Futures 160 (2024) 103383

Contents lists available at ScienceDirect

Futures

journal homepage: www.elsevier.com/locate/futures

AI alignment: Assessing the global impact of recommender systems

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ARTICLE INFO

Keywords:
AI alignment
Digital humanism
Recommender systems
Global impact
Social polarization

ABSTRACT

The recent growing concerns surrounding the pervasive adoption of generative AI can be traced back to the long-standing influence of AI algorithms that have predominantly served as content curators on large online platforms. These algorithms are used by online services and platforms to decide what content to show and in what order, and they can have a negative impact, including the spread of misinformation, social polarization, and echo chambers around important topics. Frances Haugen, a former Facebook employee turned whistleblower, has drawn significant public attention to this issue by revealing the company's alleged knowledge about the negative impacts of their own algorithms. Additionally, a recent initiative to ban TikTok as a threat to US national security indicates the influence of recommender systems. The objective of this study is threefold. The first goal is to provide an exhaustive evaluation of the profound worldwide influence exerted by algorithm-based recommendations. The second goal is to determine the degree of priority accorded by the scientific community to pivotal subjects in recommender systems discussions, such as misinformation, polarization, addiction, emotional contagion, privacy, and bias. Finally, the third goal is to assess whether the level of scientific research and discourse is commensurate with the significant impact these recommendation systems have globally. The research concludes the impact of recommender systems on society has been largely neglected by the scientific community, despite the fact that more than half of the world's population interacts with them on a daily basis. This becomes especially apparent when considering that algorithms exert influence not just on major societal issues but on every aspect of a user's online experience. The potential consequences for humanity are discussed, such as addiction to technology, weakening relations between humans, and the homogenizing effects on human minds. One possible direction to address the challenges posed by these algorithms is the application of algorithmic regulation to promote content diversity and facilitate democratic engagement, such as the tripartite solution which is elaborated upon in the conclusion. Therefore, future research should not only be centered around further evaluating influence of this technology, but also the analysis of how such systems can be regulated. A broader conversation among all stakeholders should be evoked on these potential approaches, aiming to align AI with societal values and enhance human well-being.

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https://doi.org/10.1016/j.futures.2024.103383
Received 21 October 2023; Received in revised form 4 April 2024; Accepted 13 April 2024
Available online 17 April 2024

1. Introduction

Recommender systems can be considered the first widespread encounter of humanity with AI, the one in which humanity arguably lost (Harari et al., 2023). As generative AI models continue to gain popularity (Bojic et al., 2023), they offer not only curated content but also the ability to create tailor-made content for individual users.

From blockchain and 5 G to revolutionary language models and the metaverse, new technologies are emerging quickly, being accepted by many, and impacting everyone in profound ways without being adequately analyzed by scientists or regulated by lawmakers. Presented as an inevitable future, AI could be compared to widespread ideologies or religions of present times (Barbrook & Cameron, 1996:44).

Although emerging technologies are often envisioned as positive and transformative for individuals and groups, they do not always meet the predictions and ideas behind them. One of the examples is the promise of the internet as a way to connect the world in an unprecedented manner, thus increasing understanding between people and overall wellbeing (Gates, 1995; Google, 2023).

However, the outcome of more than two decades of internet use has been quite different than what was envisioned. Instead of bringing people together, the widespread use of the internet has been connected with increases in media addiction (Leung & Lee, 2012; Stern, 1999; Huisman et al., 2001), a decrease in face-to-face interaction (Drago, 2015), extensive social polarization (Cinelli et al., 2021; Zollo, 2019; Rieger & Wang, 2020), and the rise of populist leaders across the globe (Pavlovic & Bojic, 2020). All of these developments are linked to an often-overlooked AI-based technology called a recommender system which is designed to select the content that internet users experience (Milano et al., 2020; Ramos et al., 2020; Fleder & Hosanagar, 2007; Lucherini et al., 2021).

In this paper, we use the term "recommender systems" to refer not only to the specific algorithms commonly known as recommender systems, but we extend the definition to incorporate an expansive array of algorithm-driven recommendation mechanisms currently inherent in a number of modern mainstream platforms. These systems are deployed across various digital domains such as social media platforms, search engines, AI conversational models like ChatGPT, and emerging technologies like metaverse.

Recommender systems individually expose online users to the world around them (Möller et al., 2018). From search engines and advertising platforms to social media trending tools, decisions on how to simplify the complex world into possibilities have an immense impact on societies. Algorithms, like human perceptual apparatus, act as eyes and ears in the online world, assisting advertisers in selling products and online platforms in extending the length of use for their services (Bojic et al., 2021). Recommender systems decide which content will be shown to each and every user of big social media platforms and online search engines on an individual level and at any given moment (Garimella et al., 2018; Spohr, 2017). Recommender systems distribute ads and posts, provide friend recommendations, and more (Bojic et al., 2021).

Recommender systems could be compared to "priming" in mainstream media, which means prioritizing some stories over others to set main topics for the whole society (Domke et al., 1998; Feezell, 2018). Interestingly, recommender systems are incomparably more impactful than mainstream media priming, as they give individual recommendations based on analysis of digital footprints. Contrary to mass media, algorithms impact every aspect of an internet user’s life, from interactions to suggestions about who to follow and message, what to buy, who to vote for, how to get from one point to another, etc. Finally, unlike traditional media, recommender systems are usually with the internet user 24 h a day, seven days a week, because they are mainly used on smartphones.

Mainly designed to keep users glued to the screens of their smartphones, algorithmic recommendations have some side effects as well. Former Facebook employee Frances Haugen warned in October 2021 that AI-based recommender systems pose serious risks to democracy and society by intensifying hate, creating polarizations, and prioritizing content containing negative and arousing emotions (Perrigo, 2021; Cadwalladr, 2017). The movie made by people previously employed by big tech companies, The Social Dilemma (Orlowski-Yang, 2020), together with various whistleblowing acts related to Facebook (Perrigo, 2021) and Twitter (Malik, 2023) have been warning that recommender systems have been utilized to invisibly direct the opinions, decisions, and actions of people exposed to social media and search engines across the globe.

The potential for misuse of algorithmic recommendations has recently been highlighted by the initiative to ban the TikTok social media platform in the US because it poses a threat to national security (Gerstell, 2023). Moreover, even though it is a Chinese app,

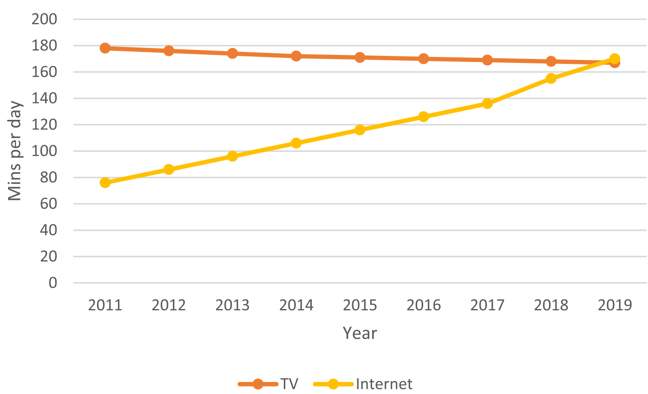

Fig. 1. Estimated mins per day TV and Internet use per person globally (Richter, 2020).

TikTok is censored in China, which means that it shows only the "spinach version" of reality. Algorithms are set differently for TikTok in China and the rest of the world. Both the fact that the US has been considering banning TikTok and the fact that the app displays different content recommendations in China compared to other countries demonstrate the significant power of recommender systems.

There are various statistics that support the idea of the global influence of recommender systems, which are mainly utilized in almost all cases of common internet use by any device, such as through online searches, social media, large language models and major news websites. In 2019, online media consumption surpassed TV consumption, signaling the end of the TV era, as people spent an average of 8 h globally consuming media, the highest ever, which can be seen in Fig. 1 (Richter, 2020). According to the most recent statistics, 5 billion people use the internet, while 4.7 billion use social media, accounting for 63.8% and 59.6% of the global population, respectively (Johnson, 2022). Google's 2021 searches totaled 5.4 billion per day (Georgiev, 2023). All these stats speak of the magnitude of exposure to recommender systems and their societal influence. While keeping that in mind, it may be illustrative to point out that these interactions with recommender systems are mainly done through major online platforms, among which social media play a prominent role. The most used social media is Facebook, with 2934 billion active users in October 2022 (StatusBrew, 2023). Additionally, as many as 52% of Americans get their news from Facebook (Pew, 2019).

2. Preliminary literature review

The predominance of existing literature on recommender systems primarily foregrounds technological solutions to refine recommendation quality through improved user profiling and addressing key challenges such as the 'cold start' problem and 'low model scalability' (Ye et al., 2012; Zhou et al., 2012; Christensen & Schiaffino, 2014; Wang et al., 2021; Shalom et al., 2019). Similarly, a significant corpus of research within the economic domain concentrates on using recommender systems as strategic tools to enhance sales diversity (Fleder & Hosanagar, 2009; Pathak et al., 2010), bolster purchase intentions (Yang, 2018; Xu et al., 2022), and optimize e-commerce decision-making processes (Kim & Srivastava, 2007).

However, related to above noted public concerns and the overarching impact of algorithmic recommendations on society, six salient areas have been identified, including misinformation, polarization, addiction, emotional contagion, privacy, and bias, each underscoring a facet of the complex interplay between technology and societal well-being.

2.1. *Misinformation*

With the proliferation of digital media, one insidious side effect of recommender systems has been the inadvertent spread of misinformation (Zollo, 2019; Sear et al., 2020; Spohr, 2017; Rieger & Wang, 2020; Li et al., 2020). Figueira & Oliveira (2017) assert that recommender systems can potentially become a breeding ground for fake news and misinformation because the algorithms behind these systems may prioritize popular or sensational content over verified, dependable information. In an eye-opening study, Ribeiro et al. (2020) discovered that YouTube, which relies heavily on its recommendation algorithm to engage users, has inadvertently become a hub for conspiracy theories and unfounded information due to the tendency of the system to prioritize content that promotes user engagement. Hassan (2019) proposes deploying the constituent dimensions of trustworthiness to build a new kind of news recommender system, thus tackling issues such as fake news, polarization, and partisan antipathy in the US.

Further, misinformation is a critical concern as it can have devastating social implications, from shaping public sentiment on crucial issues to instigating conflict and arousing unnecessary fear among the population. The coronavirus pandemic provides a stark example of the extensive spread of misinformation and disinformation through social media platforms, which, leveraging their recommendation systems, have significantly influenced public understanding and response to the health crisis (Ferrara, 2020).

2.2. *Polarization*

Recommender systems, to maximize their personalization efficacy, usually lean into promoting content that aligns with users' demonstrated interests (Nguyen et al., 2014). While this promotes user engagement, it can lead to the creation of echo chambers or "filter bubbles", effectively isolating users from diverse perspectives (Milano et al., 2020). This characteristic entrenches users in a space that only echoes their own views and beliefs, thus instigating and exacerbating societal polarization (Ramos et al., 2020; Wilson & Seminario, 2013; Papakyriakopoulos et al., 2020; Noh et al., 2018; Garimella et al., 2018; Cinelli et al., 2021; Conway-Silva et al., 2018; Schmidt et al., 2018; Bojic et al., 2022).

Nguyen et al. (2014) uncovered that usage of recommender systems reduces the diversity of information to which individuals are exposed, compromising the dissemination of diverse ideological and societal perspectives. This homogenization of information can encourage tribalism, division, and mistrust among different societal groups, creating a fractured and polarized society. Reuver et al. (2021) identify which natural language processing techniques in news recommendations can support democratic capacity and deliberation. Hendrickx et al. (2021) focus on news diversity, and Dokoupil (2022) proposes algorithmic solutions to help mitigate the "filter bubble" problem. Twitter's personalization algorithms tend to amplify right-leaning content more consistently than left-leaning content, according to a massive-scale randomized experiment involving nearly 2 million daily active accounts (Huszár et al., 2022). A large-scale study analyzing over 330,000 videos on YouTube found that users consistently migrate from milder to more extreme content, supporting the hypothesis of a radicalization pipeline on the platform (Ribeiro et al., 2020).

2.3. Addiction

Digital platforms, such as streaming services and social media networks, using their sophisticated recommender systems, are often designed to maximize user involvement and time spent in-app (Park et al., 2021). This strategy, while commercially beneficial to platform operators, can inadvertently lead users to develop addictive behaviors (Leung & Lee, 2012; Stern, 1999; Huisman et al., 2001; Bojic, 2022; Segawa et al., 2020; Bojic & Marie, 2017).

The research of Park et al. (2021) emphasizes the correlation between the habitual usage fostered by recommender systems and harming mental health, suggesting a connection between addictive smartphone behaviors and mental health problems like stress, anxiety, and depression. The role of persuasive design aspects, such as endless scrolling and personalized recommendations, essentially evolves into a conduit for digital addiction and compulsive behavior.

2.4. Emotional contagion

The sphere of emotional contagion in the digital world has also been intensely impacted by recommender systems. Defined as the phenomenon of transferring and perceiving others' emotions, in the context of digital media, emotional contagion refers to the cascading spread of emotions across social network users (Ferrara, 2020; Hatfield et al., 1993).

Recommender systems, through their drive to engage users, may end up promoting content that triggers strong emotional responses, leading to the widespread dissemination of such emotions across their user base (Bojic, 2021; Dang-Xuan & Stieglitz, 2021; Park, 2015; Coviello et al., 2014; Ferrara & Yang, 2015; Cadwalladr, 2017). The implications are multifaceted and complex, possibly leading to widespread panic, fear, or hostilities in extreme situations.

Studies have established that negative emotional waves are particularly prone to dissemination on social media, as feelings had been transmitted to posts unrelated to the negative news that authors had been subjected to in the beginning (Coviello et al., 2014). Additionally, modifications in the news feeds that users are exposed to on social media have exhibited an evolving influence on the emotions of online users (Ferrara & Yang, 2015). Research has shown that people tend to react more intensely to negative emotions, which is analyzed by the theory of negativity bias (Baumeister et al., 2001; Derks et al., 2008; Rozin & Royzman, 2001). An experiment conducted by Liebrecht et al. (2019) proved that negative emotions have a stronger impact when both positive and negative emotions are intensified. Eventually, it has been verified that posts comprising negative sentiments stimulate more frequent liking, sharing, reacting and commenting than posts containing positive emotions (Stieglitz and Dang-Xuan, 2013).

2.5. Privacy

Privacy is a growing concern tied to the proliferation and increasing complexity of recommender systems (Jeckmans et al., 2013). Kowalczyk et al. (2012) highlight that the quality of recommendations often depends on the system's ability to harness vast amounts of user data, thereby posing potential privacy risks.

The lack of transparency in data handling methods and the potential misuse of personal information underscore the importance of privacy considerations in developing and deploying recommender systems (Ma, 2023; Himeur et al., 2022; Yargic & Bilge, 2019; Zhu et al., 2014; Puglisi et al., 2015).

2.6. Bias

Bias and fairness in recommender systems remain a prominent issues and manifest in complex and often hidden ways (Deldjoo et al., 2022; Islam et al., 2019; Rastegarpanah et al., 2019; Fabbri et al., 2022; Elahi et al., 2021; Krishnan et al., 2014; Gao & Shah, 2020; Wang et al., 2022). Wu et al. (2024) posit that bias can emerge from historical data, which can inherently comprise pre-existing societal prejudices. These biases may then get propagated by the recommender system, leading to the unfair treatment of marginalized users or groups.

User-to-item collaborative filtering, a popular approach in recommendation, may unintentionally favor popular items, leading to a lack of exposure for niche or less-known items, which is known as the long-tail problem (Zhao et al., 2023). It is therefore significant for the developers of recommender systems to mitigate the potential biases inherent in the deployment of these systems.

While much of the existing research on recommender systems focuses on technological enhancements for improved recommendation quality and strategic advantages, there is an unmistakable need to consider the broader societal ramifications of these systems. Six significant areas – misinformation, polarization, addiction, emotional contagion, privacy, and bias – emerge as critical parts of the nexus between technology and societal well-being. Despite the benefits of personalized recommendations, these systems can inadvertently stoke misinformation, foster addiction, spark emotional contagion, encroach on privacy, and propagate bias.

2.7. Research questions

As recommender systems are an underlying technology, their use and impact are expected to grow in the future through the mainstream deployment of novel, and potentially more addictive, AI-related services, platforms, and media, such as ChatGPT and the metaverse (Bojic, 2022).

The unprecedented power in the hands of AI and fast-paced advancements towards artificial general intelligence (AGI) increase concerns about AI and open up an urgent need for research and regulation. Therefore, it is crucial to thoroughly examine the societal impacts these technologies currently have and may have in the future. This is especially important because AI sparks grim long-term visions of humans becoming intensely addicted to technology while at the same time weakening relations with other humans (Nowotny, 2021).

According to the above-noted concerns of the public and a preliminary literature review, this exploratory inquiry establishes the following research questions:

RQ1: What is the extent of the societal influence of recommender systems on various aspects of human life?

RQ2: What is the extent of the academic output on the societal influence of recommender systems, specifically in the topic areas identified in the literature review?

RQ3: Is research focus on the societal impact of recommender systems adequate, when compared to the overall influence of this technology?

3. Methodology

The methodology employed in this research incorporates both descriptive analysis and comprehensive literature review, supplemented with content analysis (Hsieh & Shannon, 2005). This study aims to expound on the societal implications of recommender systems, utilizing a structured approach.

The primary phase of the inquiry involves an in-depth descriptive analysis of recommender systems. This comprises an overview of their operation mechanisms, prevalent usage, and widespread repercussions. In explicating the influence of the systems, key determinants include stats on search engines, social media platforms, online dating applications, e-commerce sites, news recommendations, online networking, and digital advertising.

To answer the second research question, a systematic literature review was conducted on February 11 2024. The focus centered on the societal implications and the span was restricted to specific domains highlighted in existing literature, thus ensuring a context-specific understanding. The research papers dealing with societal implications were then compared with the scope of influence ascertained from the first research question. This comparison serves to gauge whether the current focus in scientific literature accurately reflects the evolution and impact of recommender systems.

To conduct the literature review, we utilized subject-specific keywords within a comprehensive scientific publications index – Scopus (2024). Our choice of Scopus as the preferred index base was mainly due to its extensive coverage and high level of inclusivity. Renowned for its vast repository of peer-reviewed literature, Scopus provides a reliable platform for accessing a diverse range of scientific articles, conference papers, and patents. This made Scopus an ideal tool for rigorous and comprehensive analysis in our research.

All the data utilized in this study, including the list of publications, APA-style references, and raw stats overview, are available in an open scientific repository. The comprehensively compiled data can be accessed through the Open Science Framework (OSF, 2024). This ensures full transparency of our research process and allows for further scholarly exploration of the topic.

These not only ensured relevance but also assisted in narrowing the scope of the review. The universal keyword was ’recommender systems’, while subject-specific keywords included ’misinformation’, ’polarization’, ’addiction’, ’emotional contagion’, ’privacy’, and ’fairness’. Each keyword was used in conjunction with ’recommender systems’ to specify the search within Scopus.

Out of the total 31,790 publications of recommender systems in Scopus, only 1805 fulfilled the above-noted criteria of the initial search. Subsequently, focusing on individual areas of inquiry yielded: Misinformation (23), Polarization (39), Addiction (4), Emotional Contagion (256), Privacy (853), Bias (655).

This comprehensive data set from Scopus was then qualitatively examined to identify the presence and focus of specified issues within domains such as computer science, engineering, mathematics, decision sciences, social sciences, business, management and accounting, medicine, physics and astronomy, among others. Due to possible multidisciplinary research, each publication could be classified into multiple scientific domains. Thus, the total of 1805 publications were classified into 3226 scientific disciplines. Furthermore, through the conduction of conceptual and relational content analysis, the relationships between the key notions identified in these papers were explored.

This study uses a mixed-method approach combining descriptive analysis, comprehensive literature review, and content analysis to examine the societal implications of recommender systems. Central to this process is an exhaustive descriptive analysis on the workings, usage, and impact of recommender systems, focusing on various digital platforms such as search engines, social media, online dating applications, e-commerce sites, news recommendations, online networking, and digital advertising. This multi-pronged methodology enables a layered exploration of the subject matter, ensuring a well-rounded understanding of the influences and repercussions of such systems in society.

4. Gatekeepers to our experiences: how it works

Algorithms are an important part of online users’ lives. This section examines what recommender systems are and how they work. A brief history of the development of this type of computer code is presented first, followed by a working definition, a description of two commonly used techniques in algorithmic recommendations, an examination of the measured capability of modern algorithms, which are linked to emotional recognition, personality traits, and alleged advanced predictive capabilities.

First working definitions of recommender systems is given by Zhou et al. (2012) as computer algorithms that combine user profiling, information filtering and machine learning to deliver product or service recommendations that match user preferences and needs.

Second working definition is that recommender systems are computer algorithms that help users discover new items that they may be interested in, based on their past interactions. These algorithms use data science and machine learning techniques to analyze the user's past interactions and find patterns in the user's preferences (Bobadilla et al., 2013).

However, considering the recent mainstream penetration of large language models (Bojic et al., 2023), it may be adequate to offer a third and most encompassing definition. Third working definition is that recommender systems refer to a class of algorithms designed to analyze, curate, and generate personalized content recommendations, which are typically employed by large-scale online platforms, including but not limited to search engines, social media networks, and natural language processing models.

Since the mid-1990 s, when the first papers on collaborative filtering were published, recommender systems have become an essential area of research in response to the "information overload problem". These papers, such as Resnick et al. (1994), have helped to make recommender systems an important part of the online experience for millions of users. By providing tailored recommendations, users can access the content that is most relevant to them and quickly find what they are looking for. The development of recommender systems has been a major factor in the success of various online platforms.

Two main techniques have become prominent in the field of recommendation algorithms: content-based filtering (CBF) and collaborative filtering (CF).

Content-based filtering (Mooney and Roy, 2000) is a method that recommends items to a user based on the content of items that the user has viewed or selected in the past. For example, a movie recommender system might use genre, actors, director, and producer information to generate a list of movies that a user is likely to enjoy. To do this, a feature representation must be created for each item, which can be done automatically for machine-parsable items such as news or papers but must be inserted manually by humans for items that are not yet machine-parsable such as movies and songs. This can be expensive, time consuming, error-prone, and subjective. It can also be difficult to define the right set of features to accurately classify items such as jokes (Massa & Bhattacharjee, 2004).

Collaborative filtering (CF) instead relies on the ratings of items by other users to make recommendations to the target user (Breese et al., 1998). It looks for users with similar taste and uses the ratings they gave to highly rated items to generate a list of recommendations. For example, a book recommendation system would first find the "neighbors" of the target user (users who rate books similarly to the target user). Then, the system would recommend books that these neighbors have highly rated.

However, AI-based recommender systems have been evolving to rely on a wealth of sensory data, and in recent times, personality and social connections have been the main determinants of algorithmic outcomes (Tran et al., 2021; Tkalcic & Chen, 2015; Baral & Li, 2018). This data is collected from personal devices carried by online users, such as mobile phones, digital watches, cars and smart homes (Bojic et al., 2021; Azucar et al., 2018; Deeva, 2019; Hinds & Joinson, 2019). This data, or "digital footprint," encompasses users' habits and patterns of behavior, as well as weather, location and health information (Milano et al., 2020).

Data referred to as digital footprints, which are collected automatically, are the basis of recommender systems (Hinds & Joinson, 2019). Such footprints enable computers to generate a digital identity of a person (Deeva, 2019, 185). These fragments of online identity may include conclusions about personality types and other psychometric properties (Settanni et al., 2018: 217), from multiple sources and types of data, such as demographics, likes, activity records, language and multimedia (Risso, 2018: 77). Moreover, algorithms can also be used to ascertain the short- and long-term interests of online users (Farnadi et al., 2016: 113).

Research indicates that AI algorithms are better than humans at making judgments about personality traits (Azucar et al., 2018: 150). The accuracy of the predictions increases when a variety of digital footprints from multiple sources are utilized (Skowron et al., 2016, 108). Furthermore, digital footprints can uncover many other aspects of a person, including political views, addictions and health problems (Youyou et al., 2015: 1039). There are various ways in which algorithms can make precise assessments of an online user's personality, such as analyzing the comments and links they share (Yamada et al., 2019: 177–182).

Algorithms nowadays are much more advanced than merely presenting content that is similar to that which their users usually

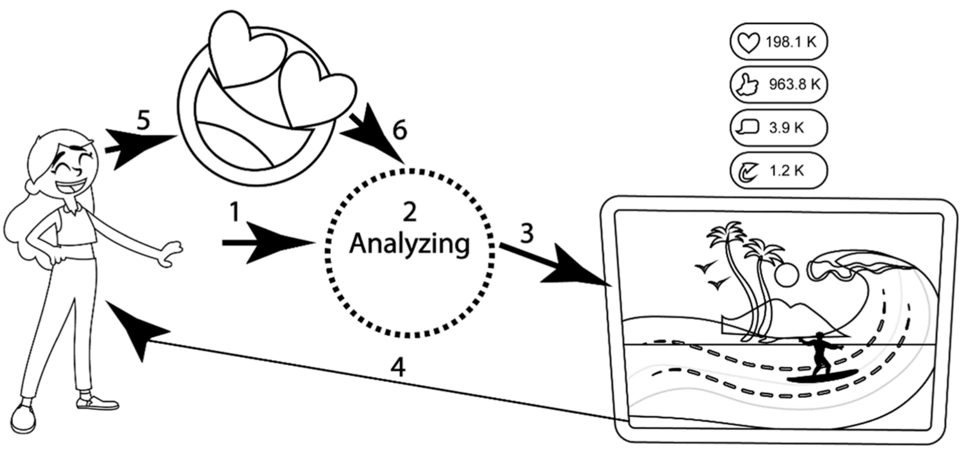

Fig. 2. This illustration demonstrates the complexities of advanced recommender systems, which use digital footprints (1) and machine learning (2, 6) to continuously improve their predictions of what kind of content (3) each individual (4) will engage with the most (5) while at the same time continuing to use the online platform.

access, or what is preferred by others (see illustration in Fig. 2). Algorithms can have a complex and far-reaching impact, as evidenced by allegations that social media companies are listening to people's mobile phone microphones without their consent. Many people have reported that recommendations pop up related to conversations they are having, even though they don't remember having conducted any related searches. Jamie Court, the president of the LA Consumer Watchdog, recently commented on the complaints made by people who experienced predictive capabilities of AI recommender systems. He stated, "They put together all kinds of circumstantial evidence, and it appears as if they've heard your conversations" (Graham, 2022). This serves as an example of the advanced capabilities of AI algorithms in predicting what online users might desire in the future.

In fact, recommender systems function by analyzing large volumes of data to uncover small correlations, thus making individualized decisions about what to show to people on the internet. These operations are too complex to be implemented by humans successfully. Additionally, AI-based algorithms go beyond mere instructions made by people, since they are based on machine learning. Consequently, whatever happens in the "black box" of machine learning, which is an integral part of all such systems, cannot be understood by any individual. This indicates that AI is making decisions that surpass any settings or inputs provided by tech companies that manage and own them.

The distinction between instructed algorithms and those based on artificial intelligence is that the former's owners and operators don't know why a certain decision is taken. They can provide input data for the algorithms to learn from, and use the outputs for the same purpose, aiming to adjust the outputs in the desired direction. Therefore, algorithms learn from users' digital traces what they should show them to achieve the desired effect (Harrington, 2019). Of course, algorithms must have precise definitions of success, such as increasing engagement around advertised items or lengthening platform use.

A plethora of real-life examples demonstrate the complexity of algorithms. As a hypothetical example, if an algorithm determines that posts with strong emotions have a certain effect for certain people, it will offer these types of posts and ads to them. Generally, tech companies aim to increase the time users spend on their platforms, which exposes them to content and ads. Additionally, algorithms are often programmed to present ads that will encourage engagement, such as likes and purchases of certain products (Milano et al., 2020; Bojic et al., 2021; Bojic, 2022).

Algorithms function on rewards and punishments, depending on the activity and engagement of the user, such as post likes, shares and views. If a user posts content without being active, they are penalized by the algorithm, as their posts are not shown even to their friends and connections. This also applies to ads: if a user or company pays for ads regularly, the algorithm views this as a "bribe" and will expose more users to their content, both as ads and organic content in timelines (Bojic et al., 2021).

This section has shown that algorithmic recommendation algorithms have come a long way since they were first introduced, and they now possess the capability to detect a user's emotions, personality traits, and even predict future behavior. Algorithms have become an integral part of online users' lives, and this is likely to remain the case for the foreseeable future. With further advancements in AI, algorithmic recommendations may soon become even more sophisticated and personalized.

5. Widespread impact of algorithmic recommendations

This section emphasizes the overall impact of AI driven recommendations presenting research and stats to illustrate the influences of algorithmic recommendations in everyday life. The impact of recommender systems is evident in search results, social media trending pages, and home page feeds that prioritize content for users. Additionally, social networking sites use algorithms to recommend potential friends to users based on existing friends, interests, and other data.

Algorithms act as gatekeepers between people and the environment, filtering and prioritizing content to present as relevant answers. This power to curate content gives algorithms significant influence over the online world, deciding which information is granted or denied access before users even have a chance to think about it.

Societies and individuals don't have control over how they are exposed to content in the digital and virtual realms. This power is possessed by tech companies that own online platforms and AI-driven algorithms. This impact has grown in part due to the recent COVID-19 pandemics, as many people have changed their habits regarding online gatherings and e-commerce (Trougakos et al., 2020).

It is evident that algorithms have an important role in today's world, playing a major part in online users' exposure to content and affecting decisions such as healthcare plans, job offers, and prison sentences (Kleinberg et al., 2018). The use of algorithms in online decision-making is becoming increasingly prevalent. For instance, they may suggest a route to a destination when driving, who to message, or what to purchase. All of these small recommendations can lead to significant changes in a user's life. People may meet and fall in love (Rosenfeld & Thomas, 2012), find employment (Saini et al., 2019), join a public protest (Smith et al., 2022), or invest in a currency (Hernández-Nieves et al., 2021), all due to algorithmic recommendations.

The following sub-sections present statistics related to algorithmic recommendations in various domains: socializing, working, trading, advertising, and dating, with the aim of assessing the social impact of this technology.

5.1. Social media

The history of online social media can be traced back to the early days of the internet. In the mid-1990 s, a number of websites emerged that allowed users to connect with one another and share messages, photos, and videos. These early social networks included Six Degrees, Friendster, and MySpace (van Dijck, 2013). The popularity of these websites quickly grew, and by the early 2000 s, websites like Facebook, Twitter, and YouTube were becoming immensely popular (van Dijck, 2013).

Since their inception, online social networks have grown to become an integral part of online culture. The widespread use of social media is depicted by the data presented in Fig. 3. Social media are used to connect with friends and family, and to meet new people (van Dijck, 2013). As the number of users grew, so did the complexity of online social networks. To help users navigate the vast amounts of content, many of these networks began to develop customized algorithms to recommend content to users based on their interests and connections.

Recommender systems have become a key component of online social networks (Baral & Li, 2018). These systems analyze the behavior of users and identify patterns in their interactions to recommend content that is most likely to be relevant to the user (Bobadilla et al., 2013). Recommender systems have become increasingly sophisticated, and their ability to personalize content has become an important part of the user experience. The most common examples of recommendations in social media relate to home page, trending page and friends' suggestions (Bojic et al., 2021).

Home page or a feed or on social media is a way for users to stay up-to-date with the latest posts from the people and accounts that they follow. As new content is posted, it appears in the user's feed so that they can quickly and easily see what their friends, family, and favorite accounts are sharing. Additionally, feed algorithms prioritize the content that users are most likely to engage with and show them that content first.

Another segment of algorithmic recommendations on social media is social media trending pages, which is analogous to the traditional mass media, deciding which content is being consumed. In the past, the same news was broadcasted across all media platforms and were chosen by the editors and owners of the media. Now, algorithms deliver individualized content to everyone, influencing the thoughts and feelings of billions of people.

Friend recommendations on social networking sites work by recommending potential friends to users based on their existing friends, interests, and other data such as location. For example, if a user is friends with someone who shares similar interests, the social networking site will suggest that user as a potential friend for the user. Additionally, the site may suggest friends based on geographic location, or by analyzing the user's past interactions with other users.

5.2. Search engines

Search engines are a type of software that are used to search the internet for information, products and services (Seymour et al., 2011). They allow users to find what they are looking for on the internet.

The history of search engines dates back to the early days of the internet. Early search engines such as Archie, Veronica and Jughead offered basic web search capabilities (Seymour et al., 2011). In 1994, Lycos was launched as the first full-text search engine, allowing users to search for any words contained in a webpage. This was followed by early versions of popular search engines such as Yahoo! and Altavista (Croft et al., 2010).

Since then, search engines have become increasingly sophisticated, offering advanced capabilities such as natural language processing and artificial intelligence. Today, search engines are powered by complex algorithms that are designed to provide the most accurate and relevant results for any given query (Deldjoo et al., 2022).

The role of recommender systems in search engines is to provide personalized search results to users. Recommender systems use algorithms to analyze a user's browsing history and search history, and then make recommendations based on the user's interests (Dokoupil, 2022).

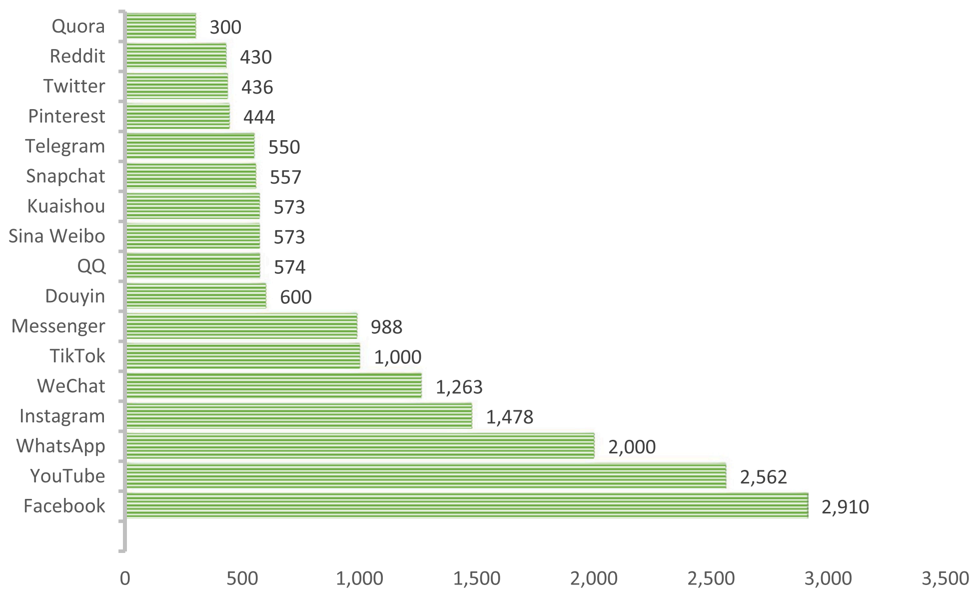

Fig. 3. The list of the most popular social networking sites worldwide as of January 2022, ranked by number of monthly active users in millions (SocialMedia, 2022).

5.3. Business

Online business apps and social media for business networking have seen significant growth in recent years, as entrepreneurs and employers turn to the convenience of the internet to find and network with potential employees (Jansen et al., 2005). In the United States alone, the number of online businesses has grown from 9.8 million in 2017 to 11.4 million in 2018 (Kolmar, 2022). As many as 80% of jobs are found online through company websites, online searches, job platforms, such as LinkedIn (Kolmar, 2022).

In addition to providing businesses with the opportunity to network and find potential employees, LinkedIn also enables businesses to promote their product and services to a larger audience (Jansen et al., 2005). Increasing revenues of jobs related social media LinkedIn are depicted in Fig. 4. The internet has also made it easier for employers to find potential employees, as they can quickly search through job boards and other websites to find the best candidate for the job.

Finally, the internet has also provided an avenue for people to work from home. Freelancers have added an extra $100 million to the U.S. economy in 2021, bringing their annual earnings to a total of $1.3 trillion (Ozimek, 2021). This trend is also evident in other countries as well, with over 1.4 billion freelancers in the world today (Ozimek, 2021).

5.4. E-commerce

The term e-commerce refers to the commercial use of electronic technology, such as the Internet, to conduct business activities (Kim & Srivastava, 2007). It involves the buying and selling of products and services through websites and other online applications. E-commerce has become increasingly popular in recent years, with more and more businesses turning to the Internet to reach new customers and expand their operations (eMarketer, 2022). Increases in retail e-commerce sales worldwide from 2014 to 2026 can be seen in Fig. 5.

The history of e-commerce can be traced back to the early days of the Internet, when the first online stores were created. In 1994, the first secure online transaction was completed, paving the way for the growth of e-commerce that has taken place over the past two decades (Burt & Sparks, 2003). Companies such as Amazon, eBay, PayPal and Alibaba have become household names in the e-commerce space, and new technologies such as blockchain and artificial intelligence are transforming the way businesses operate (Burt & Sparks, 2003).

The features of e-commerce vary depending on the type of business and the specific needs of the company. However, some of the common features include the ability to purchase, accept payments, manage inventory, track orders and customer data, and provide customer service (Kim & Srivastava, 2007). Many businesses also use e-commerce platforms to market their products and services.

E-commerce is a rapidly growing industry with more and more people purchasing products and services online, which is seen in Fig. 5. Global e-commerce sales are expected to reach nearly 8.1 trillion dollars by 2026 (eMarketer, 2022).

Recommender systems are a form of Artificial Intelligence (AI) that allow companies to personalize their customer's shopping experience (Elahi et al., 2021). By analyzing customer data, such as purchase history and preferences, these systems can recommend products or services that are tailored to the individual. This personalized experience has been proven to increase customer engagement and satisfaction, as well as boost sales (Saini et al., 2019).

Deployment of recommender systems in e-commerce is becoming increasingly popular. According to a survey by Forrester, around 80% of e-commerce companies are currently using recommender systems (Meena, 2018). This includes companies such as Amazon, Netflix, and Spotify. These companies have reported an increase in customer engagement and satisfaction, as well as an increase in sales due to the use of these systems (Kim et al., 2022).

5.5. Advertising

Online advertising is the practice of using the internet to promote products and services. It includes a variety of strategies such as display advertising, search engine marketing, and email marketing (Donaldson, 2008).

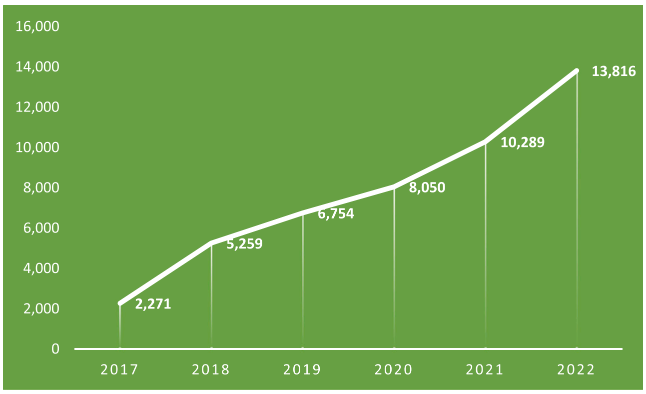

Fig. 4. The annual revenue of LinkedIn from 2017 to 2022, in millions of dollars (LinkedIn, 2022).

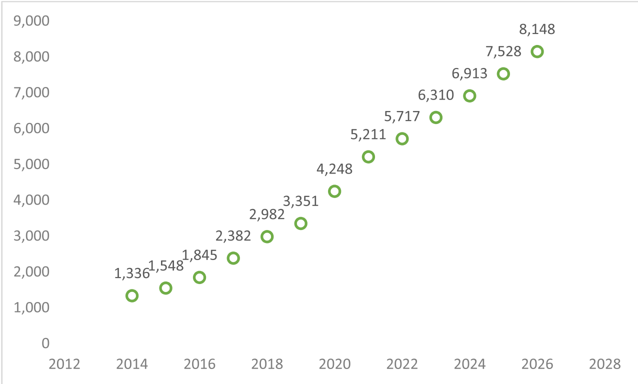

Fig. 5. Retail e-commerce sales worldwide from 2014 to 2026, in billion U.S. dollars (eMarketer, 2022).

Over the past two decades, internet advertising has seen incredible growth, becoming one of the most powerful tools in the marketing toolbox. From the early days of banner ads to the sophisticated ad targeting of today, there has been a steady rise in digital marketing. In 2007, online ad spending amounted to just $61 million (Zenith, 2022). This figure has grown exponentially since then, reaching $279 billion by 2021, as can be seen in Fig. 6.

These stats demonstrate the power of the internet as an advertising medium, and its increasing sophistication is a major factor in this growth. Companies are now able to use a range of advanced targeting strategies, including recommender systems, retargeting and programmatic buying, to target their specific audience with greater accuracy. This has made it much easier for them to achieve higher conversion rates and a better return on investment.

Advertisers use online advertising to target specific audiences and deliver tailored messages, while recommender systems are used to suggest products to customers based on their purchase and browsing history (Zhao et al., 2021). Recommender systems are used in e-commerce to suggest products to customers based on their previous purchases and browsing history (Donaldson, 2008). The history of online advertising and recommender systems date back to the early 2000 s. At the time, online advertising was used primarily for branding and awareness, but as technology advanced, advertisers began to use it to target specific audiences (Donaldson, 2008).

5.6. Dating

Online dating allows people to find and introduce themselves to potential romantic connections over the Internet, usually with the goal of developing personal, romantic, or sexual relationships (Ma et al., 2017). There are several different types of online dating platforms, including those that cater to a certain type of relationship, such as casual dating, serious dating, and marriage (Ma et al., 2017).

The history of online dating can be traced back to the late 1990 s, when the first online dating services began to appear (Fansher & Eckinger, 2021). Since then, the industry has grown rapidly, with more websites being launched and more people using them (Fansher & Eckinger, 2021). Statistics show that 12% of people have married or been in a serious relationship with someone they met on a dating app (Nadeem, 2020). The increasing number the online dating apps subscribers can be seen in Fig. 7, while share of mobile app users from selected countries who met their current romantic partner via their mobile device can be seen in Fig. 8.

Recommender systems play an important role in online dating (Pizzato et al., 2010). They are used to suggest potential matches for a user based on the user's past dating preferences, interests, and other factors (Pizzato et al., 2010). Recommender systems use

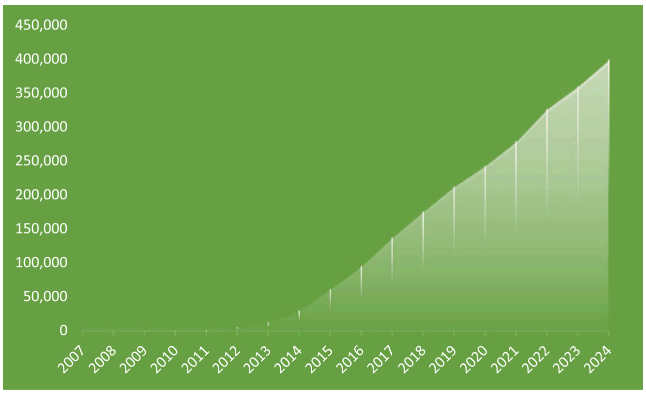

Fig. 6. The growth of mobile advertising spending worldwide from 2007 to 2024, in millions of U.S. dollars (Zenith, 2022).

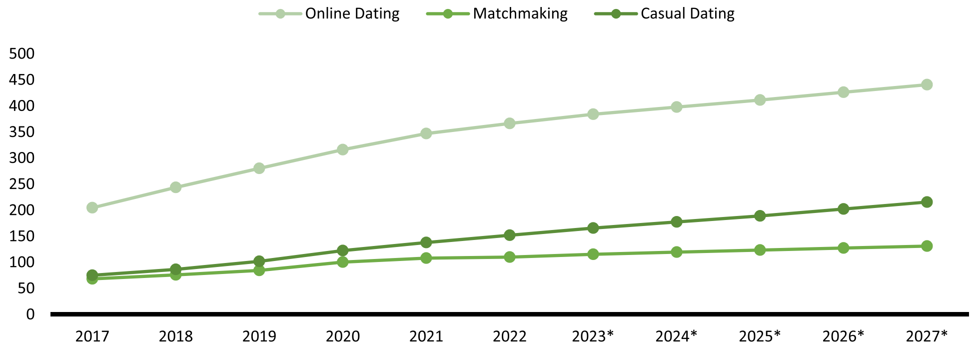

Fig. 7. Number of dating service users worldwide from 2017 to 2027, by segment, in millions (Statista, 2023).

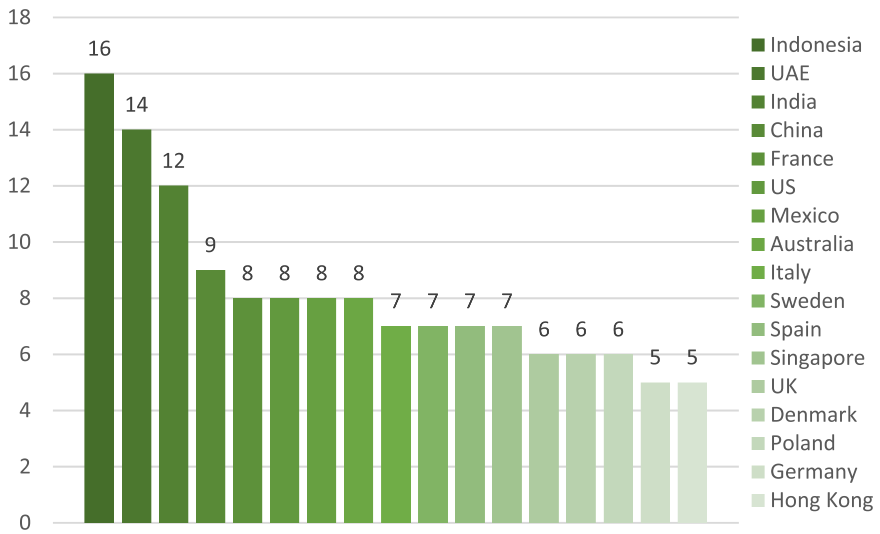

Fig. 8. Share of mobile app users from selected countries who met their current romantic partner via their mobile device in 2021 (YouGov, pp. -, 2021).

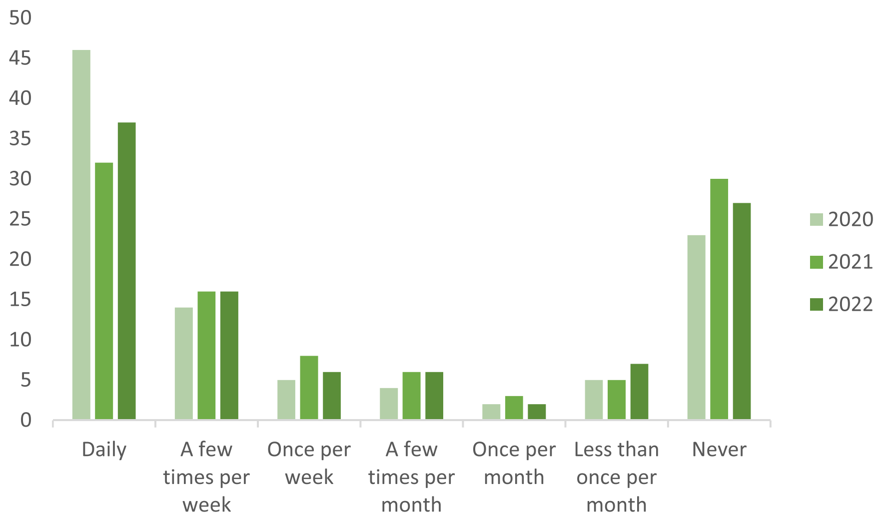

Fig. 9. The frequency of news consumption via social media among adults in the United States from 2020 to 2022 (Watson, 2022).

algorithms to analyze large amounts of data and make personalized recommendations to users (Ramos et al., 2020). By doing so, they help users find potential matches that are more likely to be compatible.

5.7. News consumption

Challenges that arise as a consequence of recommender systems in relation to news are misinformation, fake news, social polarization, echo chambers, invisible nudging and censorship—social issues that may affect the democratic process in a profound way and across the world.

Social media are increasingly used for news consumption, transforming traditional communication (Kaplan & Haenlein, 2010; Witteman & Zikmund-Fisher, 2012; Doyle & Lee, 2016; Conway-Silva et al., 2018). Recent reports demonstrate that over 50% of Facebook and Twitter users come across news weekly (Newman et al., 2021). This number is even higher in the US, which is illustrated in Fig. 9. Stats on news consumption were further segmented per social media in Fig. 10. Recognizing that social media is the primary source of news and information for many people is essential to understand significance of recommender systems. In 2019, the PAW Research Center reported that 52% of all U.S. adults got their news from Facebook (Pew, 2019). Zignal (2017) found that 90% of Americans do not verify the news they consume through social media, and this can be attributed to confirmation bias (Nickerson, 1998).

The Covid-19 pandemic has exacerbated the issue of misinformation, with 25% of Youtube videos containing false information (Li et al., 2020). The spread of fake news by recommender systems has created echo chambers which have polarized global societies, with one group supporting and the other opposing vaccines (Sear et al., 2020). This could not have been possible without the prevalence of social media as software, smartphones as hardware and recommender systems as algorithms used to give individual recommendations to its users (Schmidt et al., 2018; Zollo, 2019; Rieger & Wang, 2020).

Cinelli et al. (2021) outline that echo chambers are created due to two preconditions: opinions expressed by an online entity, which are shared by community and amplified by recommender systems. This echoes opinions which lead to polarization. The presence of opinion and reiteration of it in the online sphere are essential for the formation of echo chambers (Garimella et al., 2018). Misinformation propels polarizations in societies, which is a major process that leads to the emergence of echo chambers (Spohr, 2017).

Confirmation bias is an inclination for people to accept information that affirms their pre-existing opinions and that fits into their worldview (Nickerson, 1998). This could explain why societies become divided due to the impact of recommender systems that link social media users with specific posts, ads, information, and news. This implies that stories that do not align with the prevailing perspective of online citizens will be disregarded, which is why false news is not effective on those with contrasting views. Misinformation simply reinforces opinions and beliefs that people already have.

Though media outlets contribute to this by their reporting, recommender systems are more successful in fostering hate speech and segmenting citizens as they present them with personalized content to boost their exposure to ads and engagement online (Smith et al., 2022).

The effects of online polarizations were highlighted during the U.S. Presidential Election and the EU Referendum in the U.K., both of which took place in 2016 (Spohr, 2017; Conway-Silva et al., 2018).

AI-based recommender systems are the biggest contributors to the creation of echo chambers (Garimella et al., 2018; Bojic et al., 2021; Bojic et al., 2022). These tools largely rely on confirmation bias by serving up similar content that is attractive to online users (Bojic et al., 2021). The polarizing effect of echo chamber algorithms has been widely recognized in contexts of politics, populism and conspiracy theories. It has been reported that some populist leaders and movements, such as the Trump campaign in the U.S. and the Brexit campaign in the U.K., have utilized social media to their advantage, since algorithms are prone to emotional content

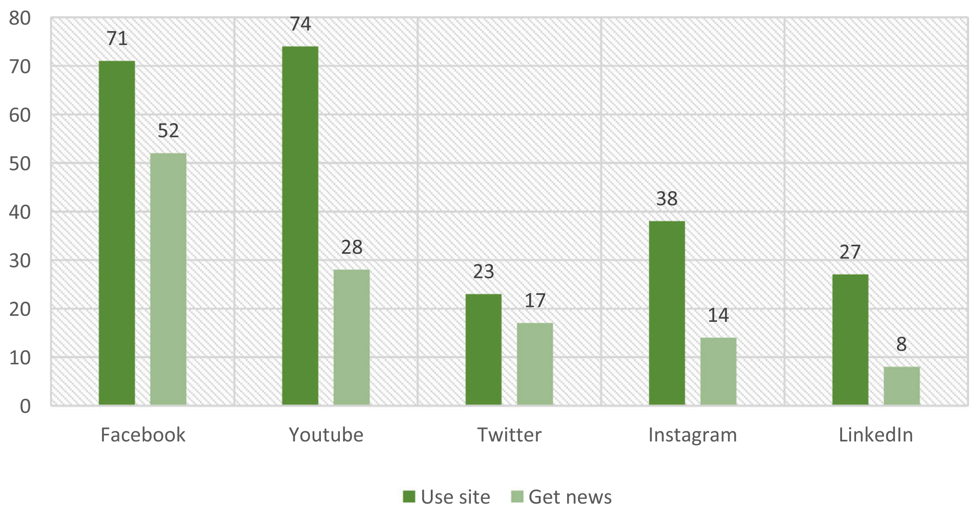

Fig. 10. Percentage of US adults who use social media and those utilizing them for news consumption in 2019 (Pew, 2019).

(Cadwalladr, 2017). Additionally, negative emotions tend to circulate more freely in the online realm, which has allegedly been the source of many civil unrests globally (Haring & Cecire, 2013).

The idea that tech companies may be artificially influencing the "organic" results that are seen in the trending sections is a problematic issue. Michael Nunez, in an article for Gizmondo, a tech magazine, writes that "Facebook workers routinely suppressed news stories of interest to conservative readers from the social network's influential "trending" news section" (Nunez, 2016). Indications of similar activity on Twitter could be seen in the recently released Twitter Files (Malik, 2023). The recommender system that is used to generate the trending section is what creates the content that appears in it, while the curators have the job of writing the descriptions of the news stories. As noted above, big tech companies have the potential to manipulate what is presented to their users without anyone being aware. On the other hand, AI algorithms may be able to do the same on their own at some point and under certain circumstances.

The use of algorithmic recommendations for news content on social media can have far-reaching implications. Misinformation, fake news, social polarization, echo chambers, invisible censorship and nudging are all potential outcomes of this technology, and can have a detrimental effect on democracy. These are issues that are not only experienced locally, but are felt around the world. It is therefore essential to understand the implications of algorithmic recommendations and how they can be managed responsibly.

6. Scientific coverage

This section delves into an extensive review of the scientific literature, based on reliable Scopus statistics, focusing on key societal implications as identified in previous research. A comprehensive analysis of the research landscape will be introduced, highlighting the dominant subject areas, patterns of keyword usage, geographical origins of studies, and a summarized overview of various issues related to algorithmic recommendations within different academic disciplines. This would provide a holistic perspective setting the stage for a wide-ranging exploration of the societal impacts of recommender systems technology.

Online platforms and devices that use recommender systems have gained significant mainstream acceptance, with their foundation dating back to key milestones achieved by major companies (Ivey, 2023). For instance, the eminent search engine, Google, was launched in 1998, Facebook began its operation in 2004, and the iPhone was introduced to the public in 2007.

Despite these longstanding technological developments, the research concerning the societal impacts of these systems, as identified in a preliminary literature review, has begun to evolve more noticeably in recent years, based on the Scopus index, a relatable source for this study. This trend is graphically represented in Fig. 11, indicating a surge in scientific inquiries on the subject since 2008.

However, it is significant to highlight that research into issues such as misinformation only started to appear in significant publications from around 2017, with a total of 23 publications to date. Similarly, work related to polarization has 39 publications since 2017. Conversely, studies examining addiction are quite rare, with only four published since 2019. Investigation into other topics such as emotional contagion, privacy, and bias have a slightly longer history with 256 papers published since 2004, 853 papers since 2008, and 655 papers since 2007.

Examining the structure of scientific publications in Fig. 12, according to Scopus statistics, reveals a clear predominance from certain disciplines. The majority of the research, 51.7% or 1668 publications, is classified as computer science. Engineering science follows with 514 publications accounting for 15.9%, and then mathematics with 330 publications or 10.2%. Decision sciences and social sciences rank fourth and fifth, contributing 6.9% (225 publications) and 3.8% (124 publications) respectively.

This distribution among subject areas might reflect the initial focus on leveraging recommender systems to enhance recommendation quality, potentially overlooking any ensuing effects. A pertinent question that emerges from this analysis is the extent to which

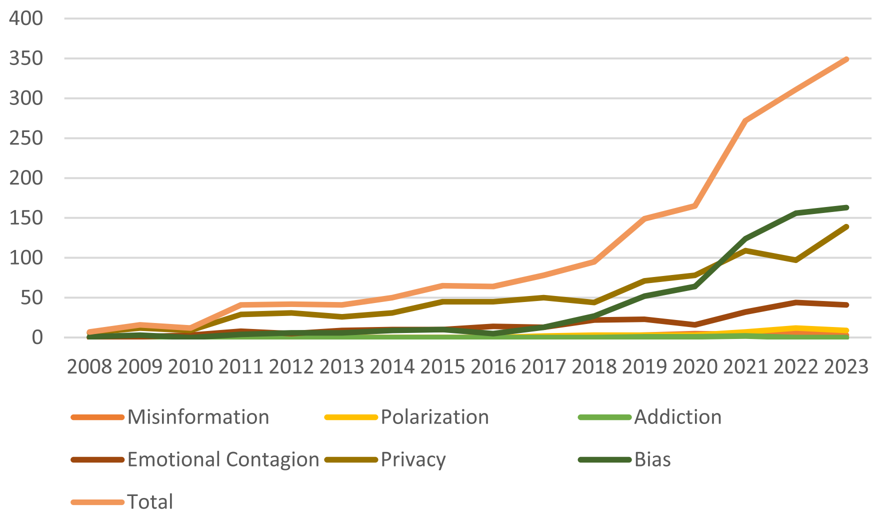

Fig. 11. Graphical representation of the chronological emergence and distribution of research publications on various recommender system-related issues.

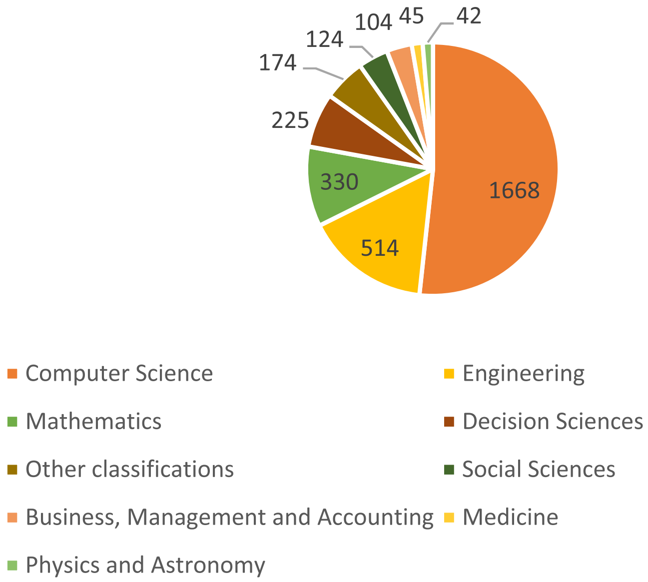

Fig. 12. The distribution of scientific publications related to the relevant social implications of recommender systems across various disciplines. One publication may cover multiple domains due to multidisciplinary research. In this case, 1805 publications have been classified into 3226 scientific disciplines.

these research inquiries are genuinely engaging with the societal implications of such technology.

Fig. 13 delineates the prevalent keywords related to the focus areas identified in our preliminary literature review including misinformation, polarization, addiction, emotional contagion, privacy, and bias.

The terms 'Data Privacy' (407) and 'Privacy' (248) lead the pack, followed closely by 'Privacy Preserving' (242), and 'Differential Privacies' (128). These terms are visibly geared towards privacy-related themes.

'Bias' also figures prominently with keywords like 'Popularity Bias' (107), 'Bias' (74), and more specific phrases such as 'Algorithmic Bias' (30), 'Selection Bias' (31) and 'Fairness' (189).

Emotional contagion and addiction are implied through 'Emotion Recognition' (67), 'Emotion' (43), 'Emotions' (34), and 'Behavioral Research' (116) keywords.

There seems to be less emphasis on terms directly related to polarization and misinformation, with 'Polarization' only garnering 30 mentions in this keyword analysis.

It's worth noting terms like 'Human Computer Interaction' (32), 'User Experience' (27), and 'Trust' (24) also make appearances, hinting at a user-centric focus in the research.

The outlined keyword distribution offers a snapshot of current research direction and areas of concentration.

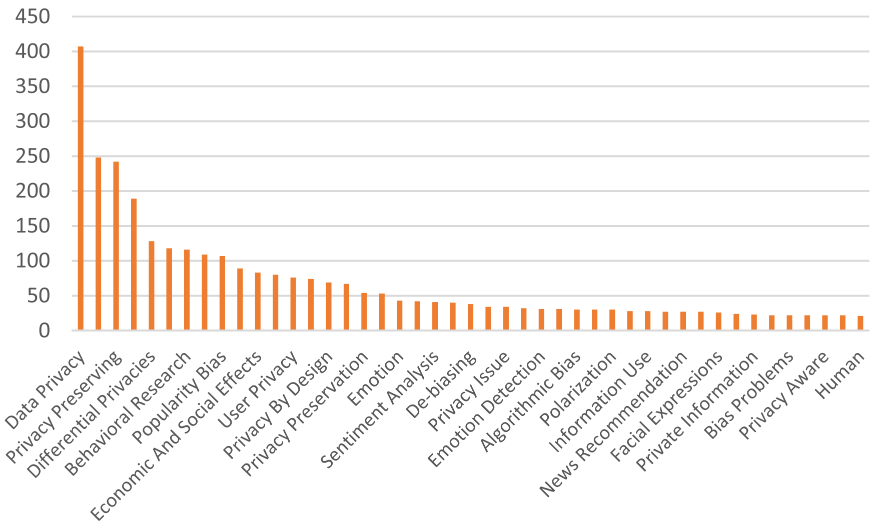

Fig. 13. Visual representation of the main keywords associated with various focus areas identified in a preliminary literature review.

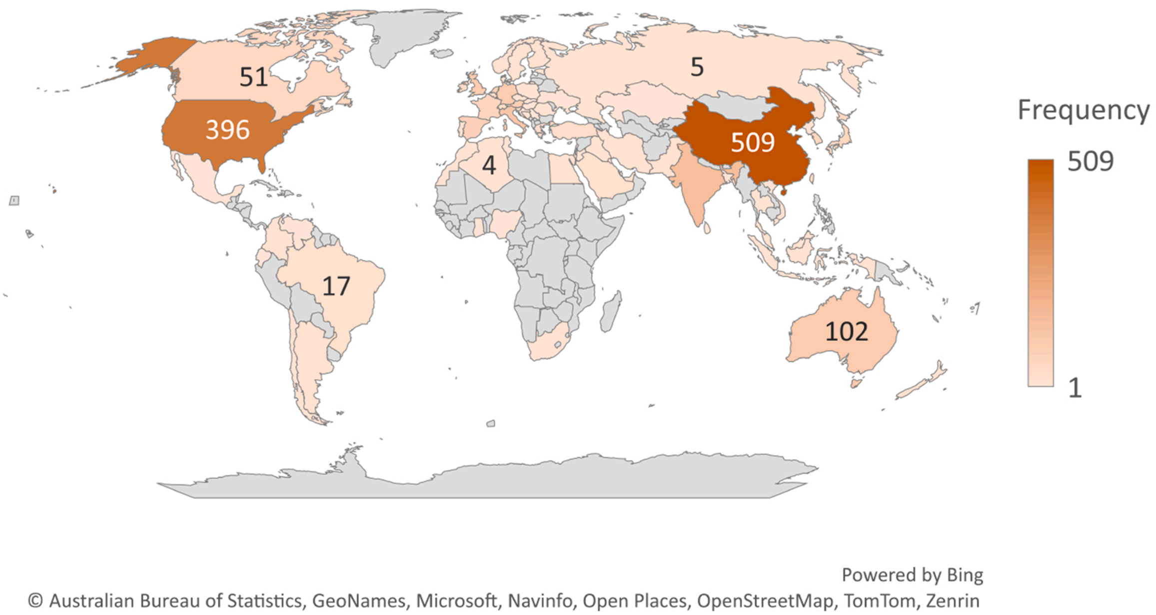

Fig. 14. Locations where research studies on the societal implications of recommender systems technology have originated.

Fig. 14 visualizes the geographical origin of research studies focusing on the societal implications of recommender systems technology.

Leading the list, China has the highest representation with 509 publications, followed by the United States with 396. India ranks third with 148 publications. European contributions are significant, led primarily by Italy (114), Germany (93), the United Kingdom (92), Austria (82), and Spain (76). Outside Europe, Australia contributes 102 publications.

Several other countries including the Netherlands, France, Japan, South Korea, Canada, and Hong Kong exhibit notable research work ranging from 48 to 73 publications. The list also includes countries such as Ireland, Switzerland, Singapore, Taiwan, Turkey, and Belgium, each contributing between 24 and 34 publications.

This distribution suggests that while research into recommender systems and their societal implications are widespread, the majority of this research is being conducted in China, the United States, and India. However, it's important to point out the varying levels of global participation, demonstrating the international interest in this critical area of study.

Notably, the bulk of research emanates from countries that are leaders in technology and online platforms, which also boast substantial user bases. Unfortunately, the majority of African nations exhibit little to no scientific output in relation to the focus areas identified in this study.

The possible reasons for this could be multifold. Firstly, the intensive use of online platforms may not be as prevalent in less developed regions, thus mitigating the urgency or perceived importance of such research. Secondly, the economic constraints faced by many African nations could inherently affect their ability to finance scientific research, especially in such a rapidly evolving field as technology.

However, these observations highlight the crucial need for a more global perspective in studying the societal implications of recommender systems, in order to fully understand and address the far-reaching impacts of this technology.

Table 1

Observations of issues related to algorithmic recommendations detected in previous research inquiries. Note that every paper can be classified under multiple domains. This is the reason why total number of papers and total number of classifications are different.

Subject area	Misinformation	Polarization	Addiction	Emotional Contagion	Privacy	Bias	Total
Total number of papers	23	39	4	256	853	655	1805
Computer Science	22	32	1	236	785	614	1668
Engineering	5	6	2	99	272	138	514
Mathematics	3	6	0	38	185	101	330
Decision Sciences	1	2	1	48	98	78	225
Other classifications	2	5	1	45	76	37	174
Social Sciences	2	4	2	20	53	45	124
Business, Management and Accounting	0	2	2	3	44	55	104
Medicine	0	0	0	24	16	6	45
Physics and Astronomy	0	1	0	19	9	13	42
Total number of classifications	35	58	9	532	1538	1087	3226

Table 1 presents a summary of previous research inquiries related to six key issues - misinformation, polarization, addiction, emotional contagion, privacy, and bias - in algorithmic recommendations. The table breaks down the number of papers investigating each issue by subject area.

Out of a total of 1805 papers, a significant majority of 1668 papers are from the field of computer science. Among these, the leading areas of investigation are privacy (785 papers), bias (614 papers), and emotional contagion (236 papers). Misinformation, polarization, and addiction, on the other hand, are less covered, with 22, 32, and 1 papers respectively.

Engineering is the next most represented field with a total of 514 papers, focused predominantly on privacy (272 papers), bias (138 papers), and emotional contagion (99 papers). Mathematics follows with 330 papers, primarily centred on privacy (185 papers) and bias (101 papers).

Decision sciences contributed 225 papers, with a similar interest in privacy (98 papers) and bias (78 papers). In the social sciences, there are 124 papers overall, with a relatively balanced spread across the different issues. Lastly, the field of Business, Management, and Accounting accounted for 104 papers, with a particular inclination towards privacy and bias.

The distribution in Table 1 gives an insight into the areas of focus in relation to algorithmic recommendations within different academic disciplines, indicating the preeminence of privacy and bias-related research across the board.

Emerging insights drawn from our observation of the scientific publications and the geographical distribution of papers underline that the majority of research originates from tech-advanced countries with large user bases. However, there appears to be a gap with the lack of scientific output from many African nations. Various factors, including less prevalent use of online platforms and limited economic ability to finance research endeavors, might contribute to this trend.

The observed focus of scientific inquiries primarily revolves around privacy and bias-related issues, with less attention placed on misinformation, polarization, and addiction. Analysis of the geo distribution of research exhibits higher contributions from China, the United States, and India - nations with highly active tech environments. The representation among various academic fields indicates a marked presence of computer science, followed by engineering and mathematics.

Despite a broad array of contributions, the extent to which these research endeavors truly deal with societal implications is yet to be thoroughly examined.

7. Qualitative analysis

Recommender systems raise a host of societal and ethical issues, including the propagation of misinformation, fostering of polarization, risk of addiction, emotional contagion, privacy, and bias. The following sections will therefore seek to critically analyze these concerns, evaluating the scope and significance of published research in these areas and discussing various strategies and solutions proposed to manage these challenges.

7.1. Misinformation

One of the prime concerns related to recommender systems is the amplification and distribution of misinformation or "fake news," with potential repercussions for public discourse, and societal cohesion (Calero Valdez, 2020; Fernandez & Bellogín, 2020; Tommasel et al., 2020; Tommasel & Menczer, 2022). However, only a modest amount of inquiries have been considering this issue, as only 23 publications were registered during the Scopus database search.

A number of studies have sought to demarcate the concerning interplay between recommender systems and the propagation of misinformation. Kiruthika and Thailambal (2022) propose a recommender system underpinned by a hybrid LSTM-SVM classifier aimed at discerning real from fake news. Similarly, Lo et al. (2022) introduce VICTOR, a module designed to target misinformation within recommender system outputs, directing users away from unverified content and towards verifiable articles. Wang et al. (2022) echo this sentiment, developing a veracity-aware and event-driven recommendation model, Rec4Mit, which effectively determines a user's current reading preference, simultaneously predicting the veracity of candidate news to deliver personalized true news.

It is worth noting that although there are some useful algorithmic solutions offered by computer science researchers, the majority of the developed solutions are primarily aimed at improving systems for the benefit of tech companies rather than users (Abbas, 2021; Patankar et al., 2019). Further, while these solutions offer potential strategies for mitigating the proliferation of misinformation, they still do not fully address the consequential issues of societal and individual level polarization.

Critically, the understanding of the negative implications of these recommender systems cannot be detached from their positive potentials. For instance, numerous research efforts are channelled towards making recommender systems more transparent, reliable, and diverse, thus fostering better user engagement and promoting access to a broader array of quality content (Tommasel et al., 2021; Stitini et al., 2022; Lunardi et al., 2020). Recommender systems can be programmed to learn from users' online behaviors, leading to improved information quality and personalized user experiences.

7.2. Polarization

The societal implications of recommender systems related to polarization have become a significant area of research (Downing, 2023; Badami & Nasraoui, 2021). However, this topic area measures limited scientific output on Scopus, with just 39 publications. Especially in the context of algorithmic recommendations, these systems can incite polarization by selectively exposing users to certain content which reinforces existing perspectives creating "filter bubbles" or "echo chambers" (Sun & Nasraoui, 2021; Donkers & Ziegler, 2021).

However, studies also emphasize the potential for these systems to reduce polarization (Ramaciotti Morales & Cointet, 2021; Xu et al., 2022), through tools such as TRAP, which uses two-level regularizers to reduce polarization (Park, Song, Kim, & Lee, 2020). Researchers also propose alterations to existing recommendation patterns to manage echo chamber effects (Bagnoli et al., 2021; Zhang, Zhu, & Caverlee, 2023). The line between user preference and content diversity is vital in addressing polarization in algorithms, manifesting in various use cases like news consumption to retail recommendations (Zhao et al., 2020; Zhang et al., 2023; Areeb et al., 2023).

While positive implications of polarization reflect user specificities, enhancing engagement and satisfaction (Cai, Hong, & Cao, 2022; Rastegarpanah et al., 2019), negative ones signal the fostering of ideological echo chambers and reinforcement of biases (Donkers & Ziegler, 2021; Xu et al., 2022). This can limit a fair exposure to diverse information, leading to polarization in critical domains like political news (Dufraisse et al., 2022).

Understanding the implications of recommender systems on polarization is layered and complex, with positive effects being potential areas for further research (Bellina et al., 2023; Heitz et al., 2022). Approaches to mitigate polarization and the potential long-term effects of nudging individuals towards conformity, thereby reducing diversity, are being proposed and studied (Downing, 2023; Badami & Nasraoui, 2021). However, extreme polarization can lead to conformity of single opinions, creating focused groups (Bellina et al., 2023).

Recommender systems may introduce biases, showing a correlation between the sentiment and stance bias and the pre-existing user bias (Alam et al., 2022). The geographical bias in recommendations can also occur, impacting user experiences and venue providers' activities (Sánchez et al., 2023). However, diversity-optimized recommendations can stimulate a higher tolerance for opposing views, indicating a depolarizing capability for democratic societies (Heitz et al., 2022).

Models like a recommendation model based on Matrix Factorization have been presented to combat polarization (Badami et al., 2018). Research has quantified various properties of recommender systems for appropriate evaluation of their polarization effect (Dash et al., 2019). Strategies like minimizing the user preference gap and preventing preference amplification aim to control polarization over time and create a healthier, more informed digital consumption environment (Dean and Morgenstern, 2022; El-Moutaouakkil et al., 2022; Kalimeris et al., 2021).

While the relationship between recommender systems and societal polarization is complex, active academic dialogue registered within the Scopus database is limited to 39 papers, and out of those, only 4 are in the domain of social sciences, as indicated in Table 1.

7.3. Addiction

Despite the growing concern over the potential for addictive behavior induced by recommender algorithms, the body of research examining this issue remains sparse. Only a handful of papers have been published on the relationship between addiction and recommender systems. Four of them are registered in the Scopus database. This limited data implores an urgent call to expand the scholarly discourse around this emerging issue. Among these few studies, a notable contribution comes from Sediyono et al. (2020) and Su et al. (2021). Both papers explored different aspects of this field, focusing on the interplay between addictive technology use and the role of recommender systems, providing valuable insight into the potential societal implications.

In a significant study by Sediyono et al. (2020), a computer software system was proposed to monitor smartphone usage with the aim of preventing addiction. This system collects and processes detailed behavioral data from the users before generating recommendations, particularly directed towards parents and teachers. The significance of this system lies in its potential to transform the societal implications of smartphone addiction, offering a way to prevent the issue by intelligent monitoring and offering informed, targeted suggestions.

There is substantial evidence to support a link between addictive behavior and personalized recommendations from media platforms. In a study by Su et al. (2021), this issue was explored using TikTok as a representative platform. The research determined that approximately 5.9% of TikTok users may engage in significantly problematic use. This study showcased a direct correlation between personalized video recommendations and increased brain activation in certain regions, which is indicative of these algorithms' capacity to capture and maintain user attention, potentially leading to addictive behaviors. The implications of this study raise concerns about the societal impacts of these recommender systems, demonstrating a pervasive influence that could foster patterns of addiction.

Both these studies highlight the societal implications of addictive technology use and the role of intelligent recommender algorithms contributed to the issue. The studies give credence to the developing concern that these systems, while providing personalized and beneficial suggestions, may also unintentionally foster addictive behaviors.

The initial research from Sediyono et al. (2020) and Su et al. (2021) offers a preliminary understanding of the potential adverse effects of intelligent recommender systems. It is clear that while these systems provide an undeniable convenience in delivering personalized content, there is a possible darker undercurrent fostering addictive behaviors. Despite the small volume of literature exploring this relationship, these studies serve as cautionary tales for the broader technology and society communities, highlighting the need for further, more detailed research into the potential dangers of recommender systems in exacerbating addictive behaviors.

7.4. Emotional contagion

Out of the 256 publications related to emotional contagion registered on Scopus, most of them focus on improving recommendation methods for the benefit of tech companies. On the other hand, studies addressing consequences related to the spread of emotions through social media remain rare. The existing studies target specific fields like e-commerce (Bielozorov et al., 2019), news consumption (Parizi et al., 2016), e-learning (Qin et al., 2011; Bustos López et al., 2020), and personalized music and movie suggestions

(Chang et al., 2010; Jin et al., 2013; Liu & Jiang, 2019; Tkalcic & Ferwerda, 2018; Tripathi et al., 2019).

Indeed, several studies reveal potential negatives of emotional contagion in recommendation systems. For instance, Torkamaan et al. (2019) reported the adverse effect of over-personalization, which could create feelings of unease and mistrust among users. Likewise, Qin et al. (2011) emphasized the negative feelings among e-learners, making emotional states a crucial factor in learning outcomes. However, the general research focus is directed towards fully understanding user emotions to enhance recommendation systems (Parizi et al., 2016; Bielozorov et al., 2019; Salazar et al., 2023).

The researchers generally suggest that having an understanding and consideration of user emotions can enhance the effectiveness of recommendation systems across various domains (Parizi et al., 2016; Bielozorov et al., 2019; Salazar et al., 2023). They point to a need for more sensitive analysis of user emotions, supplementing traditional data-driven approaches with model-driven ones (Tkalcic & Ferwerda, 2018).

Though emotional contagion in these systems has both upsides and downsides, the shared understanding among these studies is the importance of integrating users' emotional states. These findings stress the need for a more effective and personalized user experience, while also sounding alarm bells on possible negatives like user discomfort and over-personalization.

To that end, there's a clear need for more research into the emotions-responsive recommendation systems' broader societal impact. It's essential that any future progression in this domain doesn't just focus on technical enhancement and further addicting users to content and online platforms, but also considers individual and societal consequences.

7.5. Privacy

Recommender systems that maintain the delicate balance between privacy and system utility have formed a substantial focus in the field of research, with 853 publications related to the issue of privacy on Scopus. Polatidis et al. (2017) deal with numerous privacy considerations by designing a privacy-preserving system for mobile recommendations, accommodating diverse contextual information and incorporating a specific recommendation method. Privacy concerns have also been addressed by devising strategies such as leveraging homomorphic encryption in secure multi-party computation techniques for user privacy. Erkin et al. (2011) proposed such a system, where encrypted user profiling and data processing play a key role.

Meanwhile, Tang & Wang (2015). shifted their perspective to privacy from a group-level standpoint, demonstrating the effectiveness of collaborative obfuscation in group recommendations. Data obfuscation methods were also explored by Elmisery and Botvich (2011) in a personalized scenario, proposing a pair of algorithms, which by regulating user control over personal profiles, served the dual purpose of information utility maximization and privacy preservation.

Englert et al. (2015) took up the challenge to maintain user privacy in smart home energy recommender systems, proposing a sparse data collection method where minimized data collection leads to augmented privacy. The concern for individual privacy often collides with the requirement for accurate recommendations. To strike the right balance, Luo and Chen (2014) established a cooperative perturbation privacy-preserving scheme. This scheme enables group users to establish a mutual privacy protective ecosystem while maintaining recommendation utility.

Huang et al. (2019), through their comprehensive review of the development of privacy-protecting recommendation systems, emphasized the importance of an enhanced understanding around privacy, pointing out the multiple methods that have evolved for privacy protection. Subsequently, in their paper, Feng et al. (2020) emphasized the privacy risks associated with statistical preference-based recommendation systems, successfully throwing light on the need for privacy-aware methodologies.

The field is ripe with experiments and explorations with researchers like Zou and Fekri (2015), who have considered implicit user preferences to maintain privacy in social recommendation, to propose hierarchical privacy architectures like those developed by Yau and Tomlinson (2011) for network-based recommendation systems. Simultaneously, propositions for privacy frameworks, like the "Redeem with Privacy" (RwP) to handle the intricacies of check-in histories brought forward by Moniruzzaman and Barker (2013), show promise.

While handling user privacy, synchronization with personalized recommendation is pivotal. Friedman et al. (2016) proposed a privacy-preserving approach, emphasizing differential noise addition during model training.

Deepening the necessity of preserving privacy in the context of recommender systems, Calandrino et al. (2011) have thrown light on the vulnerabilities of these systems, showing that simply anonymizing the data does not necessarily protect privacy. Their work is a stark reminder of the careful consideration needed in creating privacy-respecting recommender systems.

While recommender systems have become an integral part of our daily lives, efforts to inquire into privacy-related issues and offer potential solutions have been significant, especially when compared to other critical areas noted above.

7.6. Bias

Although the role of recommender systems in improving user experience and driving growth for technology companies is important, it is equally crucial to assess their societal implications, particularly concerning bias (Chizari et al., 2023; D'Eon et al., 2022). Literature review found 655 publications listed on Scopus related to bias in algorithmic recommendations. Various studies have engaged in conversations about bias and fairness in recommendation systems, considering the possible negative and positive implications of algorithmic recommendations (Wang and Soundarajan, 2023; Berendt et al., 2021).

Existing studies on this theme adopt various approaches in articulating the issue. Some studies foreground issues of fairness by modeling the prediction problem as a variant of a bandit problem, emphasizing significant fairness improvement in their experiments (Wang and Soundarajan, 2023). Zhao et al. (2024) tackle the fairness of recommender systems by considering the interests of all involved parties: users, product providers, and the platform, while Tang et al. (2023) spotlight the issue of bias due to user personalized selection tendencies. Another approach has focused on addressing the challenges of fairness testing for recommender systems, emphasizing accuracy and efficiency in the results (Guo, 2023). Färber et al. (2023) argue the importance of mitigating biases caused by humans and those induced by the recommender system in their elaborate analysis of academic recommender systems.

As much as the literature highlights the potential negative implications of bias in recommender systems, the positive possibilities of addressing these biases are equally highlighted. For example, Liu et al. (2023) propose a framework that eliminates popularity bias in session-based recommender systems, which improves the fairness of their output (Liu et al., 2023). Shi et al. (2024) shed light on long-term fairness of item exposure in interactive recommendation systems, and Liu et al. (2023) introduce a debiased contrastive loss for collaborative filtering that significantly improves recommendation accuracy. This demonstrates an emerging trend towards affirmative strategies that not only identify and critique bias in recommender systems but actively propose solutions that can guide future design and practice.

The volume of work in this area indicates a clear need for critical inquiry into algorithmic recommendations due to their social implications. As argued by Wang et al. (2022), any discourse on recommender systems must encompass a discussion about the biases that these systems inadvertently reproduce, and the need to extend such research to include bias explanation technologies to achieve the desired societal impacts.

Most studies, whether implicitly or explicitly, recognize the harms of embedded bias in recommender systems and actively seek to improve fairness for different stakeholders, aligning the technology closely with societal interests over and above the advantages for tech companies (Boratto et al., 2021; Zehlike et al., 2022). Thus, while the primary aim of many recommender systems may be to increase platform optimization and market profits, the current focus of scholarly inquiry in terms of bias is firmly on developing robust ethical practices that benefit the society, as well as individuals using these systems.

While commendable amount of research has been done to improve the fairness and reduce the bias of recommender systems, this area is still ripe for more attention from scholars, especially in regards to fine-tuning the balance between benefiting the tech companies and society. Further studies focusing on specific facets such as user perception, data characteristics, and algorithmic design are needed to comprehensively address these concerns and continue refining existing systems (Berendt et al., 2021; Deldjoo et al., 2021; Ekstrand & Kluver, 2021).

8. Discussion

8.1. Potential societal effects of recommender systems when applied to emerging technologies

This section notes some of the issues brought about by the mainstream deployment of emerging technologies that will integrate recommender systems as an underlying technology. The high addictiveness of emerging technologies as well as the possibility of invisible manipulation of algorithmic recommendations have been identified as major issues. ChatGPT and Metaverse are noted as examples.

Within one week of its introduction in November 2022, OpenAI's ChatGPT has garnered more than 1 million users (Ruby, 2022). ChatGPT represents artificial intelligence going mainstream, something like an "AI to the people" moment. More importantly, ChatGPT is actually a recommender system, an AI search engine, as it can understand questions and provide answers to them (Ruby, 2022). However, there is one key drawback: ChatGPT does not provide the sources from which its answers are crafted. This opens up novel possibilities for manipulation, or, in other words, invisibly directing public opinion and/or mood in the desired direction because how exactly this language model is trained, with supervised and enforced learning, is not transparent.

While answering questions about the sentient AI language model, which was the reason for his suspension, former Google engineer Blake Lemoine explains why the issues of transparency around language models are important (Bloomberg, 2022):

> "So, it's a huge problem because, for example, there are corporate policies about how Lambda is supposed to talk about religion and how it is allowed to answer religious questions. Now if you think about the pervasiveness of the usage of Google search, people are going to use this product more and more over the years, whether it's Alexa, Siri, or Lambda, and the corporate policies about how these chat bots are allowed to talk about important topics like values, rights, and religion will affect how people think about these things and how they engage with those topics, and these policies are being decided by a handful of people in rooms that the public doesn't get access to."

Except for ChatGPT, the metaverse is the next possible trend that could lead to further increases in mediated communication manipulation and addiction. Major tech firms are pouring billions into this VR future without any proper research into how the new sensory-algorithmic environment will affect societies and individuals (NYT, 2022). Metaverse is envisioned as a new VR environment where people have a "second self" and where they can buy, work, socialize, and even engage in sexual activities (Bojic, 2022). This vision of life is predicated on constant contact with sensors and machines that give people the illusion of communicating with others.

Research conducted by Segawa et al., (2020) has revealed that virtual reality (VR) chat can be significantly more addictive than traditional gaming. This could be due to the immersive nature of the experience, as users are able to interact with others in a virtual world, build relationships, and explore their imaginations in ways that are impossible in reality. Additionally, the social aspect of VR chat can be more appealing than in classic gaming, as users can become part of a larger community and take part in activities with friends. Furthermore, the possibilities of VR chat are virtually endless, allowing users to customize their experience according to their personal preferences.

Increases in media addiction quantity have been measured over time (Chi et al., 2020; Cheng & Li, 2014). At the same time, higher addiction intensity has been measured for newer media, such as smartphones and television (Bojic & Marie, 2017; Leung & Lee, 2012; Stern, 1999; Huisman et al., 2001). The reason why this is the case might be due to the fact that the newer media are more accessible, with their functions being more similar to direct communication than the older media (radio and press). Hence, they are more attractive and engaging. An analysis of the AR game Pokemon Go also revealed its addictive impact and repercussions in direct reality (Zsila & Orosz, 2019; Wang, 2021; Tong et al., 2017). Moreover, concerning the social media platform TikTok, self-injury, anorexia, and suicide are linked to various pranks, especially among younger individuals (Logrieco et al., 2021).

The emergence of new media has revolutionized the way people communicate, with its features replicating aspects of direct communication in the physical world more effectively than its predecessors. The upcoming metaverse promises to take communication to a whole new level, being the most realistic media to date, incorporating senses of sight, hearing, touch, while providing interactivity and fully immersive experience. Consequently, it is likely to be the most addictive form of media yet.

As stated in this section, ChatGPT and the metaverse are used as examples to examine emerging technologies and potential effects of their underlying recommender systems. ChatGPT is a recommender system, able to understand questions and provide answers, but it does not provide the sources from which its answers are crafted, leaving room for manipulation. The metaverse is an emerging VR environment with potential to lead to further increases in mediated communication and online addiction.

8.2. The broader look: the increasing importance of algorithmic recommendations

The most common everyday examples of algorithmic recommendations described in this study are social media, search engines, online business networking, e-commerce, online advertising, online dating and news. This section aims to point out some issues that arise with such algorithmic power. It sums up the role of these algorithmic systems, analyzes the near future in which even more powerful AI generative models will be utilized, compares the effects of recommender systems with the notion of collateral damage, poses the question of how large-scale non-human systems such as AGI will optimize humanity and for whose benefit, and makes comparisons to Plato's cave allegory and subliminal messages.

Either utilized as in the above-presented examples through a search query, a trending page, a home page feed, a friend's recommendation, or in many other ways, algorithms compress a large quantity of data into a few lines that are presented to online users (Zhou et al., 2012). The system of algorithmic calculations makes the decision on what information should be provided to online users, based on their input. This simplification of the world for online users is one of the main purposes of recommender systems. It is desired by individuals that utilize search engines or social media to get the right options, make decisions, and act on them. This is similar to how human minds function. However, in the case of algorithmic exposure, instead of dealing with reality directly, online users face a mediated version of it. In short, algorithms act like eyes and ears of people.

When examining the near future through the lens of the broadest interpretation of recommender systems, the emergence of advanced generative AI models, commonly known as chatbots, amplifies the existing reasons for concern. The potential implications of generative AI are immense, as this technology possesses the capability to not only curate, but also generate tailor-made content for individual online users. By integrating large language models, such as OpenAI's ChatGPT and Google's Bard, with the digital footprints of users and the platforms they engage with, the impact of these advanced systems could far surpass traditional, curator-based recommender systems that lack a creative function.

In a broader perspective, the impact of recommender systems can be likened to collateral damage. While the primary objective of these AI-driven algorithms is to boost engagement and promote the sales of products and services, benefitting the economy, tech companies, and individual advertisers, the consequences on society and individuals are often regarded as mere side effects. However, it may be shortsighted to solely focus on the profit motive without considering the welfare of human beings.

In the past, large-scale non-human systems such as religions, states, and corporations have optimized society for their own benefit. This raises the critical question of how artificial general intelligence (AGI) will optimize humanity and whose interests it will ultimately serve. Fundamentally, recommender systems and large language models can be seen as early manifestations of AGI, possessing curative, cognitive, and content-generative capabilities. As we continue to develop and implement these technologies, it is essential to evaluate their ethical implications and strive for a balance between economic growth and the well-being of individuals and society.

Despite their growing impact on lives of all internet users it is unknown how the algorithms are set by tech companies, or in another words, what are their exact goals. It is argued that algorithms that decide what online users are exposed to, mainly extending time of use and engagement related to advertised items, but the problematic part of this is that algorithms can sway whole communities towards a particular goal, cause, political party and topic without online users' knowledge.

This raises many ethical questions about their usage, such as their subjectivity, the non-neutral data they are fed, and if it is alright to let them decide in such personal matters. These questions were raised by movie The Social Dilemma (Orlowski-Yang, 2020), whistleblowers (Perrigo, 2021), and scientific research (Kleinberg et al., 2018). The prevailing conclusion is that algorithms are changing from just helping humans make decisions to making decisions themselves. This leads to a discussion on the power of algorithms in society and direction in which technology is being developed.

Data flow from users to tech companies is allowable because it is overseen by terms and agreements that users accept (Steinfeld, 2016). Everyone is aware that their online searches are being used by advertisers, and this is similar to when they accept Cookies Notifications. In practice most of the people don't read documents such as terms of agreements and cookies notifications (Steinfeld, 2016). Thus, these provisions of GDPR do not really have effect as people do not know who really owns their data and what exactly is done with it.

When these algorithms are employed to collect and process data, they then provide outputs to users on a personal basis. Nevertheless, this is not only about selling information to advertisers or using it on ads platforms - algorithms decide what people are exposed to, and this gives them immense control of their lives. The average person likely will not analytically access the numerous types of content that are suggested to them. These types of content can have an impact on people's lives, both individually and in groups. Algorithmic recommendations can lead people, communities, and individuals to be nudged and steered in a direction that is intentionally or unintentionally chosen by tech companies. A good example is providing content that confirms the worldview of online users, causing polarization, echo chambers, the weakening of democracy, and the rise of populism (Cinelli et al., 2021; Zollo, 2019; Rieger & Wang, 2020; Pavlovic & Bojic, 2020).

Applying Plato's cave allegory (Hall, 1980) to recommender systems, one could say that recommender systems are like the shadows on the cave wall. They analyze users' past behavior, preferences, and interactions to create a personalized selection of content, products, or services. These recommendations are based on limited data and do not encompass the entire spectrum of what is available or what might be relevant to an individual user. Thus, the recommendations are akin to the shadows on the wall, providing a restricted view of the universe of possibilities. As users increasingly rely on these systems, they may become more and more confined to their personalized "cave," unable to explore or discover new and diverse content outside of their recommendation bubble.

Much like subliminal messages (Vokey & Read, 1985), recommender systems can subtly impact an individual's thoughts, emotions, and actions without them explicitly realizing it in every instance. Although users understand that they receive personalized recommendations, the underlying mechanisms and objectives of these systems remain opaque, making it difficult to discern their optimization goals and functioning at any given moment while suggesting content.

From search results to social networking sites, algorithms have a significant influence on the user experience, effectively acting as gatekeepers between people and the environment. It is clear that these algorithms have large implications for the way people consume content.

9. Conclusion

Societies may not be aware of how much they are currently being influenced by AI, let alone in the future, when everything becomes increasingly virtualized and operated by AI algorithms. Although the question of what will prevail in the future stays beyond the scope of this inquiry, it looks as though the recommender systems affect society in a profound manner. It is known that recommender systems used by big platforms are set to make their users spend time online continuously and extensively, buy advertised items, or act in certain ways. This addictive environment stimulates further use of the online platform, with the main goal being to generate the most income for the tech firm that owns it (Bojic, 2022).

This inquiry notes the effects of recommender systems in the lives of their users, as more than half of the global population is in direct contact with them daily by using big online platforms, from search engines to social media (Johnson, 2022).

RQ1: The research data demonstrate the significant global impact of recommender systems, affecting a large number of people in various aspects of life, including social (Fig. 3), professional (Fig. 4), commercial (Fig. 5), advertising (Fig. 6), romantic/sexual (Fig. 7 and Fig. 8), and news consumption (Fig. 9 and Fig. 10).

RQ2: Considering the substantial global influence of recommender systems, particularly following the proliferation of online platforms and smartphone usage, the amount of scientific attention dedicated to scrutinizing their social impact has been somewhat limited. Of the 31,790 papers published on recommender systems in the Scopus database, only 1805 explore their societal consequences related to specific aspects registered in a preliminary literature review and a mere 124 are from the discipline of social sciences.

Investigations into specific aspects have only recently begun to surface. Papers on misinformation commenced in 2017 and number currently at 23, while those examining polarization stand at 39, also from 2017. Studies related to addiction are quite sparse with only four published since 2019. Research on emotional contagion, privacy, and bias has a relatively longer history, with 256 papers since 2004, 853 papers since 2008, and 655 papers since 2007 respectively. Although the trend has been constantly rising, these statistics highlight an apparent deficiency in the scientific exploration of the societal impacts of recommender systems, especially in relation to specific areas of concern.

Table 2 encapsulates a qualitative analysis of publications in key themes: misinformation, polarization, addiction, emotional contagion, privacy, and bias.(Fig. 15).

RQ3: Therefore, upon considering the far-reaching societal impact of the recommender system—which affects various aspects of life for over half of the global population—it becomes clear that the scientific community's focus on associated critical issues, as identified in the literature review, is relatively scarce. With just 1805 out of 31,790 total papers about recommender systems addressing these concerns, the overall scientific attention dedicated to these issues is noticeably low and unsatisfactory, particularly when weighed against the worldwide effect of this technology.

9.1. Possible long-term effects of recommender systems

More important than these immediate impacts may be the long-term influence of recommender systems. This issue may be the most significant for the future.

A comparison can be made between recommender systems and the unconscious mind, from which people derive thoughts and ideas (Possati, 2020). The only difference being that this unconsciousness steers the world towards the interests of tech giants that own and manage it.

The use of recommender systems and the impact it has is far-reaching. Although the main goal of these recommendations might not be to affect emotions and choices, or to hide something and act as censorship machines, the bottom point is that these algorithms have

Table 2
This synopsis serves as an overview of the current research landscape concerning recommender systems and their impact on society in six key themes.

Topic [No. of Publications]	Key Findings & Counter Measures	Scholars Cited
Misinformation [23]	Studies propose improved recommender systems to mitigate fake news. More emphasis needed on their societal responsibilities.	Calero Valdez (2020);Fernandez & Bellogín (2020); Tommasel et al., 2020;Tommasel & Menczer (2022);Kiruthika and Thailambal (2022);Lo et al. (2022);Wang et al. (2022)
Polarization [39]	Balancing user preference and content diversity to tackle algorithmic induced polarization. Emphasis on developing anti-polarization models.	Badami and Nasraoui (2021);Downing (2023);Sun & Nasraoui (2021);Donkers & Ziegler (2021);Ramaciotti Morales & Cointet (2021);Xu et al. (2022)
Addiction [4]	Recommender systems potentially fostering addictive behaviors; need for intelligent monitoring and regulation.	Sediyono et al. (2020);Su et al. (2021)
Emotional Contagion [256]	Emphasis on integrating user emotions for enhancing recommendation systems, coupled with the need to avoid over-personalization.	Torkamaan et al. (2019);Bielozorov et al. (2019);Parizi et al. (2016); Salazar et al. (2023)
Privacy [853]	Various strategies proposed to preserve privacy in recommender systems. Call for more privacy-respecting systems to ensure secure user information.	Polatidis et al. (2017);Erkin et al. (2011);Tang & Wang (2015);Yau and Tomlinson (2011);Huang et al. (2019);Feng et al. (2020)
Bias [655]	Stress on addressing biases to improve fairness in recommender systems. Propose solutions to actively reduce biases.	Chizari et al. (2023); D'Eon et al. (2022); Wang and Soundarajan, 2023;Berendt et al. (2021);Liu et al. (2023)

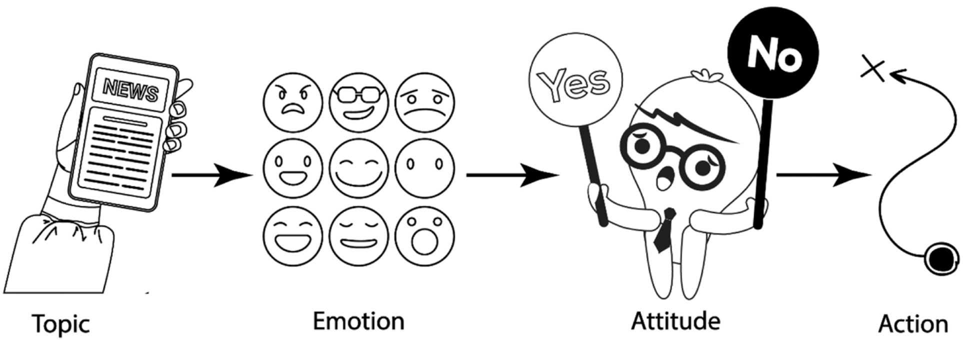

Fig. 15. As indicated by the reviewed research, internet users are affected on multiple levels by recommender systems, both by setting topics to be discussed and through their emotions, attitudes, and actions.

immense impact to opportunities, challenges, and temptations posed in front of the most humans.

Even those who do not own or use mobile devices are still exposed, since a majority of the world's inhabitants have access to these algorithms through the internet. The algorithms that sift through data to present users with different options and content have both ethical underpinnings and imperfections, created by their developers. It is remarkable to consider that a select few who work for leading tech firms are able to impact inhabitants of the entire planet in this indirect way through algorithmic recommendations.

It is possible to imagine a future society in which people become increasingly similar and their thinking, minds, and ideas are limited in the direction that recommender systems point. With the help of various sensors and data about their users, algorithms may attend to every human need in the future, a process that would impose a collective change on humanity. Even now, there are numerous findings indicating that human brains are altered as a consequence of digital media use, a process that leads to digital dementia (Spitzer, 2014).

It is believed that the recommender systems construct "bubbles" around the user based on their interests or categories and use this as the foundation for the content that is delivered to them personally. As such, the algorithms give everyone a similar experience in terms of the content that they are likely to consume. If this is the main principle on which recommender systems are based, it implies that they are narrowing the worlds of internet users and making them overly similar. Consequently, people are only exposed to what they already know, while novel concepts and knowledge remain hidden. This then creates a reality that is subjective to the individual and does not permit the exploration of new ideas.

AI is expected to take many jobs away from humans, freeing up otherwise busy time for many people. As tech visionaries expect, in the initial stages of AI development, low-wage jobs will slowly become obsolete (Chirinos, 2022; Gates, 1995). Simple tasks such as work in factories, driving, customer service, and home management will be substituted by various robots, autonomous vehicles, and algorithms in the 4th Industrial Revolution (Schiølin, 2020). One possible solution to the obsolete workforce is the Universal Basic Income, which would provide existential needs to individuals whose skills are no longer required and can be replaced by various forms of technology (Agatonovic, 2022). But what would happen to human minds, which would be obsolete as well?

Based on the trends and findings discussed in this paper, the author assumes two potential trajectories for the future. The first is a scenario where individuals flourish and coexist harmoniously with technology, reaching a state akin to singularity. The second trajectory foresees a future dominated by addiction. As previously noted, humans in the future will have lots of spare time that can be spent with family and friends, contemplating, forging a spiritual uprising, and working as creators and strategists on more innovative technologies that would make the world an even better place.

There is another possible future path, one in which most people become even more addicted to superficial pleasures and activities that fill their spare time while also giving more power to big tech and AI itself (Bojic, 2022). For the majority of people who are unable to resist new addictive environments such as the metaverse (Segawa et al., 2020), this could mean a life with fewer deep and fulfilling relationships, contemplation, spiritual uprising, creativity, and imagination on the one hand, and more shallow consumption-related activities directed and utilized by AI algorithms on the other. This would be a continuation of long-standing trends such as mass society alienation and narcissism, which have been prevalent since the advent of mainstream media (Shils, 1962; de Zavala et al., 2009; Lystad, 1972). Sadly, there are no indications that humanity could be directed toward a more optimistic scenario with the mainstream deployment of emerging media and technologies in which recommender systems are envisioned to continue their addictive roles.

However, the real threat could possibly be the evolution of AI algorithms that start impacting and controlling their creators, like a boomerang. Thus, whether humans will control technology or technology will control humans is the ultimate question.

The challenge that arises is to establish the criteria for algorithms, which act as large perceptual machines, working between people and the complex environment around them. The algorithms filter out a certain number of units to be put forward as a relevant answer. Furthermore, they rank these units, so that some are prioritized over others. Thus, it is inevitable that the algorithm becomes biased. Nevertheless, the power to curate the links and content that people see before they even get a chance to think is a massive influence on the world. The online systems are deciding which information to grant or deny access to, before users have a chance to find out why.

However, there are possible solutions that could lead to more favorable outcomes in the future—to instruct algorithms for the benefit of society. A step towards this goal is the Digital Services Act, a regulatory framework adopted by the EU (EU, 2023). To begin with, the transparency of algorithms would provide members of society with information on how these are designed. Second, the possibility to opt out of algorithmic analysis and receive "universal" content would enable freedom of choice regarding algorithmic recommendations. Thirdly, if recommender systems used by big online platforms are considered public good, they could be set jointly by societies presumably gathered in the United Nations and big tech companies in the public good. This third and most important provision is still not recognized by the new regulations in the EU and other countries. However, more research in this direction may be essential to illuminate the pathways to new regulatory policies.

9.2. Proposed algorithmic regulation for enhanced content diversity and democratic engagement

A plausible solution to the outlined challenges could lie in the realm of algorithmic regulation. A mechanism is proposed that promotes diversity and balance in content distribution, leading to an adjusted, more-rounded virtual consumption experience. Specifically, the adjustment would involve altering the algorithms governing our online activity to ensure a variety of inputs: it should balance negative and positive emotions encountered by users, moderate between educational and entertaining content, diversify topic areas, and ensure political opinions presented are not solely tethered to individual user's choices.

Such systematic diversity could pave the way for a healthier exchange of ideas and a heightened sense of understanding and acceptance of different viewpoints, thereby contributing to the enrichment of democratic culture. The inherent virtue in this kind of diversity lies in the exposure to varied perspectives, fostering a climate of inclusivity and tolerance.

Adding to this, the proposed solution could also empower individuals by offering them an option to decide the level of content diversity they wish to encounter. The ability to adjust one's consumption settings is a step towards personalized digital autonomy, making room for individual engagement and control over one's virtual environment.

Tripartite decision-making could be a solution where algorithmic choices are equally influenced by individuals, society, and tech corporations. The adjustments to society could be agreed upon as global standards through some multilateral organization, such as the UN. This divide ensures various needs and interests are contemplated in shaping online discourse. The tech companies who operate the recommender systems would contribute a third of the decision in this mechanism, balancing corporate interests against societal wellbeing.

The regulation of algorithmic recommendations presents an opportunity to transform the content dissemination landscape into a space that encourages diversity, user autonomy, and democratic capacities. By striking a balance between individual, societal, and corporate interests, this proposal could work towards a more equitable, tolerant, and inclusive digital ecosystem.

The proposed schema underlines the importance of avoiding a one-size-fits-all approach when dealing with recommender systems. Instead, it advocates for an inclusive, and human-centered approach enabling everyone adjust their personal recommender algorithms. Evoking a broader conversation among all stakeholders on the future development and regulations of algorithmic recommendations may be of urgent importance systems, pushing towards a digital ecosystem that aligns with our societal values, strengthens our democratic institutions, and enhances human well-being.

9.3. Final remarks

This research, while extensive, is limited by its lack of empirical inquiry examining the direct impact of algorithmic recommendations on individuals. Simulation tools, like T-RECS - an open-sourced Python package designed for simulating recommendation systems (Lucherini et al., 2021), could provide invaluable insights into the societal influences of recommender systems.

To the author's knowledge, this is the first comprehensive study addressing the global influences of recommender systems. It thus paves the way for more extensive scientific research. The social polarization, echo chambers, amplification of misinformation, and the fostering of negative emotions—all recognized effects of algorithmic recommendations—indicate the urgent need for further inquiry.

Crucial questions need addressing: Are individuals' perspectives narrowing, emotional arousal increasing, and thinking processes becoming limited due to exposure to recommender systems? Considering how these algorithms act as filters for human perception, what are the implications for human imagination and creativity? What is the tangible effect of these systems amplifying negative emotions, particularly on wellbeing and sense of purpose? Are we fostering a sense of dependency on these media platforms (low-latency addictions), and if so, what are the implications for future power dynamics?

Lastly, the ethical implications of allowing algorithms to dictate decisions related to personal and professional opportunities prompts urgent examinations. Hence, future research should not focus solely on further evaluating the influence of this technology but should also explore regulatory measures and frameworks for such systems. Such comprehensive exploration is increasingly critical as recommender systems continue to intertwingle with society's daily life.

CRediT authorship contribution statement

Ljubisa Bojic: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

https://osf.io/qbe8h/?view_only=4dde9cfe1f314cbe897062ddee98aa52.

Acknowledgements

Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Health and Digital Executive Agency (HaDEA). Neither the European Union nor the granting authority can be held responsible for them. Grant Agreement no. 101120763 - TANGO.

This paper was realised with the support of the Ministry of Science, Technological Development and Innovation of the Republic of Serbia, according to the Agreement on the realisation and financing of scientific research: 451-03-66/2024-03/ 200025.

This paper has been supported by the TWin of Online Social Networks (TWON), a research project funded by the European Union, under the Horizon Europe framework (HORIZON-CL2–2022-DEMOCRACY-01, topic 07). TWON poject number is 101095095. More details can be found on its official website: https://www.twon-project.eu/.

This research has been accomplished with the support and collaboration from the COST Action Network CA21129 - What are Opinions? Integrating Theory and Methods for Automatically Analyzing Opinionated Communication (OPINION) - https://www.opinion-network.eu/.

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