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The Role of Social Media Algorithms in Shaping the Information Environment and Human Cognition

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Abstract **Original Research Article**

Social media platforms have fundamentally transformed the contemporary information environment by replacing traditional editorial gatekeeping with algorithmically driven content personalization. Rather than presenting identical information to all users, digital platforms selectively prioritize content according to individual behavioural patterns, interests, and previous online interactions. While previous studies have extensively examined algorithmic filtering, echo chambers, and filter bubbles, comparatively limited attention has been devoted to understanding how algorithmic personalization interacts with cognitive biases to influence users' perception and interpretation of information. This study addresses this research gap by investigating the relationship between algorithmic personalization, information exposure, and perception formation within social media environments.

A convergent mixed-methods research design was employed, integrating quantitative and qualitative approaches. The quantitative phase consisted of an online survey administered to 100 social media users aged 18-65 years, while the qualitative phase involved semi-structured interviews with eight professionals working in social media management, marketing, and political communication. Quantitative data were analysed using descriptive statistical methods, whereas qualitative data were analysed through thematic analysis following Braun and Clarke's (2006) framework.

The findings demonstrate that social media constitutes the primary source of information for the majority of respondents and that algorithmic personalization substantially influences users' perceived relevance of information, selective exposure, and trust in digital content. Although respondents generally expressed high levels of confidence in algorithmic recommendation systems, they simultaneously supported greater transparency and stronger user control over algorithmic decision-making. Interview findings further revealed that professionals perceive algorithms as mechanisms that reinforce confirmation bias, increase emotional engagement, fragment public discourse, and contribute to the construction of individualized information environments.

The study argues that algorithmic influence should not be interpreted as a deterministic process through which technology directly controls human thinking. Rather, algorithmic personalization functions as a cognitive amplification mechanism that systematically reinforces existing behavioural tendencies and cognitive biases by continuously optimizing personalized information exposure. By integrating perspectives from communication studies, cognitive psychology, and digital media research, this article contributes to a more comprehensive understanding of the mechanisms through which algorithmic systems shape perception within contemporary digital societies.

Keywords: algorithmic personalization, social media, cognitive bias, information environment, perception formation, mixed-methods research.

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Introduction

Human beings have always perceived reality through intermediaries: under the influence of religion, ideology, culture, and other symbolic systems. In the digital age, a distinctive place among these intermediaries has been occupied by the social media algorithm - a data-driven recommendation system that, based on the analysis of a user's digital behavior, selects and prioritizes content, determining which information becomes visible to a particular user. As a technology, the algorithm shows content that matches the user's interests and past behavior, artificially creating an information environment tailored specifically to them. It operates on the following principle: what you watch on social media and react to is, through the principle of repetition, shown to you more, while what you do not click on disappears from your information space. As a result, the user receives a personalized information environment - an individually tailored content flow shaped on the basis of their past behavior. For example, if you watch one side of political content, algorithmic logic means the other side appears less frequently in your feed. This process reveals two important circumstances: first, that a person's areas of interest and attitudes are fixable and usable by the algorithm; and second, that the user may become, to some extent, dependent on the information flow provided, since the algorithm not only reflects their interests but also gradually shapes them.

As of 2024, the number of active social media users worldwide exceeds 5 billion, which constitutes 62% of the global population (DataReportal, 2024). Given this scale, social media is no longer an auxiliary channel of communication - it has become the environment in which people perceive reality, are shaped, and make decisions. It is precisely the architecture of this environment - algorithmic systems - to which the present study is devoted.

The provision of information tailored by technology to a user's interests is not, in itself, a paradox and could even be assessed as one of the advantages of social development. While traditional media created a shared information space based on editorial policy, algorithmic communication provides an individually tailored information environment, which, at first glance, could also be interpreted as an expansion of informational pluralism. However, the nature of the problem is multifaceted. In social theory, algorithmic personalization is linked to tendencies toward polarization and radicalization; however, the focus of the present study is more specific and concerns the interaction between the algorithm and the individual. Specifically, the study seeks to answer the question of how the algorithmic environment influences an individual's perception and behavior, and which cognitive mechanisms - that is, systemic mental tendencies in how humans process information — act as catalysts for this process (Tversky & Kahneman, 1974; Kahneman, 2011; Zajonc, 1968). Particular attention is devoted not only to cognitive biases and the formation of homogeneous information spaces, but also to the possibility that knowledge of how an algorithm operates, combined with an awareness of human cognitive vulnerabilities, could be used for the psychographic profiling of an individual — that is, data-driven analysis of their interests, values, and behavioral tendencies — for the creation of targeted content and, ultimately, for correcting the direction of their perception and behavior. It is precisely the analysis of this mechanism that the present study aims to undertake.

The existing scholarly literature examines this issue along three main directions. The first direction concerns the technological architecture of platforms and the operating principles of algorithmic recommendations (Ricci, Rokach & Shapira, 2011; Gillespie, 2014). The second direction focuses on phenomena identified in the formation of the information environment — the filter bubble (Pariser, 2011) and the echo chamber (Sunstein, 2001; 2017) — and their social consequences. The third direction examines digital systems, from a broad political-economic perspective, as instruments of power (Zuboff, 2019), which is historically connected to Bernays's concept of the "engineering of consent" (Bernays, 1928) — the idea that public opinion can be deliberately shaped in such a way that this process remains unnoticed by the population. Today, this process is reinforced by algorithmic platforms, personalized content, data analytics, and artificial intelligence. These three directions — the technological, the information-ecosystem, and the political-economic perspectives — together form an extensive theoretical foundation that confirms the influence of algorithmic systems on the information environment. It is no longer in dispute that, in reality, algorithms construct digital reality.

However, despite this rich theoretical framework, the majority of research operates at the macro level — analyzing social polarization, electoral behavior, or the dissemination of information — and pays less attention to the specific cognitive mechanisms that determine the depth of algorithmic influence at the individual level. The aim of the present study is to examine and identify the mechanisms through which an algorithmically constructed information space influences human perception and the thinking process. Specifically, the study examines how the algorithmic environment interacts with existing human cognitive biases, and through what specific mechanisms this interaction may influence perception and decision-making. We are attempting precisely to uncover this logic — is social media a neutral conduit of information, or can it, through algorithmic systems, itself create a reality that shapes our attitudes and values?

Based on this aim, the study seeks answers to the following research questions: How does the algorithmic recommendation system affect the user's information environment? Which cognitive mechanisms determine the depth of algorithmic influence at the individual level? Can the algorithmic information environment influence the user's perception and decision-making? And can this algorithmically mediated influence be deliberately used — in marketing and political contexts — to shape the user's decisions?

To answer these questions, the study has the following objectives: first, to analyze the operating principles of algorithmic recommendation systems and their connection to the formation of the information environment; second, to identify the cognitive mechanisms that make humans particularly vulnerable to algorithmic influence; and third, to assess this influence within specific practical contexts — social media, marketing, and political communication — where changes in decision-making become measurable.

1.1 Social Media Algorithms: Technology, Concepts, and Theories

In order to analyze the functioning of social media's algorithmic systems, this chapter examines existing theoretical frameworks and empirical research. Social media platforms present themselves as "neutral intermediaries" (Gillespie, 2014); however, the reality is different — they actively participate in determining which content becomes visible to the user and which remains beyond attention. At the center of this process stands the algorithmic recommendation system, which creates a personalized information space based on data concerning the user's behavior, interests, and social connections. As a result, two people on the same platform see entirely different content. This is a software mechanism that automatically selects and arranges content based on the user's behavioral data, with the goal of maximizing engagement and time spent on the platform (Ricci, Rokach & Shapira, 2011).

The American sociologist and researcher of the contemporary digital age, Shoshana Zuboff, in her work The Age of Surveillance Capitalism (2019), examines digital systems as an economic system in which companies collect users' behavioral data — what they search for, what they watch, where they are located — and use this data both to sell advertising and to predict and manage behavior. Major technology companies (e.g., Google, Facebook, and others) collect our personal data and use it: to analyze our behavior; to sell advertisements; and, at times, to influence our behavior. Zuboff considers the system of contemporary algorithms to be the principal instrument in this process. She develops the idea that algorithmic recommendations serve as a tool in the hands of digital companies to observe our lives and, based on this data, to direct our attention. To break this down in more detail, algorithms monitor: what you search for on Google; what you watch on YouTube; what you linger on in Instagram; and where you are via GPS — all of this constitutes behavioral data. Based on the analysis of user behavior, algorithms construct a personal digital profile and predetermine what information might appeal to you next. According to Zuboff's analysis, algorithms perform three interconnected functions: surveillance, prediction, and modification (of behavior). Thus, the algorithmic system is not a passive instrument — it represents a mechanism that governs the user's attention and, in Zuboff's assessment, also influences their behavior.

The empirical findings of the study showed that approximately 90% of respondents confirm that, after searching for or interacting with a particular topic, social media platforms continually offer them similar content. This finding indicates that, at a practical level, the algorithmic recommendation system creates a personalized information environment, which aligns with the surveillance–prediction–modification model described by Zuboff (2019). At the same time, it should be noted that the algorithm does not create the user's interests from nothing, but rather builds upon already existing behavioral signals and reinforces them. As a result, it not only reflects the user's interests but further consolidates them, thereby contributing to the homogenization of the information environment.

The mechanism of "algorithmic control" described by Zuboff is not, in essence, a new phenomenon. Its historical foundation can be traced to the works of Edward Bernays, the founder of public relations. He was the first to formulate the idea that public opinion can be deliberately shaped through the use of psychological techniques and mass media. In his work Propaganda (Bernays, 1928), Bernays demonstrated that the direction of public opinion can be determined through covert mechanisms — in such a way that the person themselves cannot perceive the external influence. According to his analysis, it is possible, through mass communication, to deliberately shape people's attitudes and behavior; however, this does not yet mean that this process can change perception itself. In Bernays's era, the instruments were the press, radio, and advertising — today, the same logic operates in the form of the algorithm, with the difference that this influence has penetrated personal space and its scale has grown to a tangible degree. Moreover, the process is entirely opaque to the user. In this sense, Zuboff's work can be regarded as a technological continuation of Bernays's concept — in both cases, human attention and behavior are treated as a controllable resource, though in the digital age this control is far more sophisticated and all-encompassing.

Within the scope of the study, in-depth interviews conducted with representatives from the fields of social media, marketing, and political communication were based on the following research questions: "In your view, what represents the most valuable resource in digital communication today?", "Based on your practical experience, to what extent is user attention manageable?", and "To what extent is it possible to plan or manage attention within the framework of a campaign?" Analysis of respondents' answers revealed common tendencies regarding the role of attention in digital communication and its manageability.

Based on the answers to the first question, the majority of respondents consider that "the most valuable resource in digital communication today is user attention," since it is precisely this that determines the effectiveness and scale of dissemination of a communicative message. As one respondent noted: "If you don't have attention, you don't have communication." Regarding the second question, it emerged that user attention is, in practice, perceived as a highly manageable and predictable resource. Respondents noted that, through the use of behavioral data and platforms' analytical tools, it is possible to identify audience interests and predetermine the direction of their attention. As one marketing specialist assessed: "Today you can already predict quite precisely what type of content a user will linger on." In their answers to the third question, respondents agreed that contemporary digital campaigns substantially rely on the principle of planning and managing attention. According to their experience, content design, timing of dissemination, and a strategy adapted to the platform's algorithms create the possibility for attention to be directed deliberately and incrementally. As one political communication specialist noted: "A contemporary campaign is not only about delivering a message, but about managing attention." At the same time, respondents emphasize that this process is not entirely controllable and depends both on the platform's algorithmic logic and on the audience's behavioral dynamics. Thus, the empirical data of the study confirmed that, in digital communication, attention is perceived as a central and practically manageable resource whose formation is possible.

The American media researcher Eli Pariser focuses on the practical consequence of the control mechanisms described by Zuboff and Bernays. He is one of the first authors to warn society about the dangers of personalized algorithms. His concept — the filter bubble — was first formulated in 2011 and indicates that personalized algorithms place each user within an informational "bubble." Specifically, the algorithm decides which information becomes visible based on the user's prior behavior — clicks, shares, viewing time. As a result, the user increasingly encounters only information that matches their interests and views, while differing perspectives and opposing opinions gradually disappear from their information space. Pariser identifies three important distinctions between the filter bubble and a traditional information environment: first, it is invisible — the user cannot see which information has disappeared from their space; second, it is individualized — every user lives in their own, unique "bubble"; third, it is involuntary — the user cannot control this process themselves. Together, these three characteristics mean that the effect of the filter bubble is far deeper and more difficult to detect than traditional "editorial bias."

The practical manifestation of the filter bubble concept is clearly visible in the operating principle of TikTok's recommendation algorithm. According to TikTok's official documentation (TikTok, 2020), the platform analyzes user behavioral data and creates an individualized information space. When a user posts a video on the platform, the first step is the "small audience test" — at this initial stage, the algorithm shows the video to a small but targeted audience — a group likely to correspond to the content's target audience. If the video achieves a certain resonance within this group, the scope of its distribution gradually increases.

In assessing user behavior, the algorithm does not rely solely on the number of "likes." Far more important are indicators such as the duration of video viewing, watching the video to completion, repeated viewing, comments, and shares. At the same time, if a user scrolls past a video within its first seconds, the algorithm interprets this as a negative signal. On the basis of this combined data, the algorithm constructs a digital profile of the user and attempts to predict which content will hold their attention on the screen the longest.

It is particularly significant that TikTok, unlike Instagram, does not rely on a network of followers but rather on the so-called "Interest Graph" — a digital map of interests derived from the user's behavioral data. As a result, the personalized main feed (the "For You" page) is formed not on the basis of popularity, but on the basis of individual prediction. This mechanism makes the filter bubble effect particularly powerful — the user falls into an increasingly narrow, personalized information space that they themselves cannot see or control.

It should be noted that content creators consciously make use of this algorithmic logic. The first seconds of a video take on particular importance, since it is precisely at this moment that the retention of the user's attention is decided. At the same time, short, repetitive videos and content designed to provoke comments are prioritized by the algorithm. In this way, the most visible content on the platform becomes not necessarily the most informative, but the content that elicits the strongest emotional and psychological reaction.

The operating principle of TikTok's algorithm represents a living manifestation of the filter bubble effect in process. However, the filter bubble concept also has its critics. The social media data scientist Eytan Bakshy and colleagues (Bakshy et al., 2015), whose research concerns the influence of algorithms on the dissemination of information and on processes of political polarization, argue, based on Facebook data, that the effect of algorithmic filtering is less significant than the user's own choices. This critique is important, since it indicates that responsibility cannot be attributed solely to the algorithm — human behavior also plays a determining role. In light of this position, the filter bubble should not be regarded as an absolute category, but rather as a tendency whose strength depends on context and on user behavior.

Closely related to the filter bubble concept, yet distinct from it, is the echo chamber effect, which the American scholar and researcher Cass Sunstein analyzed in detail (Sunstein, 2001, 2017). While the filter bubble is primarily a technical result of algorithmic filtering, the echo chamber is a product of broader social dynamics — an environment in which people, through interaction with others who hold similar views, reinforce and strengthen their own beliefs. Sunstein shows that, within this environment, users are continually exposed to similar types of narratives and views, and that the constant repetition of similar content produces two significant effects. The first is the illusion of the credibility of information: a person perceives information as trustworthy simply because they encounter it frequently, regardless of its actual accuracy. The second is polarization: interaction among people with similar views, over time, makes their positions increasingly radical. Algorithmic systems reinforce both of these effects, since they are optimized for engagement — and emotionally charged content that confirms existing views generates the highest engagement.

It is important to recognize the distinction between the filter bubble and the echo chamber. The filter bubble is a passive process — the algorithm filters information without the user's awareness. The echo chamber, by contrast, is an active social dynamic — the individual themselves chooses an environment of like-minded people. In the digital age, these two phenomena reinforce one another: the algorithm creates the "filter bubble," while the people who end up within this "bubble" form an echo chamber. As a result, society becomes increasingly divided into homogeneous groups, between which a shared information space and shared facts become ever rarer.

However, the echo chamber concept is also contested within academic circles. The Australian media researcher Axel Bruns (Bruns, 2019) argues that the echo chamber effect is empirically overstated, and that in real digital environments people encounter a greater diversity of views than the theoretical model assumes. According to his analysis, the problem lies not in the homogeneity of the information space, but rather in how people process differing information — that is, the issue shifts from access to information toward its interpretation. In light of this critique, the echo chamber, too, is not an absolute given — it is, rather, a tendency whose strength depends on an individual's media literacy and capacity for critical thinking.

Closely connected to the concepts of the filter bubble and the echo chamber are two further important theories, which reveal other dimensions of the influence of the algorithmic environment.

The first is Agenda-Setting theory, formulated by McCombs and Shaw in 1972. The theory holds that the media does not tell us what to think, but determines what we think about — that is, it shapes the priorities of public attention. Under conditions of traditional media, this function belonged to editorial decisions. In the digital age, the algorithm performs this role at the individual level — it decides, in a personalized manner, which topic becomes the object of a particular user's attention and which remains beyond their information space. As a result, agenda-setting does not disappear in the digital age — it merely shifts from a mass to a personalized form, which makes its influence even more difficult to detect.

The second is Framing theory, analyzed in detail by Entman in 1993. According to this theory, information never arrives "neutrally" — it is always presented within a particular frame, which determines how the user interprets the content received. The algorithm not only chooses what information reaches the user, but also how: with what emotional tone, in what context, alongside what other content. This framing process directly influences perception — the same fact, presented within a different frame, leaves an entirely different impression. It is precisely for this reason that framing theory serves as a bridge between the technological analysis in this chapter and the cognitive mechanisms discussed in the following chapter —

the algorithm chooses the frame, and the frame shapes perception.

The empirical validation of this theoretical framework also emerged within the study. Respondents were asked: "How would you describe the contemporary user/voter in the digital environment?" and "To what extent does he or she make decisions independently?" In their assessment, the contemporary user is a behaviorally predictable subject, whose reactions depend significantly on correctly selected content and informational framing. As one respondent noted: "If you select the audience and the content correctly, their reaction is fairly predictable." At the same time, respondents agree that decision-making independence is not absolute and is, to a significant degree, determined by the informational frame created by the platforms.

The theories discussed — agenda-setting, framing, the filter bubble, and the echo chamber — together demonstrate that algorithmic systems are not merely a technical instrument. They actively participate in shaping the information environment, the priorities of public attention, and the frames through which information is interpreted. The social consequences of this process manifest in three principal problems.

The first is polarization. As different users increasingly live within different information spaces, shared discourse and a common factual foundation gradually disappear. Groups not only arrive at different conclusions — they perceive different "realities." This undermines a fundamental precondition of democratic dialogue: a shared information space.

The second is the spread of disinformation. Since the algorithm prioritizes emotional and sensational content, the most visible information is often not the most reliable, but rather the content that provokes the greatest reaction. The study by Vosoughi, Roy, and Aral (2018) showed that false information spreads on social media six times faster than the truth — precisely because it is more emotionally charged.

The third is the degradation of democratic discussion. Together with the "spiral of silence" effect, the algorithm creates an illusion of the "normality" of certain positions, while systematically rendering alternative voices invisible. As a result, public discussion becomes not only fragmented but also homogenized — not as a result of consensus, but as a result of algorithmic filtering.

Yet it is precisely here that a fundamental question arises, one that technological analysis alone cannot answer: if the algorithm simply reflects our existing interests and provides us with the information we ourselves became interested in — where, then, does influence lie? Where does our free choice end, and where does algorithmic shaping begin? The answer to this question cannot be found at the level of technology alone. It is necessary to move to a second level — the analysis of human cognitive mechanisms, which determine the extent and manner in which the algorithmic environment may influence individual perception and decision-making.

2.1 Cognitive Mechanisms of Perception Formation and Algorithmic Influence

The theoretical review has shown that algorithmic systems actively participate in shaping the information environment. However, in order to understand what role this may play in individual perception, it is necessary to examine the key mechanisms of cognitive psychology — specifically, what makes a person vulnerable to external influence.

Research in contemporary cognitive psychology shows that human perception is never a passive or objective process. On the contrary, the mind actively constructs a subjective model of reality, which results from the integration of sensory information, cognitive expectations, and emotional evaluations. In other words, a person does not "see" reality — they "construct" it (Neisser, 1967; Bruner, 1990). In the terminology of cognitive psychology, this is the principle of top-down processing, whereby the brain does not passively receive sensory data but actively interprets it through prior expectations and experience. In the digital environment, it is precisely at this stage that the algorithm intervenes — it predetermines what "material" is supplied to the brain for construction, which in turn determines what reality is built. As Van Dijck and colleagues note

(Van Dijck, Poell & de Waal, 2018), in platform society, perception is shaped precisely through the mediation of these socio-technical systems. A person always processes new information through existing cognitive schemas, which means that consciousness prioritizes information that is most relevant to its schemas. In the digital age, a new and powerful factor is added to this natural process — algorithmic filtering, which determines what information enters the user's perceptual field, in what context, and with what emotional tone.

The constructive nature of human perception takes on particular significance in light of the cognitive mechanisms that are systematically biased in the processing of information. The first and most fundamental mechanism is negativity bias (Rozin & Royzman, 2001) — a theory demonstrating that negative events affect a person far more strongly than positive ones, even when both are of equal intensity. This is an evolutionary inheritance: a rapid reaction to signals of danger was vital for survival. As a result, the human brain is particularly sensitive to conflictual, threatening, and negative information. Within the study, representatives of marketing and political communication were asked: "Which type of content provokes a stronger reaction in the audience — positive or negative?" and "Which topics receive higher engagement — success stories, or criticism, scandal, and problems?" Analysis of the answers revealed the same tendency in both fields: negative content attracts attention and generates engagement significantly more effectively. As one political communication specialist noted: "During elections, a negative message spreads much faster and provokes a much stronger emotional reaction." A marketing representative similarly observed: "People like positive content, but they react to negative content." Thus, the results of the interviews confirm that negativity bias is reflected in practice both in marketing and in political communication, and represents one of the central mechanisms for capturing audience attention.

The second important mechanism is cognitive dissonance, formulated by Festinger (1957). A person experiences psychological discomfort when new information contradicts their existing beliefs. To reduce this discomfort, a person tends either to reject the contradictory information or to seek out confirming evidence. This mechanism is directly linked to confirmation bias (Nickerson, 1998) — a person's tendency to seek out, interpret, and remember information in a way that confirms their prior beliefs. While cognitive dissonance explains why a person avoids contradictory information, confirmation bias explains why they seek confirming evidence — both operate in the same direction and reinforce one another. The quantitative part of the study clearly confirmed this tendency: the majority of respondents indicated that they rarely, or almost never, encounter information that contradicts their already existing beliefs, while they follow, with far greater interest, content that reinforces their position. Similar assessments emerged in the in-depth interviews as well. Respondents note that the audience reacts far more actively to content that aligns with their prior dispositions. As one political communication specialist noted: "People choose information that aligns with their position, not information that would change their mind — they don't like change much." A marketing representative similarly assessed: "If a message contradicts the audience's existing belief, it is simply ignored or met with hostile feedback." Thus, the combination of quantitative and qualitative data confirms that, within the digital environment, cognitive dissonance and confirmation bias are transformed into real informational behavior and significantly determine the user's content choices and perception.

The third mechanism is the mere exposure effect (Zajonc, 1968), which shows that a person perceives something they encounter more frequently as more acceptable and trustworthy — regardless of its actual value. This effect is particularly significant in the context of the algorithmic environment: repeated exposure to the same type of information gradually creates a sense of normality. What once appeared peripheral becomes, through repetition, central and acceptable.

The fourth mechanism is the availability heuristic (Tversky & Kahneman, 1973) — a cognitive shortcut according to which a person considers something important and probable if it comes to mind easily. The algorithm, in turn, determines precisely what will come to mind easily — that is, which information appears frequently, which topic becomes visible, and which fact remains in memory. As a result, the user's assessment of what is important, probable, or real becomes, in part, algorithmically constructed.

At the societal level, another important mechanism is Noelle-Neumann's (1974) "spiral of silence." This phenomenon explains well why a person may fall silent and align with the position of the majority. People tend to express only those views that they consider to be dominant in society, while remaining silent about minority positions for fear of social isolation. As a result, public discussion becomes increasingly homogeneous — not because differing views do not exist, but because people avoid expressing them. In the study, the majority of respondents (85%) indicated that they avoid publicly stating a differing opinion. Similar assessments emerged in the in-depth interviews as well. One political communication specialist noted: "People are particularly cautious in online spaces — if they feel their opinion is in the minority, they often don't write anything at all." A marketing representative similarly observed: "In comments, people quickly conform to the dominant tone."

2.2 The Algorithm as Catalyst

The cognitive mechanisms discussed are significant individually, yet their connection with algorithmic systems acquires particular strength. In the case of negativity bias, this connection is especially clear. The algorithm is optimized for engagement — and emotionally charged, conflictual content generates the highest engagement precisely because of negativity bias. The existence of this influence is revealed in exactly this way: the algorithm detects that you linger three seconds longer on a negative post than on a neutral one. This is behavioral data, not your conscious choice. The algorithm learns from this and shows you more negative content — as a result, the information space becomes increasingly emotionally charged.

In the case of cognitive dissonance and confirmation bias, the algorithm relies on these natural human tendencies. The user reacts more actively to content that confirms their views; the algorithm learns this behavior and supplies increasingly similar content. In this way, a reinforcing cycle is formed: existing beliefs are consolidated, the space for critical evaluation narrows, and the risk of polarization gradually increases. The algorithm does not give the user time for "cognitive dissonance," since it continually supplies them with information that is comfortable for them, thereby narrowing the space for critical thinking.

The combination of the mere exposure effect and the availability heuristic produces an even deeper consequence. When the algorithm systematically shows the same type of information, two parallel processes occur: this information becomes normal through repetition, and important through availability. As a result, the user cannot assess how much their information space has changed — the change happens unnoticed, while each individual step appears natural.

The "spiral of silence" effect acquires a qualitatively new dimension in the contemporary digital environment. On social media platforms, visibility tools — shares, comments, and "likes" — artificially create the illusion of the "dominance of public opinion." The algorithm prioritizes viral content, which intensifies the user's sense of the "normality" and lack of alternative to certain views. The position of the minority does not disappear from the public space because people have changed their minds, but because algorithmic logic systematically renders their voice invisible.

If the algorithm simply learns our behavior and supplies us with the information we ourselves became interested in — then where might we look for influence?

The answer lies not in the relationship between the algorithm and the human being, but in the interaction between the algorithm and human cognitive biases. A person chooses A — this is their behavior. The algorithm learns A and reinforces it — this is technology. To put it briefly, the answer is found not in a simple dichotomy between algorithm and human, but in the cognitive-algorithmic interaction that exists between them, in which both sides jointly create the process of perception formation. The individual initially chooses a particular type of information (A), which constitutes their behavioral expression. The algorithm learns this behavior and, through optimization logic, reinforces its visibility, thereby technologically consolidating the existing choice. However, within this process a third-level dynamic emerges — the interaction between cognitive mechanisms and algorithmic repetition. Through the action of the mere exposure effect, repeated exposure to particular content leads to its normalization; as a result of the availability heuristic, the same content is perceived as more important and more easily accessible in memory; while, by the logic of confirmation bias, the individual increasingly accepts, over time, variations of information that correspond to their prior beliefs. As a result, influence does not manifest as a single or abrupt change. Rather, it forms as a gradual cognitive-algorithmic shift, in which each individual step appears logical, yet their cumulative effect produces a structural transformation of perception and of informational frames.

Human cognitive vulnerability and the logic of algorithmic systems complement and reinforce one another. The algorithm does not create cognitive biases — they exist naturally within human beings. However, the algorithm systematically exploits and amplifies these biases, with the result that human perception is increasingly determined not by reality itself, but by an algorithmically constructed information space. Technology is not, in itself, the problem — the problem is the symbiosis that forms between human psychological structures and the optimized algorithm. It is precisely this symbiosis that explains where and how influence occurs — and it is precisely the study of the practical manifestation of this influence to which the next chapter is devoted.

3.1 Algorithmic Influence in Practical Contexts: Marketing and Politics

The theoretical framework discussed and the empirical data of the study have clearly demonstrated the mechanism through which the algorithm influences the information environment. However, this influence manifests most clearly not in the abstract, but in specific contexts where behavioral change becomes measurable. Two such contexts deserve particular attention: commercial marketing and political communication. Before examining these contexts, however, it is important to raise one fundamental question: if the algorithm itself has no goal of its own — where, then, does the danger lie?

The answer can be found in the analysis of Zeynep Tufekci (2015): the algorithm indeed has no goal. But someone who understands the logic of the algorithm may have one. This is precisely the difference between a "harmless technology" and a "dangerous weapon." Tufekci, like others, argues that algorithms are not neutral technical instruments — they are a system of power asymmetry, in which three levels operate with entirely different information.

The first level is the ordinary user. They do not know what is happening. They see content and consider it their "natural" information space. Their cognitive biases — confirmation bias, the mere exposure effect, the availability heuristic — operate covertly, and the system appears "comfortable" to them.

The second level is the platform. It knows everything. It has the data, it has the algorithm, it has a complete picture of each user's psychological profile — what they search for, what they linger on, what emotional stimuli they react to.

The third level is whoever purchases this knowledge or makes use of the system — political campaigns, marketing companies, Cambridge Analytica. They see the user's psychological profile, while the user does not know that they are being seen. It is precisely this asymmetry — someone knows, you do not — that constitutes the most dangerous dimension of algorithmic influence. And this dimension manifests most clearly in these two specific contexts.

In the in-depth interviews, respondents were asked: "What role does the social media algorithm play in your communication strategy?" Both political communication specialists and marketing representatives unanimously noted that the algorithm is an integral part of their strategy. As one respondent assessed: "Communication on social media is, in effect, communication with the algorithm — if you don't account for the algorithm's logic, you cannot reach the audience."

The second question was: "To what extent does your message change in light of algorithmic logic?" The answers clearly indicate a practice of message adaptation. Respondents note that the form, tone, and emotional charge of content are often determined by the type of content the algorithm prioritizes. As one marketing specialist noted: "Often we don't write what we want, but what 'works in the algorithm.'" A political communication representative similarly noted: "The message changes not ideologically, but in form — how to say it so that it spreads faster." The results of the interviews practically confirm the power asymmetry described by Tufekci: while the user perceives the flow of information as natural, communication professionals work deliberately, taking into account the algorithm's logic.

The Marketing Context: The Formation of Consumer Decisions

In the commercial sphere, algorithmic influence manifests in the most transparent and measurable way. In-depth interviews conducted within the study, whose participants were social media managers and marketers, demonstrate that algorithmic personalization has a systematic influence on consumer perception. As one respondent explained: "If you know what interests a person and how they react, you can show them exactly the kind of content that will affect their decisions — and that is already serious power."

Specifically, this mechanism operates as follows: a user engages with a product once — searching for it, browsing it, or hesitating over it. The algorithm remembers this behavior and, through repeated exposure — by the logic of retargeting — creates an effect of familiarity. According to the mere exposure effect (Zajonc, 1968), repeated contact with information increases the sense of its trustworthiness and appeal — even when the user is unaware that this exposure is deliberate. At the same time, by the logic of the availability heuristic, a product that you see frequently is perceived as important and trustworthy — not because of its quality, but because of its visibility.

The quantitative component of the study also confirms this tendency: a significant portion of respondents indicated that active interaction with the platform — registering reactions or writing comments — leads to similar types of content appearing more frequently. This means that consumer decisions are increasingly shaped not only by one's own judgment, but also by the influence of an algorithmically constructed environment. As one respondent noted: "You think you're choosing for yourself, but in reality you are being offered a choice among already filtered options."

In this context, a change in perception does not mean a radical shift in values. It manifests in a specific, measurable gradient: a product that was previously unfamiliar becomes familiar due to the mere exposure effect; familiar becomes important due to the availability heuristic; important becomes desirable due to confirmation bias; desirable becomes purchased. This gradient confirms that algorithmic exposure plays a real, measurable role in shaping consumer perception.

The Political Context: Swing Voters and the Effect of Marginal Change

In the field of political communication, the issue of algorithmic influence can be interpreted through the lens of Tufekci's concept of asymmetry. Interview participants in this study also identified political communication as a particularly sensitive domain for algorithmic influence, noting that: "This is particularly sensitive in the process of political communication and the formation of public opinion."

It is important to emphasize that contemporary models of political influence do not primarily focus on complete attitudinal conversion — such as transforming an opponent into a supporter of an opposing party. Instead, the main strategic focus is often placed on so-called swing voters — undecided individuals whose political attitudes remain fluid. These "borderline" voters represent a group in which small shifts in perception may have disproportionate effects. The Cambridge Analytica case is frequently cited in academic and public discourse as an illustration of the potential of psychographic targeting in digital political communication, although its actual impact and the extent of its effectiveness remain subject to ongoing scholarly debate. The case gained global attention in relation to Donald Trump's 2016 election campaign and the broader discussion on data-driven political advertising. The process described in this context is typically presented in three stages. First, large-scale data collection occurred through a Facebook application, which initially gathered data from approximately 270,000 users. Due to the platform's then-existing permissions structure, data from users' networks was also accessed, resulting in large-scale secondary data exposure. Second, psychographic profiling was conducted using the OCEAN model (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism), where digital behavioral traces — such as likes, shares, and comments — were used to infer psychological traits. In this framework, online behavior was interpreted as a proxy for psychological disposition. Third, targeted messaging strategies were applied, where different user groups were exposed to tailored political content. In academic interpretations of the case, such messaging is often described as aligning content with inferred psychological traits, including emotional framing for more neurotic users or polarizing content for users with low agreeableness. However, it is important to note that the extent to which such targeting directly altered voting behavior remains contested in the literature.

Rather than representing a proven mechanism of deterministic political manipulation, the Cambridge Analytica case is better understood as a widely discussed example of the potential capabilities and risks of data-driven microtargeting within algorithmic media environments. In this sense, it is often used to illustrate broader theoretical concerns about asymmetries in informational power rather than to demonstrate definitive causal electoral outcomes. This logic is also reflected in the empirical material of the present study. As one respondent noted: "When the algorithm shows you the same type of views over time, you start to believe this is the only correct view, because you simply no longer encounter anything else." In the context of swing voters — whose political identities are not yet fully stabilized — such repetitive informational exposure may contribute to perceptual narrowing.

From a theoretical perspective, this can be interpreted through cognitive mechanisms such as the mere exposure effect and the availability heuristic, which suggest that repeated exposure increases perceived validity and cognitive accessibility of information. Additionally, Noelle-Neumann's "spiral of silence" theory acquires renewed relevance in algorithmically structured environments, where visibility of dissenting opinions may be reduced. In such conditions, users may perceive dominant algorithmically curated narratives as social consensus, which can influence behavioral alignment not through direct persuasion, but through perceived normalization of viewpoints.

The Shared Logic of the Two Contexts

The marketing and political contexts represent two manifestations of the same underlying mechanism. In both cases, Tufekci's three-level asymmetry operates: the user does not understand why they are being shown what they are shown; the platform operates according to its own logic; and the third party makes use of its knowledge of the platform's logic. In both cases, influence does not mean complete conversion — it means marginal change among "borderline" subjects: those in consumer hesitation or political uncertainty. And in both cases, cognitive mechanisms — the mere exposure effect, the availability heuristic, confirmation bias — serve as catalysts for the algorithm.

Within the study's in-depth interviews, additional critical questions were posed, aimed at analyzing the boundary between personalization and manipulation, as well as the ethical aspects of targeted communication. Respondents were asked the following questions: "Where is the line between personalization and exerting influence?", "Can targeted communication be perceived as control?", and "How ethical do you consider it to influence behavior on the basis of data?" The following question was also added: "In your opinion, who has more control over the communication process: the user, the platform, or the author of the campaign?" To analyze practical experience, the following questions were posed: "Can you recall a case in which a campaign changed significantly based on user reactions or data?" and "Has there been a case in which audience behavior directly changed your communication strategy?"

The answers to these questions showed that respondents do not unambiguously attribute control to any single party, and instead view the communication process as a system shaped through interaction. In their assessment, the platform determines the framework of visibility, the campaign's author creates the strategy and content, while the user, through their own behavior, generates feedback, which in turn further influences the structure of communication. Accordingly, control is perceived as distributed and dynamic, rather than as a force concentrated in any single actor.

It is precisely within this dynamic — where a person's decision on a given issue is still fluid — that, if the algorithm's logic falls into someone's hands, it can correct that person's view. However, it is important to note that the influence described is neither absolute nor unlimited. Its depth depends on the user's media literacy, capacity for critical thinking, and individual context — which constitutes both a limitation of this study and a direction for future research.

4. Research Methodology and Design

Despite the growing body of literature examining algorithmic personalization, several important research gaps remain.

First, previous studies have primarily investigated algorithmic recommendation systems from technological, computational, or communication perspectives, whereas comparatively limited attention has been devoted to integrating cognitive psychological theories into explanations of algorithmic influence. Although concepts such as confirmation bias, selective exposure, and heuristic information processing have been extensively examined independently, relatively few empirical studies investigate how these mechanisms interact with algorithmically curated information environments.

Second, existing empirical research predominantly relies on either quantitative surveys or computational analyses of platform behaviour. While these approaches provide valuable evidence regarding user behaviour and platform dynamics, they often fail to capture the professional perspectives of individuals directly engaged in digital communication. The integration of expert interviews with quantitative survey data therefore remains comparatively underrepresented within current literature.

Third, previous research has largely focused on observable behavioural outcomes such as political polarization, misinformation dissemination, or online engagement. Less attention has been devoted to examining users' own perceptions of algorithmic influence and the extent to which they recognize the role of personalized recommendation systems in shaping their information environments.

To address these limitations, the present study adopts a convergent mixed-methods research design integrating quantitative survey findings with qualitative expert interviews. By combining perspectives from communication studies, cognitive psychology, and digital media research, the study seeks to provide a more comprehensive explanation of how algorithmic personalization contributes to perception formation within contemporary information environments.

4.1 Research questions

Based on the theoretical framework and identified research gaps, the study addresses the following research questions:

RQ1. How do social media users perceive the influence of algorithmic personalization on the information they receive through digital platforms?

RQ2. To what extent does algorithmic personalization contribute to selective information exposure and the perceived emergence of filter bubbles?

RQ3. How do communication professionals interpret the role of social media algorithms in shaping users' perception, opinion formation, and online behaviour?

4.2 Research hypotheses

Drawing upon previous theoretical and empirical research, the following hypotheses were formulated:

H1. Users perceive algorithmic personalization as having a significant influence on the information they receive through social media platforms.

This hypothesis is derived from studies demonstrating that recommendation systems actively prioritize personalized content according to users' previous online behaviour, thereby influencing information visibility and exposure (Gillespie, 2014).

H2. Algorithmic personalization reinforces selective information exposure by increasing users' exposure to information consistent with their existing interests and behavioural preferences.

This hypothesis builds upon theories of selective exposure (Stroud, 2011), confirmation bias (Nickerson, 1998), cognitive heuristics (Kahneman, 2011), and the filter bubble phenomenon (Pariser, 2011), which together suggest that algorithmic recommendation systems strengthen existing cognitive tendencies and narrow the diversity of encountered content through repeated personalized content selection.

H3. Although users generally trust algorithmically personalized content, they simultaneously support greater transparency and stronger user control over algorithmic recommendation systems.

This hypothesis reflects the emerging literature on algorithmic governance and transparency, suggesting that users increasingly recognize both the benefits and potential risks associated with algorithmic personalization within digital communication environments.

4.3Research design

This study employed a convergent mixed-methods research design, integrating quantitative and qualitative approaches to obtain a comprehensive understanding of how algorithmic personalization influences users' information environments and perception formation. Mixed-methods research combines the strengths of quantitative and qualitative methodologies, enabling researchers to examine complex social phenomena through complementary forms of evidence (Creswell & Plano Clark, 2018). Within this design, quantitative data provided measurable evidence regarding users' social media behaviour and perceptions of algorithmic systems, while qualitative interviews offered deeper insights into the mechanisms through which professionals interpret algorithmic influence in digital communication.

The convergent design was selected because it allows quantitative and qualitative findings to be analysed independently and subsequently integrated during the interpretation stage. This methodological triangulation enhances the credibility of findings by allowing results obtained through one method to complement and contextualize evidence generated through the other. Consequently, the study not only identifies behavioural patterns but also explains the processes underlying those patterns.

The study was guided by three research questions and three hypotheses derived from the theoretical framework presented in the previous chapter. The quantitative component primarily addressed the hypotheses through descriptive statistical analysis, whereas the qualitative component provided explanatory depth regarding users' perceptions and professional interpretations of algorithmic personalization.

4.4 Quantative phase

The quantitative component of the research was conducted using a structured online questionnaire specifically designed for this study. Prior to the main data collection, the questionnaire was pilot-tested with a small group of respondents to evaluate the clarity, logical sequence, and comprehensibility of the questions. Based on participants' feedback, minor revisions were introduced to improve wording and ensure greater consistency before the questionnaire was distributed to the final sample.

The final survey included 100 respondents aged between 18 and 65 years. Participants were recruited using a non-probability convenience sampling strategy, and the questionnaire was distributed online. Participation was entirely voluntary and based on informed consent.

The questionnaire consisted of two principal sections. The first collected demographic information, including gender, age, educational attainment, and place of residence. The second examined behavioural characteristics associated with social media use, including frequency of platform usage, preferred social media platforms, perceptions of algorithmic personalization, trust in social media content, awareness of recommendation systems, and attitudes toward algorithmic transparency and user control. In the questionnaire, transparency and control were assessed as a single combined item ("users should have greater transparency and control over algorithmic recommendation systems"); consequently, the results reported in section 4.4 represent one joint indicator rather than two separately measured constructs.

The objective of the quantitative phase was to identify general behavioural tendencies regarding social media consumption and users' perceptions of algorithmic recommendation systems.

4.5 Qualitative Phase

The qualitative component consisted of semi-structured in-depth interviews with eight professionals employed in fields directly associated with digital communication, including social media management, marketing, and political communication. Participants were purposively selected because of their professional expertise and practical experience in managing digital communication strategies and analysing online audience behaviour.

All interviews were conducted via the Zoom platform and lasted approximately 40–45 minutes. A semi-structured interview guide was employed to ensure consistency across interviews while allowing respondents sufficient flexibility to elaborate on their professional experiences and interpretations.

Interview questions focused on several interrelated themes, including:

- perceptions of algorithmic personalization;
- selective exposure and filter bubbles;
- cognitive biases in digital communication;
- emotional engagement and algorithmic amplification;
- public discourse and information diversity;
- algorithmic transparency and platform accountability.

All interviews were recorded with participants' permission, transcribed verbatim, and anonymized prior to analysis to ensure confidentiality.

4.6 Data Analysis

Quantitative data were analysed using descriptive statistical techniques, including frequencies and percentages, in Microsoft Excel. Descriptive statistics were considered appropriate because the primary objective of the quantitative component was to identify general patterns in respondents' social media behaviour, perceptions of algorithmic personalization, and attitudes toward algorithmic transparency.

The qualitative data were analysed using thematic analysis following the six-phase analytical framework proposed by Braun and Clarke (2006). The analytical process involved familiarization with the interview transcripts, generation of initial codes, identification of recurring themes, thematic review, definition of themes, and interpretation of findings.

Several dominant themes emerged during analysis, including:

- algorithmic personalization;
- confirmation bias;
- selective information exposure;
- emotional amplification;
- fragmentation of public discourse;

- perceived manipulation;
- algorithmic transparency;
- trust and convenience in algorithmic use.

Following independent analyses of both datasets, quantitative and qualitative findings were integrated during the interpretation stage. This process enabled the comparison of statistical trends with professional interpretations, strengthening the explanatory capacity of the study and enhancing the overall validity of the findings.

4.7 Ethical consideration

The study was conducted in accordance with internationally accepted ethical principles governing research involving human participants. Participation in both the quantitative survey and qualitative interviews was entirely voluntary. Before data collection, all participants received information regarding the objectives of the research, the anonymous and confidential treatment of collected data, and their right to withdraw from the study at any stage without negative consequences.

Informed consent was obtained from all participants prior to participation. No personally identifiable information was collected during the survey, and all interview quotations included in this article have been anonymized to protect participants' identities. The study was conducted within the framework of academic research at Alterbridge University in accordance with institutional ethical principles for social science research.

4.8 Methodological Considerations

Although the convergent mixed-methods design provides a comprehensive understanding of algorithmic personalization, the quantitative and qualitative components served complementary rather than identical purposes. The survey identified general behavioural tendencies among social media users, whereas the interviews provided contextual explanations regarding the mechanisms underlying those patterns.

The integration of behavioural data with expert perspectives enabled methodological triangulation, thereby increasing the credibility and interpretative depth of the findings. Rather than treating quantitative and qualitative evidence independently, the present study combines both approaches to construct a more comprehensive explanation of algorithmic influence on perception formation.

4.9 Results

This chapter presents the findings obtained through the quantitative survey and qualitative interviews. Following the principles of convergent mixed-methods research, quantitative and qualitative findings are presented in an integrated manner to provide a comprehensive understanding of how algorithmic personalization influences users' information environments and perception formation. Rather than treating both datasets independently, qualitative evidence is used to explain and contextualize the quantitative findings.

Respondent Characteristics

Table 1 presents the demographic profile of the survey participants.

Table 1. Demographic Characteristics of Respondents (N = 100)

Variable	Category	n	%
Gender	Female	65	65.0
	Male	35	35.0
Residence	Tbilisi	71	71.0

	Other regions	29	29.0
Education	Secondary	28	28.0
	College	32	32.0
	Higher education	40	40.0

The survey sample consisted primarily of female respondents (65%), while approximately two-thirds resided in Tbilisi, Georgia. Participants represented diverse educational backgrounds, although respondents with higher education constituted the largest subgroup (40%). Respondents' ages ranged from 18 to 65 years, consistent with the eligibility criteria of the study; this variable was recorded on a continuous scale rather than in discrete categories and is therefore not presented as a separate row in Table 1. The demographic diversity of the sample provided an appropriate basis for examining perceptions of algorithmic personalization across different categories of social media users.

Social Media Use and Information Behaviour

The survey findings indicate that social media platforms have become the principal source of information for respondents. Facebook remained the dominant platform (64%), followed by Instagram (25%) and TikTok (8%). Furthermore, almost half of the respondents (45%) reported spending between one and three hours daily on social media, while an additional 44% reported spending more than three hours each day combined across the remaining usage categories. These findings suggest that social media occupies a central position within participants' daily information environments.

Rather than functioning solely as communication platforms, social media increasingly serves as the primary gateway through which individuals access news, public affairs, entertainment, and interpersonal communication.

Table 2. Patterns of Social Media Use

Indicator	Category	%
Most frequently used platform	Facebook	64
	Instagram	25
	TikTok	8
	Other	3
Daily social media use	1–3 hours	45
	3–5 hours	27
	More than 5 hours	17
	Other	11
Primary source of information	Social media	72

	Traditional media	11
	Both	8
	Other	9

The dominance of social media as an information source provides an important context for understanding the potential influence of algorithmic personalization. Since nearly three-quarters of respondents primarily obtain information through social media, algorithmic recommendation systems inevitably play a significant role in shaping everyday information exposure.

Algorithmic Personalization and Information Exposure

One of the central objectives of this study was to examine whether users perceive algorithmic personalization as influencing the information they receive through social media platforms. The survey findings strongly support this assumption.

As presented in Table 3, 62% of respondents considered algorithms to have a very significant influence on the information displayed in their social media feeds, while an additional 25% perceived a moderate influence. Moreover, 56% stated that the content appearing in their feeds was highly personalized according to their interests, whereas only 15% believed that personalization was limited. In addition, 38% of respondents reported rarely encountering differing viewpoints in their feeds, and a further 14% reported never encountering alternative perspectives.

These findings indicate that users are generally aware that information exposure within social media is not random but algorithmically curated.

Table 3. Algorithmic Personalization and Information Exposure

Survey Finding	**%**	**Interview Theme**	**Representative quotation**
Algorithms strongly influence information received	62	Algorithms actively determine information visibility	"Today, the user no longer receives information naturally; the algorithm decides in advance what they will see, what they will ignore, and what will hold their attention." (Participant 3, Marketer)
Content is highly personalized	56	Behavioural learning	"The algorithm constantly learns what you watch, what you linger on, and then supplies you with exactly the same type of material, as if no other opinion exists around you at all." (Participant 5, Social Media Manager)

Different viewpoints are rarely encountered	38	Filter bubbles	"When a person sees the same narrative every day, they come to feel that this is the dominant and the only correct position in society." (Participant 2, Political Communication Specialist)
Different viewpoints are never encountered	14	Filter bubbles	(see representative quotations above; theme corroborated across multiple interviews)

The qualitative findings substantially reinforce the quantitative evidence. While survey respondents recognized the influence of algorithmic recommendation systems on information exposure, interview participants explained the mechanisms underlying this process. Across all interviews, professionals consistently described algorithms as active mediators that prioritize content according to previous user behaviour rather than objective informational diversity.

Several respondents emphasized that personalization gradually narrows exposure to alternative viewpoints by continuously reinforcing behavioural patterns. This interpretation provides a theoretical explanation for the survey findings, where more than one-third of respondents reported rarely or never encountering information that challenged their existing perspectives. Rather than deliberately excluding opposing viewpoints, algorithms optimize engagement by recommending content similar to users' previous interactions, thereby increasing the likelihood of selective exposure and filter bubble formation.

Taken together, the finding that 62% of respondents perceive a strong general influence of algorithms on the information they receive provides strong empirical support for Hypothesis 1. The complementary findings that content is perceived as highly personalized (56%) and that differing viewpoints are rarely or never encountered (38% and 14%, respectively) provide corroborating support for Hypothesis 2, as they speak specifically to selective exposure rather than to the broader perception of algorithmic influence addressed in H1.

Trust in Algorithmic Systems and Demand for Greater Transparency

An important objective of this study was to examine whether users trust algorithmically curated content and recommendation systems while simultaneously recognizing the need for greater transparency and user control. The findings reveal an interesting pattern. Although respondents generally expressed considerable trust in both social media content and algorithmic recommendations, they also demonstrated a strong preference for increased transparency and accountability regarding algorithmic decision-making.

As shown in Table 4, 69% of respondents reported trusting information encountered on social media, while 71% indicated high trust in algorithms responsible for selecting content displayed in their feeds. Nevertheless, 79% simultaneously believed that users should have greater transparency and control over algorithmic recommendation systems (measured as a single combined survey item; see section 3.2).

This finding suggests that trust in algorithmic systems does not necessarily imply unconditional acceptance. Rather, respondents appear to recognize both the practical benefits and the societal influence of personalized recommendation systems, creating a demand for greater transparency regarding how information is prioritized and distributed.

Table 4. Trust in Algorithmic Personalization and Perceived Need for Transparency

Survey Finding	%	Qualitative Theme	Representative quotation
Trust social media content	69	Trust and convenience	"Personalization is very convenient, but it is precisely this comfort that turns a person into a passive consumer—they no longer seek out a different opinion because they believe they already know everything." (Participant 7, Marketer)
High trust in algorithms	71	Trust and convenience	"Algorithms save users time by showing information they are most likely to need. The problem is not personalization itself, but the lack of transparency regarding how these decisions are made." (Participant 1, Social Media Manager)
Support greater algorithmic transparency and control	79	Algorithmic transparency	"People trust algorithms because they work efficiently, but efficiency should never replace transparency. Users deserve to understand why particular information reaches them." (Participant 4, Political Communication Specialist)

The qualitative findings explain why trust and demands for transparency coexist rather than contradict one another. Interview participants consistently emphasized that recommendation systems improve user experience by reducing information overload and increasing the relevance of displayed content. However, professionals also argued that personalization becomes problematic when users remain unaware of the mechanisms governing information visibility.

Consequently, respondents' demand for greater transparency and control reflects not a rejection of algorithmic recommendation systems but rather a desire for increased accountability and user autonomy. This distinction is particularly important because it demonstrates that public concern is directed less toward personalization itself than toward the opacity of algorithmic decision-making.

These findings provide partial rather than full support for Hypothesis 3. While the trust component of the hypothesis was clearly supported (69% and 71%), and the demand for transparency and control was even more strongly endorsed (79%), the hypothesis was tested through two conceptually related but separately-worded expectations — stable trust alongside a simultaneous demand for oversight — rather than through a single joint measure capturing both conditions at once. Because the transparency/control item was somewhat higher than the trust items rather than equal to them, the pattern is consistent with, but does not conclusively confirm, the specific co-occurrence proposed in H3. Support is therefore classified as partial pending a future measure that captures trust and demand for transparency within a single instrument.

Cognitive Biases, Emotional Amplification, and Perception Formation

Beyond influencing information exposure, interview participants consistently argued that algorithmic personalization reinforces existing cognitive tendencies by repeatedly presenting users with emotionally engaging and behaviourally relevant content. Across all interviews, respondents emphasized that algorithms prioritize material capable of generating prolonged attention and user interaction, thereby increasing the visibility of emotionally charged information.

Several participants specifically referred to confirmation bias, explaining that users increasingly encounter information that validates pre-existing opinions while contradictory perspectives become progressively less visible.

> *"When you constantly see content that confirms your position, any other opinion starts to seem wrong—or even aggressive." (Participant 6, Social Media Manager)*

This observation complements the quantitative findings presented in Table 3, indicating that 38% of respondents rarely encounter differing viewpoints and 14% reported never seeing alternative perspectives within their social media feeds. Together, these findings suggest that algorithmic personalization may contribute to selective information environments in which repeated exposure reinforces existing beliefs.

Participants further argued that algorithms systematically prioritize emotionally engaging content because emotional reactions increase user engagement.

> *"The more emotional the content, the longer it holds the user's attention, and accordingly the algorithm also distributes it more actively." (Participant 8, Marketer)*

These observations indicate that algorithmic systems may influence perception indirectly by amplifying emotionally salient information rather than objectively important information. Consequently, emotional engagement becomes an important mechanism through which algorithmic personalization affects users' interpretation of social and political events.

Interview participants also discussed the phenomenon of fragmented realities, suggesting that different users increasingly inhabit distinct informational environments.

> *"Two people might be talking about the same event, but have received such different information that it's as if they live in different countries." (Participant 2, Political Communication Specialist)*

This quotation illustrates how algorithmic personalization extends beyond individual information selection to influence collective communication. When different users receive substantially different representations of identical events, opportunities for shared public discourse may become increasingly limited.

Integrated Interpretation of Mixed-Methods Findings

One of the principal strengths of the present study lies in the integration of quantitative and qualitative evidence. Rather than treating survey findings and interview data as independent sources of information, the convergent mixed-methods design enabled the identification of complementary patterns that strengthened the interpretation of the results.

Table 5. Integrated Mixed-Methods Findings

Research Theme	**Quantitative Evidence**	**Qualitative Interpretation**	**Hypothesis**
Algorithmic influence on information exposure	62% perceived strong influence	Algorithms actively determine information visibility	H1 – Supported
Personalized content selection	56% perceived high personalization	Algorithms continuously learn user behaviour	H2 – Supported
Limited exposure to differing opinions	38% rarely, 14% never encountered alternative viewpoints	Filter bubbles and confirmation bias reduce informational diversity	H2 – Supported
Trust in algorithmic recommendations	69–71% expressed high trust	Personalization increases convenience but requires transparency	H3 – Partially Supported
Demand for greater algorithmic transparency and control	79% supported stronger transparency/control	Users seek accountability rather than rejecting personalization	H3 – Partially Supported

The integration of both datasets demonstrates a high degree of convergence between users' perceptions and experts' professional interpretations. Quantitative findings established that respondents recognize the significant influence of algorithmic recommendation systems on information exposure, whereas qualitative evidence explained the cognitive and communicative mechanisms underlying these perceptions. Professionals consistently interpreted algorithmic personalization as an adaptive process that reinforces behavioural preferences, confirmation bias, emotional engagement, and selective exposure.

Importantly, the findings suggest that algorithmic influence should not be interpreted as direct behavioural control. Rather, recommendation systems shape the informational environments within which cognitive biases operate, thereby increasing the probability of particular interpretations and behavioural responses. This interpretation supports the central theoretical argument of the present study and provides a more nuanced understanding of algorithmic influence than deterministic explanations frequently presented in public discourse.

Overall, the findings provide strong support for Hypotheses 1 and 2, while Hypothesis 3 received partial support, for the reasons outlined in section 4.4. Although respondents generally trusted algorithmically personalized content, they simultaneously expressed a clear preference for greater transparency, accountability, and user control. This pattern suggests that contemporary users perceive algorithmic personalization as both beneficial and socially consequential, highlighting the growing importance of transparent algorithmic governance.

Discussion

The purpose of this study was to investigate how algorithmic personalization influences users' information environments and contributes to perception formation within contemporary social media platforms. By integrating quantitative survey findings with qualitative evidence obtained from communication professionals, the study provides a comprehensive understanding of algorithmic influence that extends beyond technological explanations and incorporates cognitive and communicative perspectives.

One of the most significant findings of this research is that users clearly recognize the influence of algorithmic recommendation systems on the information they receive through social media. More than half of the survey respondents perceived algorithmic influence as substantial, while interview participants consistently described algorithms as active mediators of information visibility rather than neutral technological tools. These findings support previous research suggesting that digital platforms increasingly perform gatekeeping functions traditionally associated with journalists and editors (Gillespie, 2014; Napoli, 2019). However, unlike traditional gatekeeping, algorithmic systems continuously adapt information selection according to users' behavioural data, producing individualized information environments that differ considerably across users.

The findings further demonstrate that algorithmic personalization should not be understood solely as a technological process but as an interaction between computational systems and human cognition. This distinction represents one of the principal theoretical contributions of the present study. Existing literature frequently explains algorithmic influence through concepts such as filter bubbles (Pariser, 2011), echo chambers (Sunstein, 2017), or algorithmic governance (Zuboff, 2019). While these perspectives provide important explanations regarding the structural consequences of personalization, the present study suggests that algorithmic influence emerges through the interaction between recommendation systems and pre-existing cognitive biases. Consequently, algorithms do not directly determine what individuals think; rather, they increase the likelihood that particular interpretations become cognitively dominant by repeatedly reinforcing existing behavioural preferences and patterns of information consumption.

The integration of quantitative and qualitative findings further demonstrated that selective exposure remains one of the central mechanisms through which algorithmic personalization influences perception. Survey respondents reported limited exposure to differing viewpoints, while interview participants explained this phenomenon through continuous behavioural learning performed by recommendation algorithms. These findings correspond with selective exposure theory (Stroud, 2011), according to which individuals naturally prefer information consistent with their existing beliefs. The present study extends this perspective by demonstrating that algorithmic systems actively reinforce this tendency through repeated personalized content selection, thereby strengthening confirmation bias and reducing opportunities for exposure to alternative perspectives.

Another important contribution concerns the relationship between algorithmic personalization and emotional engagement. Interview participants consistently emphasized that algorithms prioritize emotionally charged content because such material generates higher levels of user interaction and prolonged platform engagement. This finding supports previous studies demonstrating that emotional content spreads more rapidly within social media environments and receives greater algorithmic visibility (Tufekci, 2015). At the same time, the present study highlights that emotional amplification is not merely an unintended consequence of recommendation systems but rather an inherent feature of engagement-based optimization models. Consequently, emotional intensity becomes a significant mechanism through which algorithmic personalization influences perception and public discourse.

The findings also contribute to ongoing discussions concerning filter bubbles and fragmented information environments. Rather than supporting deterministic interpretations suggesting that users become completely isolated within homogeneous information spaces, the present study indicates a more nuanced process. Respondents continued to encounter differing opinions to varying degrees; however, both quantitative and qualitative evidence demonstrated that repeated exposure to behaviourally congruent information substantially increases the perceived dominance of particular narratives. Thus, the findings support contemporary research arguing that algorithmic personalization modifies the probability of information exposure rather than completely determining individual beliefs.

Perhaps the most intriguing finding concerns the apparent coexistence of trust and scepticism toward algorithmic systems. Although most respondents expressed considerable trust in personalized recommendation systems, they simultaneously advocated greater transparency and stronger user control over algorithmic decision-making. This finding suggests that users increasingly recognize both the practical benefits and societal consequences of algorithmic personalization. Rather than rejecting personalization itself, respondents questioned the opacity of recommendation processes and the limited opportunities available to users for understanding or influencing algorithmic decisions. These observations are consistent with recent discussions regarding algorithmic accountability and digital platform governance, which argue that transparency constitutes a fundamental prerequisite for maintaining public trust in algorithmically mediated communication.

From a theoretical perspective, the present study proposes a conceptual interpretation of algorithmic influence that differs from deterministic explanations frequently encountered in both academic literature and public debate. The findings suggest that algorithmic systems function primarily as cognitive amplification mechanisms. Instead of directly shaping opinions, algorithms repeatedly reinforce existing cognitive tendencies through personalized exposure to behaviourally relevant information. Consequently, perception formation emerges through the interaction between algorithmic recommendation systems and human cognitive processes rather than through technological determinism alone.

This interpretation represents the principal theoretical contribution of the present study. By integrating communication theory with cognitive psychology, the research demonstrates that understanding algorithmic influence requires simultaneous consideration of technological infrastructures and psychological mechanisms of information processing. Consequently, future research examining digital communication should move beyond purely technological explanations and increasingly investigate the reciprocal relationship between computational systems and human cognition.

Study Limitations

Despite providing valuable insights into algorithmic personalization and perception formation, several limitations should be acknowledged when interpreting the findings.

First, the quantitative phase relied on a non-probability convenience sample of 100 respondents. Although this sampling strategy was appropriate for exploratory research, it limits the generalizability of the findings beyond the study population. Future studies should employ probability-based sampling techniques and larger sample sizes to enhance external validity.

Second, the sample was geographically concentrated, with most respondents residing in Tbilisi (71%). Consequently, the findings primarily reflect perceptions of users within one national and urban context. Comparative studies involving respondents from different regions or countries could provide a broader understanding of cultural differences in algorithmic perception.

Third, the study relied predominantly on self-reported perceptions of algorithmic influence rather than direct observation of algorithmic recommendation systems. Since proprietary recommendation algorithms remain inaccessible to researchers, the study examines users' perceptions and experiences rather than the technical operation of recommendation systems themselves.

Fourth, although qualitative interviews provided substantial explanatory depth, only eight communication professionals participated in the interview phase. While thematic saturation was achieved within the scope of the study, future research could include experts from additional disciplines such as computer science, behavioural economics, journalism, and public policy.

Fifth, transparency and user control were measured as a single combined survey item rather than as two independently worded questions. While this simplified the questionnaire for respondents, it also means the study cannot fully disentangle the relative strength of the demand for transparency from the demand for control; future studies should measure these constructs separately.

Finally, social media algorithms continuously evolve in response to technological developments and platform policies. Consequently, users' experiences of algorithmic personalization may change over time, suggesting the value of longitudinal research examining how perceptions develop as recommendation systems become increasingly sophisticated.

These limitations do not diminish the value of the present findings but rather identify important directions for future investigation.

Practical Implications

The findings of this study have several important implications for researchers, policymakers, digital platform developers, educators, and media literacy practitioners.

For policymakers, the results highlight the importance of promoting greater transparency regarding algorithmic decision-making processes. Users increasingly recognize the influence of recommendation systems on information exposure while simultaneously expressing a desire for greater accountability and opportunities to understand how personalized content is selected.

For social media platforms, the findings suggest that improving user trust requires more than technological efficiency. Platforms should consider implementing transparent personalization settings, allowing users greater control over recommendation criteria and increasing awareness regarding the factors influencing content visibility.

The study also has significant implications for media literacy education. Traditional media literacy programmes have primarily focused on evaluating the credibility of information sources. However, the findings demonstrate that contemporary digital literacy must also include algorithmic literacy, enabling individuals to understand how recommendation systems shape information environments, reinforce cognitive biases, and influence everyday information consumption.

Finally, the findings may assist communication professionals, journalists, and digital marketers in developing more responsible communication strategies that balance audience engagement with informational diversity and ethical considerations.

Conclusion

This study examined how algorithmic personalization influences users' information environments and contributes to perception formation within contemporary social media platforms through a convergent mixed-methods research design integrating quantitative survey data with qualitative interviews.

The findings demonstrate that social media algorithms have become influential communication infrastructures shaping information visibility, selective exposure, and perceived relevance of digital content. Users generally recognize the significant influence of personalized recommendation systems while simultaneously expressing strong support for greater transparency and user control over algorithmic decision-making.

Perhaps the most important contribution of the study lies in demonstrating that algorithmic influence should not be conceptualized as technological determinism. Rather, algorithms operate as cognitive amplification mechanisms that reinforce existing behavioural tendencies and cognitive biases through repeated personalized information exposure. Consequently, perception formation emerges through the interaction between computational personalization and human cognitive processes rather than through algorithmic control alone.

By integrating communication studies, cognitive psychology, and digital media research, this article contributes to a more comprehensive understanding of how algorithmic systems shape contemporary information environments. The findings further emphasize the growing importance of algorithmic transparency, digital literacy, and responsible platform governance as essential components of democratic communication in increasingly algorithm-driven societies.

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