Impact of Recommendation Algorithms on Media Configuration

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Abstract

This study examined the impact of recommendation algorithms in media configuration. The rationale for this study stems from the growing importance of recommendation algorithms in media configuration. This study was anchored on the filter bubble theory by Eli Pariser (2011), which explains how personalised recommendation systems influence the type of information users receive, potentially limiting their exposure to diverse viewpoints. The researchers used a survey research design and collected data through questionnaire, with the target population of 1,304,998 for residents of Egor, Oredo and Ikpoba Okha and the sample size of 400, as determined by the Taro Yamane formula, with an error margin of 0.05. The findings showed that there is a high level of exposure and engagement with media content recommended by algorithms. Also, there is skepticism about the effectiveness of these algorithms, but this is not so with the business sector as recommendation systems benefit businesses by improving advertising and marketing strategies. The researchers, therefore, recommend that users should be educated to help them understand how algorithms shape their media consumption and empower them to make informed choices. Platforms should implement measures to prevent filter bubbles and echo chambers.

Keywords: Recommendation, Algorithm, Media, Configuration, Recommendation Algorithm, Media Configuration

Introduction

In today's digital world, people consume media in ways that were not possible in the past. With the rise of online streaming services, social media platforms, and news websites, people no longer rely only on traditional television and newspapers for information and entertainment. Instead, they are exposed to a large amount of digital content every day. To help users find what they like, many platforms use recommendation algorithms. These computer programmes suggest content based on a user's past choices, making it easier to discover new material (Smith, 2020).

According to Ricci (2011), a recommendation algorithm is a set of rules used by computer programs to suggest content, products, or information based on a person's past behaviour, interests and preferences. These algorithms help platforms like social media,

streaming services, and online shops show users things they are most likely to enjoy or find useful. Jones & Patel (2021) note that recommendation algorithms analyse user data, such as search history, clicks and ratings, to predict and suggest relevant content. They are designed to improve user experience by filtering large amounts of information and showing only what seems most relevant to each person. As explained by the authors, recommendation algorithms work by collecting and analysing data on user behaviour. For example, when a person watches a movie on Netflix or listens to a song on Spotify, the platform records their activity. Based on this information, the system suggests similar content the user might enjoy. This process makes media consumption more personalised and engaging (Jones & Patel, 2021).

Brown (2019) asserts that a major benefit of recommendation algorithms is that they improve user experience. Instead of searching through countless options, people receive suggestions tailored to their interests. This saves time and makes entertainment more enjoyable. Businesses also benefit from these systems because they increase user engagement. Platforms like YouTube, Facebook and Amazon rely on recommendation algorithms to keep users active for longer, which helps them earn more revenue. Pariser (2011) avers that despite its benefits, recommendation algorithms also have some disadvantages. One of the issues is the creation of "filter bubbles." This happens when a user is only shown content that matches their existing views. Over time, this can limit exposure to different perspectives and create an echo chamber, where people only see opinions that reinforce their beliefs. This can negatively affect critical thinking and reduce awareness of diverse viewpoints.

Another concern is data privacy. Recommendation systems collect large amounts of personal data, raising questions about how this information is stored and used. Many users are concerned that companies might misuse their data or share them with third parties without their consent. Data breaches and privacy scandals have made people more cautious about how their information is handled online. Additionally, Wardle & Derakhshan (2017) posit that misinformation is another challenge linked to recommendation algorithms. Since these systems prioritise content that generates high engagement, they may suggest misleading or false information if it attracts attention. This has been a major issue on social media platforms, most especially during political events or global crises. The spread of misinformation can influence public opinion and sometimes cause harm.

Gillespie (2018) explains that recommendation algorithms can reinforce bias because they learn from past user behaviour. This means they may favour certain types of content, making it harder for users to see balanced information. If a person for instance mostly interacts with one type of news, the algorithm will keep showing similar articles, even if they are biased. While these algorithms have changed how people find and use media, they also raise ethical concerns. If they focus more on engagement than accuracy, they might spread false information and limit different viewpoints. As digital media grow, it is important to study these effects and find ways to make recommendation algorithms more responsible. With this in view this study therefore examines the Impact of Recommendation Algorithms in Media Configuration.

Statement of the Problem

Recommendation algorithms have become an important part of how people consume media. These systems help users find content quickly, but they also create challenges. Many people do not fully understand how these algorithms work, which can lead to concerns about privacy, fairness and the spread of false information. When users are repeatedly shown content based on their past choices, they may not be exposed to new ideas or different viewpoints. This can create a narrow way of thinking and reduce diversity in the information they receive.

Additionally, there is a risk that recommendation systems prioritise content that keeps people engaged rather than content that is accurate or balanced. This can make it easier for false or misleading information to spread, especially on social media. There are also concerns about how much personal data is collected and whether users have control over their own media experience. As recommendation algorithms continue to shape digital media, it is important to understand their impact and find ways to make them more transparent and responsible. Thus, this study investigated the impact of recommendation algorithms in media configuration.

Objectives of the Study

This study sought to:

1. Examine the role of recommendation algorithms in shaping media consumption.
2. Identify the benefits of recommendation systems for users and businesses.
3. Investigate the challenges and ethical concerns linked to these algorithms.

Understanding Recommendation Algorithms

Recommendation algorithms are systems that help people find content based on their interests and past choices. These algorithms are widely used in digital platforms such as streaming services, online shopping websites and social media. They work by analysing user behaviour, such as what they watch, buy or search for and then, suggesting similar items. For example, when someone watches a movie on Netflix, the system suggests other films they might like. Similarly, online stores like Amazon recommend products based on what a person has viewed or purchased before (Russell & Norvig, 2020).

Ricci *et al* (2015) note that algorithms use different methods to make recommendations. A common approach is collaborative filtering, which looks at the behaviour of many users to find patterns. If two people have watched and liked the same movies, the system assumes they have similar tastes and suggests other films that one of them has enjoyed. Another method is content-based filtering, which focuses on the characteristics of the items themselves. A music app may recommend songs that have the same genre, artist, or tempo as the ones a user already listens to. Aggarwal (2016) pinpoints that many platforms combine different recommendation methods to improve accuracy. This approach is called hybrid filtering. YouTube for instance, uses both collaborative filtering and content-based filtering to suggest videos. The system looks at what similar users have watched and also examines the details of the videos, such as keywords and descriptions.

Davidson *et al* (2010) argue that one of the biggest advantages of recommendation algorithms is that they make it easier for users to discover new content. Without these systems, people would have to spend a lot of time searching for books, movies or music that matches their interests. Instead, algorithms help by providing quick and personalised suggestions. This makes online experiences more convenient and enjoyable, as users can access content that suits their preferences without much effort. However, recommendation algorithms are not perfect. It suffers from filter bubble, where users are only shown content similar to what they have already engaged with. This limits their exposure to different viewpoints, making it harder to discover new ideas or diverse perspectives. A situation where a person watches only political videos from one side of an argument, the system may keep showing them similar content, reinforcing their existing beliefs. This can reduce critical thinking and create an imbalanced view of the world (Pariser, 2011).

In addition, recommendation algorithms can sometimes promote misleading or harmful content. Since many platforms aim to keep users engaged for longer periods, they may suggest content that is more sensational or emotionally charged rather than accurate or educational. This is a serious problem on social media, where false news and conspiracy theories can spread quickly. Platforms like Facebook and YouTube have faced criticism for allowing such content to be promoted through their recommendation systems (Tufekci, 2018).

Understanding Media Configuration

According to McQuail (2010) media configuration is the way media systems are organised, structured, and designed to deliver content to audiences. It includes the technologies, policies, and strategies used by media companies to distribute information across different platforms. This concept is sacrosanct in the digital age, where traditional and online media coexist, as it shapes how people consume news, entertainment, and educational content. The way media is configured affects what people see, hear and read, influencing their opinions and choices.

Pavlik & McIntosh (2018) say that one of the key aspects of media configuration is technological infrastructure. The media industry relies on various tools and systems to produce and distribute content. Traditional media, such as newspapers and television, use printing presses, broadcast towers, and satellite networks. Meanwhile, digital media depends on the internet, cloud storage and artificial intelligence to reach audiences worldwide. The shift from analogue to digital technology has changed how media operates and made content more accessible and interactive. Another important part of media configuration is content distribution. Media companies use different strategies to ensure their content reaches the right audience at the right time. Television networks schedule programmes based on viewer preferences, while social media platforms use algorithms to personalise content for users. Streaming services like Netflix and YouTube rely on data-driven recommendations to keep viewers engaged. These distribution methods affect how people interact with media and the kind of information they receive (Napoli, 2011).

Regulation and ownership also play a major role in media configuration. Governments and regulatory bodies set rules to control how media operates, ensuring fairness, accuracy and ethical standards. Some countries have strict regulations to prevent misinformation, while others have more relaxed policies that allow free expression. Media ownership is another factor, as large corporations control many media outlets, influencing the type of content produced. When a few companies own multiple news channels, newspapers, and websites, there is a risk of biased reporting and reduced media diversity (Doyle, 2013). Also, audience engagement is a growing focus in media configuration. Modern media systems aim to make content more interactive, allowing users to participate in discussions, share opinions and even create their own content. Social media platforms, for instance, encourage user-generated content, making audiences part of the media process. This shift has changed the traditional one-way communication model, where media organisations simply broadcast information to passive audiences. Now, people can influence media narratives by sharing their thoughts and reactions instantly (Jenkins, 2006).

McStay (2018) asserts that as technology advances, media configuration has continued to evolve. Artificial intelligence, virtual reality, and blockchain technology are expected to shape the future of media. AI is already used for content creation, personalised recommendations and automated news reporting. Virtual reality is changing the way stories are told, providing immersive experiences for users. Blockchain technology is being explored to improve transparency and copyright protection in media. These innovations show that media configuration is not static but constantly adapting to new trends and audience demands.

Role of Recommendation Algorithms in Shaping Media Configuration

Recommendation algorithms help shape media by affecting how content is made, shared and used. Gillespie (2018) explains that these algorithms use data to personalise media, making sure users see content that matches their interests. As digital media grows, recommendation systems have become important for platforms like Netflix, YouTube, Facebook and Spotify. They have changed how people interact with media, making it easier to find content that suits their preferences.

Bodó (2019) states that recommendation algorithms shapes media by delivering personalised content. In the past, traditional media shared the same content with everyone. But now, digital platforms use algorithms to study what users like and how they interact with content. This helps them suggest media that matches each person's interests. As a result, people enjoy what they watch or read more, making them stay longer on these platforms. Pariser (2011) argues that recommendation algorithms affect media diversity. They help users find content they like, but they can also create "filter bubbles" and "echo chambers," where people keep seeing the same kinds of views. This means they might not get different information or opinions. To avoid this problem, media platforms usually balance personalisation by offering a variety of content.

Recommendation algorithms also affect how content is made and how media businesses work. Platforms like TikTok and YouTube use these algorithms to share content, so creators make videos that match what the algorithm prefers. This has changed

how stories are told, how videos are made, and how people try to get more views. Media companies now create content that fits what the algorithm likes, focusing on things like watch time, user engagement, and how fast a video spreads to reach more people and make more money (Napoli, 2019). Additionally, Zuboff (2019) asserts that recommendation systems also affect how media makes money, especially through advertising. Digital platforms use algorithms to study user data and show personalised advertisements. This helps advertisers reach the right people, making ads more effective. However, some people worry about privacy and whether these ads are fair. As a result of this, there are ongoing discussions about making recommendation systems more open and honest.

Furthermore, recommendation algorithms also help media change in real time. Unlike old media, which follows set schedules, digital platforms update content based on what users like and do. This helps media companies keep up with audience trends and improve recommendations. With this, media distribution has become more flexible and based on data, instead of relying only on fixed decisions by editors (Van Dijck, Poell & de Waal, 2018).

Empirical Review

Liu *et al* (2023) conducted a study titled "A Field Test of Bandit Algorithms for Recommendations: Understanding the Validity of Assumptions on Human Preferences in Multi-armed Bandits." The study aimed to test the assumptions of multi-armed bandit (MAB) algorithms in real-world settings, particularly whether human preferences remain constant over time. Researchers engaged participants in a comic recommendation scenario, where each option represented a different comic category and users provided feedback after each recommendation. The findings revealed that human preferences are dynamic and change over time, challenging the core assumption of fixed preferences in MAB algorithms. The study concluded that recommendation systems should account for these evolving preferences to enhance their effectiveness. While the reviewed study used experimental design, the current study is based on survey. The geographical locations of both studies differ. This is the gap the current study sought to fill.

Anwar, Schoenebec & Dhillon (2023) published "Filter Bubble or Homogenisation? Disentangling the Long-Term Effects of Recommendations on User Consumption Patterns." The objective was to explore how recommendation algorithms impact user behaviour over time, specifically regarding content diversity and exposure to varied viewpoints. Using an agent-based simulation framework, the study examined how traditional recommendation systems influence both the similarity of content consumed among different users (homogenisation) and the variety of content consumed by individual users (filter bubbles). The results indicated that while these algorithms reduce differences in content consumption between users, they do not significantly affect the diversity of content consumed by individuals. The study concluded that to address both homogenisation and filter bubble effects, new recommendation approaches should consider multiple aspects of content diversity. While the reviewed study looked at how recommendation leads to media consumer behaviour, the current study examined how recommendation algorithm leads to change in media set up, design or outlook.

Theoretical Framework

This study adopts the filter bubble theory by Eli Pariser (2011) as its theoretical framework. This theory explains how personalised recommendation systems influence the type of information users receive, potentially limiting their exposure to diverse viewpoints. Pariser (2011) introduced the concept of the "filter bubble" to describe how recommendation algorithms personalise online experiences by curating content based on a user's past behaviour, preferences and interactions. He argued that while these algorithms enhance user engagement, they also create an "informational bubble," where users are mainly exposed to content that aligns with their existing beliefs and interests. This leads to lack of diverse perspectives, reinforces biases and reduces exposure to opposing viewpoints.

The tenets of the theory include:

- Algorithms create media content to individual users based on their past activities, preferences and interactions.
- Users are more likely to see information that aligns with their pre-existing beliefs, reducing the likelihood of encountering diverse opinions.
- Recommendation systems may prioritise certain types of content, unintentionally shaping public discourse and influencing media consumption patterns.
- Since algorithms focus on engagement, they may promote homogenous content, limiting users' exposure to varied perspectives.
- Users within filter bubbles interact mostly with like-minded individuals, reinforcing their viewpoints and reducing critical thinking about opposing ideas.

This theory is relevant to this study because recommendation algorithms play a crucial role in shaping how media is configured and consumed. As algorithms filter and rank content based on user behaviour, they influence what information is accessible to individuals. This affects media diversity, audience engagement, and even public opinion. Understanding the filter bubble effect helps to critically assess whether recommendation algorithms promote or hinder the exposure to diverse media content. By applying this theory, the study can examine whether recommendation algorithms contribute to media homogenisation, reinforce biases, or enhance personalised content experiences. Additionally, it allows for a discussion on possible solutions to ensure that algorithms maintain diversity and provide balanced media exposure.

Methodology

This study used a survey research design and collected data through questionnaire. The target population of 1,304,998 (National Populations Commission 2024) included residents of Egor, Oredo and Ikpoba Okha. The sample size was determined using the Taro Yamane formula, with an error margin of 0.05.

The formula is: $n = \frac{N}{1 + N(e^2)}$

$$\frac{1{,}304{,}998}{1 + 1{,}304{,}998(0.1^2)}$$

Where: n is the sample size, N is the total population, e is the margin of error (usually 0.1). Using this formula, the sample size was calculated as:
n= 400.

A total of 400 participants were selected using the stratified sampling technique to group respondents and examine the Impact of Recommendation Algorithms in media configuration. Copies of the questionnaire were given to participants directly. The collected data were then analysed using simple percentages and frequency distribution tables to present the findings.

Data Presentation and Analysis

Four hundred (400) copies of questionnaire were distributed to study participants in Edo State and from the instrument administered; only 375 copies were retrieved, resulting in a 94% return and 6% loss.

Table 1: Exposure and Engagement with Media Content recommended by Algorithms

Variables	No. of Respondents.	Percentage
Strongly agree	95	25%
Agree	178	48%
Neutral	58	16%
Disagree	42	11%
Strongly disagree	0	0%
Total	375	100%

Table 1 shows that a majority of the respondents are exposed to and engage with media content recommended by algorithms. This is evident from the data, where a combined 73% of respondents (25% strongly agreed and 48% agreed) acknowledged their exposure and engagement with algorithm-driven media content. Additionally, 16% of the respondents remained neutral, while 11% disagreed and none strongly disagreed. This shows that recommendation algorithms significantly influence media consumption patterns, as most respondents actively engage with content suggested by these systems. The findings highlight the growing role of algorithms in shaping user interactions with digital media platforms.

Table 2: Recommendation Algorithms help me discover New Content that I would not have found on my Own

Variables	No. of Respondents.	Percentage
Strongly agree	128	34%
Agree	67	17%
Neutral	29	8%
Disagree	100	27%
Strongly disagree	54	14%
Total	**375**	**100%**

Table 2 shows that a significant number of respondents believe that recommendation algorithms help them discover new content they would not have found on their own. This is evident as 51% of the respondents (34% strongly agree and 17% agree) acknowledged the role of algorithms in content discovery. These findings indicate that while many users benefit from algorithm-driven recommendations, a notable percentage remain skeptical and do not rely on them for content discovery.

Table 3: Recommendation Algorithms make it Easier to find Content that matches my Interests

Variables	No. of Respondents	Percentage
Strongly agree	219	58%
Agree	100	27%
Neutral	36	10%
Disagree	20	5%
Strongly disagree	0	0%
Total	**375**	**100%**

Table 3 shows that a majority of the respondents believe recommendation algorithms make it easier to find content that matches their interests. This is evident as 85% of the respondents (58% strongly agree and 27% agree) acknowledged the effectiveness of recommendation systems in personalising content. These findings reveal that recommendation algorithms play a key role in helping users' access relevant content, improving their media experience.

Table 4: Recommendation Systems help Businesses improve their Advertising and Marketing Strategies

Variables	No. of Respondents.	Percentage
Strongly agree	112	30%
Agree	263	70%
Neutral	0	0%
Disagree	0	0%
Strongly disagree	0	0%
Total	**375**	**100%**

Table 4 shows that all respondents believe recommendation systems help businesses improve their advertising and marketing strategies. A significant majority (70%) agreed in that direction. This indicates that recommendation systems play a crucial role in modern marketing by enabling businesses to target the right audience more effectively.

Table 5: Recommendation Algorithms Prioritise Profit over Accuracy and Fairness

Variables	No. of Respondents	Percentage
Strongly agree	118	31%
Agree	163	43%
Neutral	32	8%
Disagree	43	11%

Strongly disagree	19	5%
Total	**375**	**100**

Table 5 shows that a majority of the respondents believe recommendation algorithms prioritise profit over accuracy and fairness. A combined 74% of respondents share this view. This indicates that many people are concerned about the ethical implications of recommendation algorithms on business interests rather than providing fair and accurate content.

Table 6: There should be more Transparency in how Recommendation Algorithms Work

Variables	**No. of Respondents**	**Percentage**
Strongly agree	175	47%
Agree	200	53%
Neutral	0	0%
Disagree	0	0%
Strongly disagree	0	0%
Total	**375**	**100%**

Table 6 shows that all respondents agree that there should be more transparency in how recommendation algorithms work. A combined 100% of the respondents answered in the affirmative. This reveals a strong public demand for openness in algorithmic processes. The lack of disagreement indicates that users feel transparency is necessary to ensure fairness, accuracy, and trust in the recommendations they receive.

Discussion of Findings

The findings from table 1 indicate a high level of exposure and engagement with media content recommended by algorithms. A majority (73%) of respondents acknowledged their interaction with algorithm-driven content, reflecting the growing influence of recommendation systems in shaping digital consumption habits. The 11% disagreement rate, however, implies that some users may either be unaware of or choose to ignore algorithmic recommendations. Furthermore, table 2 reveals a divided perception regarding the role of recommendation algorithms in content discovery; while 51% of the respondents acknowledged that algorithms help them find new content, a significant portion (41%) either disagreed or strongly disagreed. This shows that while algorithms introduce users to new material, skepticism remains about their effectiveness. This finding aligns with research by Smith & Anderson (2022), which indicates that personalised content recommendations increase user engagement on digital platforms. The findings also agree with prior studies, such as Jones *et al* (2021) which highlight that users often feel restricted by algorithmic filtering, leading to concerns about content diversity.

In table 3, findings showed that 85% of respondents believe. This supports the notion that recommendation systems enhance user experience by delivering personalised content, a claim supported by the filter bubble theory (Pariser, 2011). However, the presence of neutral (10%) and disagreeing (5%) respondents showed that some users still experience challenges in finding personally relevant content. Table 4 highlights the

unanimous belief that recommendation systems benefit businesses by improving advertising and marketing strategies. The 100% agreement rate underscores the critical role of these systems in targeted marketing, aligning with research by Kaplan & Haenlein (2023) which states that businesses leveraging AI-driven recommendations experience increased consumer engagement and sales. This reinforces the notion that recommendation algorithms are indispensable tools in digital marketing.

Additionally, table 5 revealed public concerns about the ethical priorities of recommendation algorithms. A significant 74% of the respondents believe that profit is prioritised over accuracy and fairness, suggesting skepticism about the objectivity of algorithmic recommendations. This supports findings by Noble (2018) who argues that recommendation systems often reflect commercial interests rather than user welfare. The disagreement from 16% of respondents, however, indicates that not all users perceive profit-driven biases in algorithmic recommendations. Finally, table 6 demonstrates unanimous support (100%) for increased transparency in how recommendation algorithms function. This highlights a high demand for openness, aligning with studies by Diakopoulos (2020), which emphasised the need for explainable AI. The complete absence of neutral or opposing views suggests that algorithmic transparency is a universal concern among users, potentially influencing future regulatory measures on digital platforms.

Conclusion and Recommendations

Conclusively, it can be deduced that there is a high level of exposure and engagement with media content recommended by algorithms. A significant number of the respondents acknowledged that recommendation algorithms help them discover new content and personalise their media consumption experience. However, concerns remain regarding the fairness and transparency of these systems, with many believing that algorithms prioritise profit over accuracy. Additionally, while recommendation systems are recognised for their benefits in marketing and advertising, there is a strong demand for greater transparency in how they function. Based on these insights, it is concluded that while recommendation algorithms enhance content discovery and engagement, issues related to bias, transparency and ethical considerations need to be addressed. Based on the findings and conclusion, the following recommendations are hereby given:

1. Developers should prioritise fairness in algorithmic recommendations, reducing biases that may favour profit motive.
2. Educational initiatives should be introduced to help users understand how algorithms shape their media consumption and empower them to make informed choices.
3. Platforms should implement measures to prevent filter bubbles and echo chambers
4. Policymakers should establish guidelines to ensure responsible use of recommendation algorithms, balancing commercial interests with user well-being.

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