

# **Analyzing the Sociotechnical System Surrounding Social Media Recommendation Algorithms**

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On my honor as a University student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments.

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## **Introduction: Social Media's Trick**

Social media use has been increasing at very fast rates over the past few years. According to a report done by Keipos, there are 4.76 billion social media users (although this could be skewed from duplicate accounts). As connectivity increases throughout the world, the amount of time spent on social media does as well. The New York Times reported a 17% increase in screen time for ages ranging from kids to younger teenagers (Moyer, 2022). With the COVID-19 pandemic resulting in more time at home, this was exacerbated. Part of how social media keeps users hooked is their recommendation algorithms. These apps have algorithms that will curate content that seems to cater towards a user's preferences. This means that without searching, it is very easy to keep on seeing something you would generally consume. Because social media is so widespread, these social media algorithms end up controlling large sources of information for people. This means that they influence what people are seeing and potentially believing. These recommendation algorithms could recommend similar types of content for controversial and polarizing topics, which would propagate through social networks resulting in echo chambers. As recommendation AI gets more data and better results, its influence on people could grow. In this paper, I analyze the complexities of the sociotechnical system surrounding social media algorithms and look for signs indicating change. To understand this system, I will use Geels' multi-level perspective (MLP) which is a framework that analyzes the current regime that enables a sociotechnical system, developing niches, and the landscape surrounding the system.

## Section 1 – The Problems with Social Media Algorithms

### *The Recommender System*

Recommender systems, or RSs, are central to social media platforms. They are used to curate content and are seen in many different online platforms, including blogs, forums, social networks, video sites, and even e-commerce websites. At their core, they work “by building a model of user preferences based on their past behavior. This model can then be used to predict how a user will rate a new item, or to recommend a set of items that the user is likely to find interesting,” (Tintarev, Masthoff, 2007). They need user data to effectively predict something the user would generally engage with.

Recommender systems can shape what users see, who they connect with, and what information they are exposed to. For example, a study by the Pew Research Center found that 63% of Americans who use social media say they get most of their news from those platforms (Anandhan, 2018). Seeing as social media algorithms are central to how content is delivered to them, this means that these algorithms are also going to be responsible for putting news on people’s feeds, meaning they are responsible for how people interpret many potentially controversial topics. And a study by the University of California, Berkeley found that people are more likely to share news articles that are recommended to them by their social media friends than articles they find on their own (Bakshy, 2015). Table I lists some of the most popular social media platforms and what they use recommender systems for.

Social Media	Use for RS
Facebook	Suggest friends, posts, and ads to users.
Twitter	Suggest accounts to follow, tweets that you are likely to be interested in. Has a “For You” tab especially for this.

YouTube	Recommend videos to watch or autoplay after completing one, as well as ads.
TikTok	Suggest videos to watch as well as ads.

Table I: Various Recommender Systems on Popular Social Media Sites (Anandhan, 2018).

As seen in Table I, some of the most influential social media sites today are heavily using these algorithms to maintain a strong user base. Going even beyond social media sites, a study from Amazon shows that 35% of its sales are from products recommended by their recommender systems (Silveira et al, 2019). Douyin (China’s TikTok counterpart) is an “algorithm-driven, content-oriented product, which means that its popularity is largely dependent on the powerful AI algorithms and content distribution strategies” (Zhao, 2021). Additionally, Zhao stated Douyin has attracted over half of China’s active internet users. To have gotten over half of the online users in the most popular country despite being a product that is completely driven by recommendation systems shows the effectiveness of these systems. They have spread across many different social media platforms, and even to other sites such as Amazon and Netflix.

*The Echo Chamber*

With recommender systems being so prevalent on so many different platforms that span many different aspects of media consumption, they effectively control information that is delivered to users. It was established earlier that most Americans get their news from social media platforms. This means that algorithms can curate political content that many people will consume. This leads to echo chambers being created. Research from the Arizona State University stated that “Recommender algorithms trap users into personalized information by using their past behaviors to tailor recommendations to their preferences” (Jiang, 2021). Whenever you click on a post on social media, the algorithm uses it as data. With whatever it collects, its goal is to recommend something that you’re likely to engage with more. This means that it is more likely

to recommend you about “similar topics in the future” which evolves into a “self-reinforcing pattern of narrow exposure and concentrated user interest caused by recommender algorithms is an important mechanism behind the echo chamber effect” (Jiang, 2021). Now combine this with social networks on media sites, where people you follow may share similar preferences. The result is that echo chambers have “homophily in the interaction networks,” or people seeking out those who share similar opinions, and “bias in the information diffusion toward likely-minded peers” (Cinelli, 2020). There is this cascading, reinforcing effect that recommendation system algorithms have on users. As you consume political content, your preferences are recorded as data for the algorithm. This results in you receiving more and more content that tailors to your preferences. Then, this content propagates throughout your social network and your followers will also get similar content. Figure I, from researchers at Arizona State University, shows this as a feedback loop and some of its psychological effects,

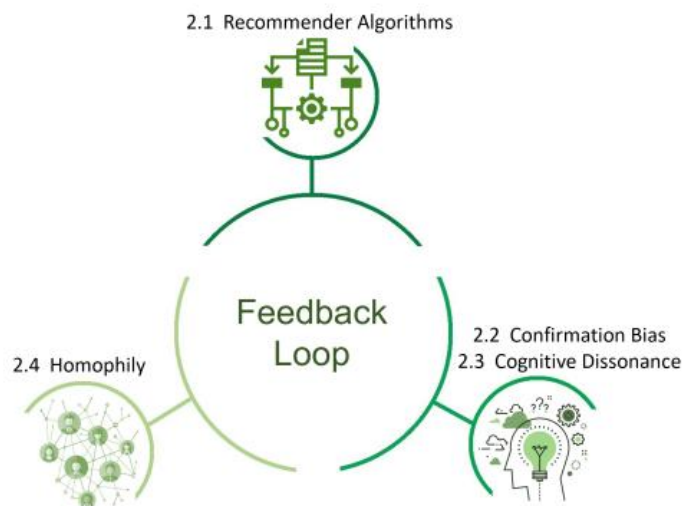


Figure I: Feedback Loop of Recommender Algorithms (Jiang et. al., 2021)

The figure shows that recommendation system leads to confirmation bias and decreases cognitive dissonance. The recommendation algorithms curate content that is of a similar opinion

to the user, so the user is more likely to favor that information, resulting in people affirming their beliefs only based on that same belief. This confirmation bias leads to a reduction in cognitive dissonance, the psychological tension from dealing with opposing information, since users consume content that conforms to the same beliefs.

### *Spread of Misinformation and Social Media Abuse*

When echo chambers form, it is very easy for misinformation to spread to them. The homophily and similar beliefs in these echo chambers make it very easy for any information to easily be believed. Confirmation bias is “the predisposition to only consume the news, or what appears to be news, that confirms our pre-existing attitudes and beliefs,” (Ling, 2020). Ling additionally said that confirmation bias is “an important element supporting the diffusion of false news via digital platforms.” As implied by the name, the bias in confirmation bias tends to stretch further and further in social networks. As algorithms and echo chambers further polarize people’s opinions, it will naturally become progressively more difficult to convince them otherwise. This leads people to easily believe things said within their social network. Thus, misinformation becomes rampant and people stubbornly believe in it. With more people online, events “such as the 2016 US presidential election and COVID-19 infodemic have evidence shown that trolls, shills, and cyborgs are actively peddling misinformation in social media” (Jiang, 2021). It is very easy to spread misinformation on social media, and introducing it into social networks and echo chambers means it is additionally very easy for people to believe it.

However, this is not only done by trolls, shills, and cyborgs. Politicians or even governments can try to abuse misinformation to gain support. Samantha Bradshaw and Philip N. Howard discovered that "governments and political parties around the world are spending significant resources to generate content, direct public attention, and manipulate the opinion of

foreign and domestic audiences via social media.” They further noted that these parties rely on computational propaganda through using social media algorithms to deceive users and that they are actively trying to generate a false consensus. This abuse of social media results in those attempts to manipulate people spreading through their echo chambers. Because of the homophily in these echo chambers, people consume the misinformation and can be manipulated or believe misinformation.

Recommendation systems are incredibly potent tools that can generate tons of useful content for users to enjoy. However, with their accuracy it means that polarizing content can propagate through their feeds and social networks and form echo chambers. These echo chambers can be taken advantage of and be abused to spread misinformation or try to manipulate people. If this system does not change, these algorithms will only grow more influential over time. More people will be part of echo chambers and the diversity in thought and opinions will be reduced. However, how this system could change is very unclear. There are many actors in it with complex relationships, including social media companies, users, political parties, and technological researchers.

## Section II – Multi-level Perspective to Understand Sociotechnical Transitions

To understand the sociotechnical systems and their transitions, this paper will apply the framework of multi-level perspective (MLP) from “The multi-level perspective on sustainability transitions: Responses to seven criticisms” by Frank W. Geels (2010). MLP involves analyzing three main levels of a sociotechnical system: niches (development of new innovations), socio-technical regimes (the established practices of the system), and socio-technical landscapes (the overall ecosystem present in the system that envelops niches and regimes). I will apply Geels’ multi-leveled perspective to help understand the dynamic of the system surrounding social media algorithms and polarization.

### *Geels’ Approach to MLP*

In “The multi-level perspective on sustainability transitions: Responses to seven criticisms,” Frank W. Geels (2010) explains the concept of MLP in the context of environmental sustainability. Geels focuses on three different levels. The first level Geels describes is the socio-technical regime. The regime is the “deep structure that accounts for the stability of an existing socio-technical system” (Geels, 2010, p.4). It consists of rules that coordinate the actions of social groups within the system. Such rules include cognitive routines and shared beliefs. When analyzing transitions in the Dutch electricity system, Geels noted the perceptions and goals of actors such as large energy companies, government interventions in changing laws, and changes in technology as dynamics of the regime (Geels, 2006, p.3). The second level is niches, which are spaces where “users have special demands and are willing to support emerging innovations” (Geels, 2010 p.4). When Geels applied this to the Dutch electricity system, he considered renewable energy a niche (Geels, 2006, p.7). Niches are very important for sociotechnical transitions, since they “provide the seeds for systematic change” (Geels, 2010, pg.27). Niches



and regimes are both major parts of the sociotechnical landscape, the third level. The landscape is the broader context that influences the niche and regime. It is the “technical and material backdrop that sustains society,” also including “demographical trends, political ideologies, societal values, and macro-economic patterns,” (Geels, 2010, pg.28). Within the landscape, there are patterns that are recognized based on the interaction between different levels, such as changes in the landscape pressuring the current regime or a regime losing stability allowing niches to gain momentum (Geels, 2010, pg.29). The three layers that Geels describes make up the sociotechnical system, and their interactions create patterns that are indicative of the potential transitions. Figure II depicts the three levels and how they interact.

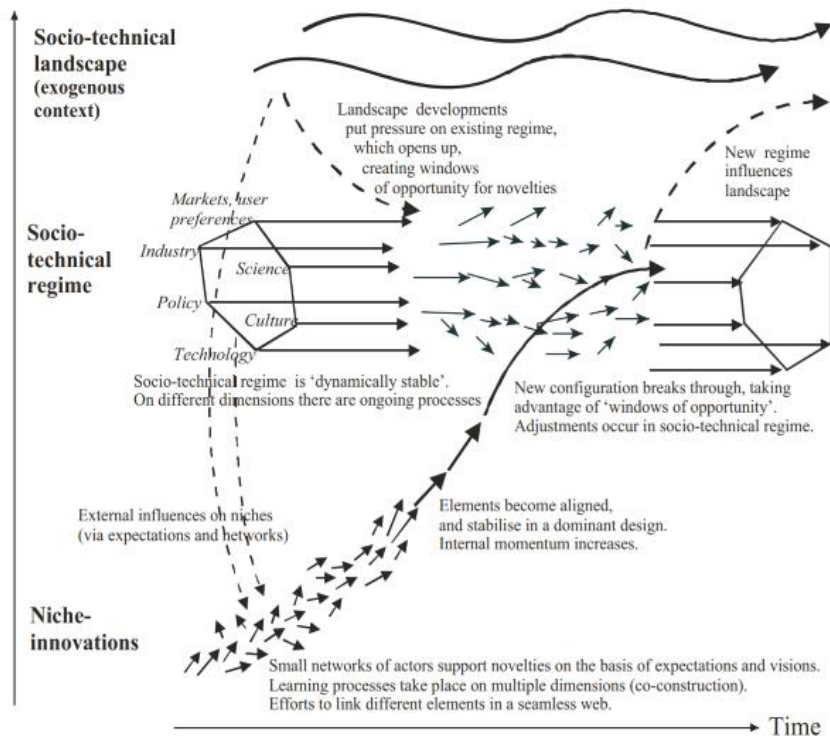


Figure II: The Multi-level Perspective on Transitions (Geels, 2010, pg.28)

The figure shows the overall landscape pressuring the socio-technical regime and giving the niche level a chance to gain momentum and break through, resulting in a transformation of

the sociotechnical system. To better understand the sociotechnical system involving social media algorithms and their effects regarding polarization, I will apply MLP and analyze the different levels in the framework. For this, I will first establish the current state of the landscape, regime, and niches, identifying the key attributes of each such as rules that are in place of the regime. After this, I will look for shifts in the landscape and how that has been influencing niches and the regime. With these findings, I will look for patterns involving sociotechnical transformation. MLP is a good framework for this problem domain due to how it accounts for many different concepts that make up a system. When considering social media algorithms, there are many complex interactions between actors within the landscape that have their own motivations. Geels used this model for sustainable energy. He identified that improvements to sustainable energy would require “deep-structural changes in transport, energy, agri-food, and other systems” (Geels, 2010, pg.24). Additionally, these improvements would offer “obvious user benefits” and “score lower on price/performance dimensions than established technology” (Geels, 2010, pg.25). These circumstances are similar to social media algorithms, where companies trying to mitigate polarization would be harming their potential profits by decreasing user engagement, and to change the entire system could potentially involve legal and societal change due to how widely used and centralized social media. Therefore, identifying patterns for sociotechnical transformation would be a more effective means of analyzing the current system.

### **Section III – Applying Multi-leveled Perspective to Social Media**

As established, MLP is a strong framework for analyzing sociotechnical transitions within a system. The three levels: landscape, regime, and niches all interact with each other and will undergo certain patterns during a transition. For social media algorithms, the landscape will be the general ecosystem: public, expectations, and current events. The regime will include the industry revolving around social media, its users and the technology surrounding it. The niches will be researchers working on improving social media platforms to avoid polarization issues. With how complex the interactions between the actors within these levels are, MLP can be used to identify patterns indicative of sociotechnical transitions.

#### *The Landscape*

The overall political atmosphere is an important part of the sociotechnical landscape since social media is a key figure in spreading political information and gaining influence. With lots of discourse on social media about events such as elections and the COVID-19 pandemic, the curation of information is extremely important. As the public uses social media more, it will become more connected to the regime. While the current regime could be seen as stable, questions regarding the ethics surrounding social media companies pressure it.

Specifically, concerns about polarized content grow as social media reaches more people, leading to pressure being placed on the regime. Facebook, one of the most popular social media platforms, suffered internal documents being leaked which exposed questionable practices. Angela Colabella detailed the leaks claiming that the company “lifted measures implemented in 2020 to prevent misinformation spread as soon as the election ended” (Colabella, 2022). Additionally, the whistleblower claimed that reducing polarization would decrease user

engagement. They would later go on to urge for a ban of engagement-based ranking when testifying to Congress (Hao, 2021). These events brought attention to the entire ecosystem that these algorithms are dangerous and promote polarization. This indicates that the landscape is currently experiencing a shift towards having more concern regarding these algorithms and their influence on people. This shift will put pressure on the current regime and could open room for niches to grow as it further develops.

Another concern in the landscape is data privacy. People trust large companies less with their data, and believe it is not truly protected. Debra Aho Williamson reported that the rate of US social media users who believe social media platforms protect their privacy and data has decreased on 9 major social media platforms (Williamson, 2022). This data is indicative of a decreasing trust of social media platforms, which puts pressure on the regime and gives room for niches to grow.

The current landscape has seen a fall in trust for social media companies. With concerns over how they treat user data and promote polarization, more people are learning about their potential dangers. Despite them being very popular for information and connectivity, the landscape is showing early signs of transition, and with more similar pressure, niches may be able to build up the influence to overtake the current regime.

### *The Regime*

The sociotechnical regime is the current structure that stabilizes the entire system. Within this regime are a few key dimensions: networks of social media companies and users, the rules, norms, and beliefs influencing actors, and the technical elements. The interactions between these

dimensions are what stabilize the regime. Considering those interactions should show the state of the regime and how it may transition.

The first of these dimensions is the networks of social media companies and the users on them, both of which have aligned interests that generally stabilize the regime. The social media companies are key actors that provide the technology. They are generally driven by profit and aim to have the strongest user base possible, which means improving the platforms for users. The users look for entertainment, information, and connectivity. All of these get satisfied by using social media platforms more. These two goals tend to reinforce the regime, with users using more social media benefiting companies and motivating them to further improve their platforms. However, as companies try to push for more profits, they may promote polarization or misinformation in their algorithms, as evidenced by Facebook earlier. This contrasts the users' desires because companies are potentially manipulating users and feeding them misinformation. As more people hear about issues with the companies such as the Facebook leaks, this dynamic between the users and companies will destabilize the current regime.

Another dimension is the current rules within the system. These include formal laws and cognitive beliefs that encourage actors, both of which are signs of stability within the regime. Currently, there is not much legal pressure on social media companies to regulate their algorithm design as evidenced by the lack of change in recommendation systems. This absence of rules is helping maintain the stability of the current system. The high usage of social media is also a cognitive rule here, with users seeing social media as a key to maintain connectivity with others, incorporating it more in their daily lives. This also helps maintain the stability of the system, since it increases the influence of the social media companies. Many of the cognitive and formal rules in this system are maintaining the stability of it.

The last dimension is the technical innovations, which are the backbone of the regime. Social media algorithms are extremely important in maintaining the relationship between users and social media platforms (and by extension companies). With these algorithms getting better over time, their influence will help keep users on the platforms, additionally helping the stability of the current regime.

From analyzing the different dimensions of the current regime, it's clear the regime is mostly stable. The interactions between actors, social rules motivating them, and technical elements surrounding the system all intertwine to keep the regime stable. There are signs from the landscape discussed earlier that have begun to pressure the regime, but due to how it reinforces itself, it will take more pressure to lead to a sociotechnical transition.

### *The Niches*

The final layer in this sociotechnical system is the niches. Niches are the ground for innovation that can gain momentum and transform into a new regime. When considering social media algorithms, niches would be research towards improved social media algorithms or platforms that offer stronger privacy and user control. Currently, no niche product has the momentum to change the regime. Much of the work to rework recommender systems around polarization is done by researchers. One such example is Mahsa Badami et. al. who proposed a polarization-aware recommender system that tries to curate “from the opposite view” and can “broaden the viewpoint spectrum” (Badmai et. al, 2021, pg.7). There are clearly many researchers aware of ways to improve social media recommendation systems, but many lack the resources. Given the data-intensive nature of machine learning and need for lots of real time testing, a niche development will need considerable support to get the influence to dethrone the regime.

*The Entire Picture*

Considering the levels, the sociotechnical system seems to be relatively stable but indicating potential to transition with the right influence. The landscape is starting to pressure the regime, which is a sign of transition, but the regime still is stable due to the connection between companies, people, and the algorithms. Niches additionally need more support and development to be able to break through a window of opportunity and become the new regime. Putting it all together, Figure III shows a map of the MLP over the problem domain.

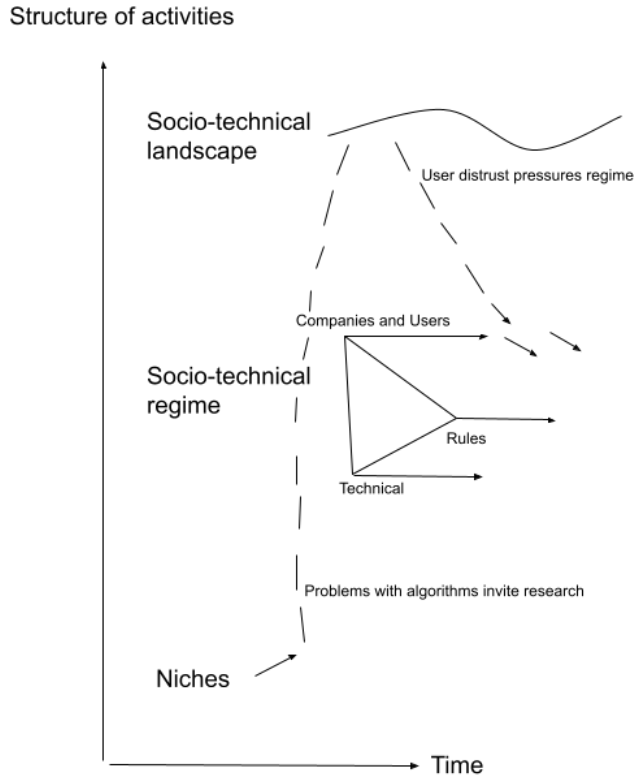


Figure III: MLP of Social Media Algorithms (Created by Author)

As seen in our figure, the regime is still mostly stable. There are some signs of instability from the landscape pressure, but they did not extend far enough to disturb the rules or technical dimension of the regime. Additionally, the niche has been given some incentive to develop, but

lacks the influence to become the regime. While there are signs of sociotechnical transition in our system, more pressure on the regime and influence for niches will be needed to overthrow the current regime.



## Section IV – Conclusion

The sociotechnical system surrounding social media algorithms and polarization is quite complex, with many actors that have varying influences and motivations. By analyzing this system using multi-level perspective, we find that the current regime is relatively stable. Additionally, niche developments lack popularity and are limited mostly to research. However, pressure from the landscape motivates more niche development and puts some pressure on the current regime. This is important because it indicates some patterns seen in sociotechnical transitions. With further developments in the landscape, more pressure can be put on the regime and people will understand the problem better. Over time, with a niche gaining influence, the current regime can transition towards one that avoids polarization. The intricate relationships between actors in this issue made MLP an effective research approach. However, it can be argued that MLP in this case is too favoring of a bottom-up approach, placing lots of faith in niches. While niches are an important part of this model, they are not the only way for improvement to occur. Even without a niche breakout, pressure from the landscape on the regime can lead to a call to change, and the current regime can be modified to improve itself. For instance, even if new algorithms or platforms never gain popularity, legal changes could force modifications to the current regime to address the problems of polarization. These interactions between other layers are still key to what makes the system stable, providing value to MLP without a niche breakout. Ultimately, by analyzing the different layers, we can understand the different elements that constitute the current sociotechnical system and what this may imply for change.

## References

- Anandhan, L. Shuib, M. A. Ismail and G. Mujtaba, "Social Media Recommender Systems: Review and Open Research Issues," in IEEE Access, vol. 6, pp. 15608-15628, 2018, doi: 10.1109/ACCESS.2018.2810062.
- Badami Mahsa, Nasraoui, "PaRIS: Polarization-aware Recommender Interactive System," 2021.
- Bakshy, Eytan & Messing, Solomon & Adamic, Lada. (2015). Political science. Exposure to ideologically diverse news and opinion on Facebook. Science (New York, N.Y.). 348. 10.1126/science.aaa1160.
- Cinelli, Matteo, et al, "Echo Chambers on Social Media: A Comparative Analysis." arXiv.Org, 20 Apr. 2020, arxiv.org/abs/2004.09603.
- Colabella, Angela, "Op-ed: Social media algorithms & their effects on American politics," 1 May. 2022, <https://funginstitute.berkeley.edu/news/op-ed-social-media-algorithms-their-effects-on-american-politics/>.
- Geels, Frank W., "The multi-level perspective on sustainability transitions: Responses to seven criticisms", 24 Nov. 2010 in Environmental Innovation and Societal Transitions.
- Geels, Frank W., Verbong, Geert, "The ongoing energy transition: Lessons from a socio-technical, multi-level analysis of the Dutch electricity system (1960–2004)," 31 Mar. 2006, in Energy Policy vol. 35.
- Hao, Karen, "The Facebook whistleblower says its algorithms are dangerous. Here's why." 5 Oct. 2021, in MIT Technology Review, <https://www.technologyreview.com/2021/10/05/1036519/facebook-whistleblower-frances-haugen-algorithms/>
- Jiang, Bohan, et al. "Mechanisms and Attributes of Echo Chambers in Social Media." arXiv.Org, 12 Aug. 2021, arxiv.org/abs/2106.05401.

Kepios, "Digital 2023 Global Overview Report." *Kepios* (2023).

<https://kepios.com/reports>

Rich Ling (2020) Confirmation Bias in the Era of Mobile News Consumption: The Social and Psychological Dimensions, *Digital Journalism*, 8:5, 596-604, DOI: 10.1080/21670811.2020.1766987

Moyer, Melinda Wenner. "Kids as Young as 8 Are Using Social Media More Than Ever, Study Finds." *The New York Times* (2022).

<https://www.nytimes.com/2022/03/24/well/family/child-social-media-use.html>

Silveira, T., Zhang, M., Lin, X. et al. How good your recommender system is? A survey on evaluations in recommendation. *Int. J. Mach. Learn. & Cyber.* 10, 813–831 (2019).

<https://doi.org/10.1007/s13042-017-0762-9>

N. Tintarev and J. Masthoff, "A Survey of Explanations in Recommender Systems," 2007 IEEE 23rd International Conference on Data Engineering Workshop, Istanbul, Turkey, 2007, pp. 801-810, doi: 10.1109/ICDEW.2007.4401070.

Williamson, Debra Aho. "User Trust in Social Platforms Is Falling, According to Our New Study." *Insider Intelligence*, Insider Intelligence, 19 Sept. 2022,

[www.insiderintelligence.com/content/user-trust-social-platforms-falling-according-our-new-study](http://www.insiderintelligence.com/content/user-trust-social-platforms-falling-according-our-new-study).

Zhao, Zhengwei. "Analysis on the "Douyin (Tiktok) Mania" phenomenon based on recommendation algorithms." *E3S Web of Conferences*. Vol. 235. EDP Sciences, 2021.

<https://www.spir.aoir.org/ojs/index.php/spir/article/view/12039>