreak of echo chambers and false news across the globe (Vosoughi, Roy & Aral, 2018). Special attention should be given to the issue of echo chamber, so that citizens get a full understanding of how challenging these kind of recommender systems might be for democracy. While filter bubbles and echo chambers are a real challenge and widely-discussed concept, it should be noted that the empirical evidence for their existence in Europe is mixed (Nguyen et al. 2014; Zuiderveen Borgesius et al. 2016). Individuals usually inform themselves by using a variety of sources among traditional and nonlinear media, and not relying solely on social media feed or internet searches. Thus the healthier media culture should be further promoted through media literacy and media education so that citizens become more aware of necessity and importance of being able to access different information, views and opinions, to critically think, responsibly interact and participate in constrictive social discussions, as it all has great impact on democratic society.

Also, **change in regulations might be needed to combat echo chambers**. This may obligate creators of recommender systems to include certain percentage of content consumed by other populations, thus introducing variety and promoting social dialogue.

Civil society organizations should have significant role initiating public discussions, presentations, workshops and lectures about changes in Internet technologies and improving awareness about potential influence of recommender systems and artificial intelligence to democratic processes and political participation.

Adoption of GDPR was a prime media event, that certainly brought more awareness about related issues. Finally, the fact that Facebook was fined by the US regulation authorities for data and privacy breaches, brought even more spotlight, leading to increased awareness and discussions about the topic. Priming the question of media literacy may be low on agenda of politicians, media and civil society organizations at the moment. However, this question should be of highest long term importance of media and executive authorities and thus needs to be addressed, because of potential harmful impact of new technologies. As there are no immediate value to be acquired by social structures to initiate the topic of recommender systems, this issue stays in the background of more “important” ones. Therefore, **state, media and civil society organizations should work together in putting forward the question of how online technologies impact societies** in both short and long run.

Media exposed data breaches in the past are steps in good direction to put the issue of data privacy in eyesight of public, but more needs to be done on examining effects recommender systems, not only data issue per se. Online data will be accessible to companies and political parties in one way or other, but in most cases with absolute compliance to GDPR and other active laws and regulations. Ultimately, the question should not be about data access, but how they are processed, bringing to focus social effects created by businesses, political parties and other organizations. We must learn about potential points of manipulation, understand how new technologies function and spread the word about this to increase awareness and maximize individual and social benefits.

Acknowledgements

This investigation was part of the Research project III 43007 founded by the Ministry of Education, Science and Technological Development, Republic of Serbia – „Climate Change and its effects on the Environment – Monitoring, Adapting and Mitigating.“

We thank 9thgn for support during the investigation.

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