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SOCIAL MEDIA RECOMMENDATION ALGORITHMS AS A TOOL FOR COUNTERING DISINFORMATION IN MASS COMMUNICATION AND PR ACTIVITIES

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In the contemporary digital environment, social media platforms act as key channels of mass communication, shaping the ways in which information is disseminated and perceived. Recommendation algorithms play a central role in forming information flows, influencing content visibility and audience behavior. In the context of advertising and PR activities, they become an important tool for managing communications and building trust in information sources. At the same time, their functioning is associated with the risks of spreading disinformation, which necessitates the study of their potential as a means of countering it.

In 2026, social media algorithms function as key intermediaries in the process of information consumption, effectively acting as primary filters of digital content. Platforms such as TikTok and Instagram generate personalized information feeds using complex algorithmic models that analyze user behavioral signals in real time. This leads to a situation in which users do not actively search for information but rather consume pre-filtered content selected by recommendation systems. Accordingly, algorithms become not merely sorting tools but fundamental factors shaping the information environment [9, p. 12].

In this context, the concept of the “filter bubble” acquires a new interpretation. In the era of short-form video content, a filter bubble represents an algorithmically constructed environment in which users are exposed to emotionally engaging videos aligned with their previous interests and interactions. A distinctive feature is the high speed of algorithmic adaptation: even a few seconds of viewing or minimal interaction (such as a like or a pause in scrolling) can significantly influence subsequent content recommendations [9, p. 48]. As a result, a cyclical information environment is formed that reinforces existing preferences while limiting exposure to alternative viewpoints [8, p. 15].

The object of this study is the process of forming personalized feeds on TikTok and Instagram, which is based on the analysis of behavioral, content-related, and social factors. Particular attention is paid to the mechanisms of content selection and ranking

that determine which videos appear in a user's feed, as well as the speed at which these systems adapt to changes in audience behavior.

In the contemporary digital environment, a significant contradiction arises between the commercial objectives of social media platforms and the needs of public safety. Services such as TikTok and Instagram are primarily focused on maximizing user time spent within the application, which is achieved through highly precise content personalization. Algorithms are optimized for engagement metrics, including views, likes, and comments. However, such optimization does not guarantee the reliability or quality of information, thereby creating risks for the dissemination of manipulative or false content.

One of the key challenges is the algorithmic narrowing of users' perspectives. The continuous adaptation of content feeds to prior preferences forms a closed information environment in which users are predominantly exposed to homogeneous content [3, p. 302]. This not only limits access to alternative viewpoints but also creates favorable conditions for the spread of disinformation. Under such circumstances, false or distorted information can quickly become reinforced, as algorithms tend to amplify content that triggers strong emotional responses regardless of its accuracy [12, p. 114].

Another important issue is the low level of transparency of algorithmic systems. Users generally lack a clear understanding of the criteria according to which their feeds are generated, the factors influencing recommendations, and the reasons why certain content is prioritized. As a result, there is a gradual loss of control over one's information environment: users not only consume curated content but are also unaware of the mechanisms behind its selection. This increases dependence on algorithmic decisions and complicates the critical evaluation of information [6, p. 156].

In contemporary academic discourse, recommendation algorithms are considered a key element of the digital media ecosystem that significantly influences the formation of the information environment and user behavior. From the perspective of mass communication theory, algorithms act as new "gatekeepers" that perform the functions of selecting, filtering, and ranking information.

Unlike traditional media, where information selection was carried out by journalists and editors, in the digital environment these functions are automated and based on the analysis of user behavioral data. This leads to a transformation of the communication process from mass communication to personalized communication.

From the perspective of cognitive psychology, algorithms reinforce confirmation bias, as users are more likely to be exposed to information that aligns with their prior beliefs. As a result, a closed information environment is formed, which reduces critical thinking and facilitates the spread of disinformation.

The issue of "echo chambers" and "filter bubbles" in the digital environment originates from the works of Eli Pariser, who introduced the concept of the filter bubble into academic and public discourse as a personalized information space shaped by algorithms based on users' prior behavior [8, p. 22]. In subsequent interpretations, this concept became a theoretical foundation for studying how platforms limit users' exposure to alternative viewpoints and reinforce existing beliefs. More recent

systematic reviews from 2025 indicate that, in contemporary research, the notions of echo chambers and filter bubbles are no longer viewed solely as media-theoretical metaphors but as measurable outcomes of recommendation systems associated with content similarity.

Current technical reports and studies in the field of recommender systems (RecSys) emphasize that platforms increasingly rely on models that predict user interactions with content. In particular, TikTok officially describes its recommendation system as one that considers three main categories of signals: user interactions, content information, and user data. Moreover, the platform explicitly acknowledges that, in certain cases, recommendations are influenced by the behavior of other users with similar interests. This suggests that the system combines both content-based and behavioral signals, potentially accelerating the formation of repetitive thematic cycles.

At the same time, academic publications from 2025 highlight that social media algorithms are optimized for engagement metrics such as clicks, likes, views, and watch time. Such models tend to amplify emotionally charged, conflict-driven, or ideologically aligned content, even when it does not correspond to users' more reflective informational needs. In a broader context, this indicates that engagement-driven ranking architectures not only enhance personalization but also contribute to the confinement of users within narrow information environments [3, p. 305].

Regarding Instagram, official explanations by Meta as of 2025 indicate that the ranking systems for Feed, Explore, and Reels are based on predicting what users will find most relevant and valuable. In particular, the Explore feature is described as using a multi-stage selection model, including retrieval, early-stage ranking, and late-stage ranking. This suggests that Instagram operates as a more distinctly hybrid system, combining signals from the social graph, behavioral indicators, and content characteristics [5].

At the same time, the analysis of existing sources reveals an unresolved issue: despite a significant body of research on echo chambers in general, the mechanisms of content isolation on TikTok and Instagram are often examined in a generalized manner, without sufficient comparative analysis between the platforms. TikTok is typically described as a system that rapidly responds to micro-interactions in a short-form video environment, whereas Instagram functions through a more complex, multi-layered ecosystem involving Feed, Reels, Explore, and social connections. Therefore, the differences in the speed of information narrowing, the types of signals used, and the degree of algorithmic closure between these two platforms remain insufficiently studied and require further dedicated research.

The methodological basis of this study combines comparative, analytical, and systemic approaches. A comparative analysis was used to examine the differences between the recommendation algorithms of TikTok and Instagram. In addition, content analysis of academic sources and platform documentation was conducted to identify the key parameters of algorithmic systems. A systemic approach allowed the algorithms to be considered as elements of a broader mass communication ecosystem.

The recommendation systems of TikTok and Instagram have fundamentally different architectures, which determine the specifics of how users' information environments are formed. TikTok primarily employs a content-based approach, in which key roles are played by content characteristics (such as tags, audio, and topics) and real-time behavioral signals from users. The system rapidly adapts even to minimal interactions, shaping the "For You" feed as a dynamic stream of personalized videos [11].

In contrast, Instagram applies a hybrid model that combines content features, collaborative filtering, and the social graph. This means that recommendations are generated not only based on user interests but also through interactions within their social network. As a result, the information environment is more stable but less responsive to rapid changes in user preferences [9, p. 91].

A key element of TikTok's algorithm is the so-called "interest graph" a dynamic model that is continuously updated based on user behavior [9, p. 48]. Even passive interactions, such as pausing on a video, can signal user interest to the algorithm. The most important metric in this system is watch time, which carries more weight than likes or comments [12, p. 116].

In addition to forming filter bubbles, recommendation systems create several additional risks. These include algorithmic bias resulting from uneven content representation, as well as the virality effect, where false information spreads faster than accurate information. Algorithms tend to amplify emotionally charged content, including fear-inducing, sensational, or controversial messages. This creates a favorable environment for manipulative content, which is often exploited in information warfare.

This mechanism leads to a rapid narrowing of content: if a user interacts several times with a particular topic, the system begins to intensively amplify that type of content. As a result, a radicalization effect of the feed emerges - content becomes increasingly homogeneous, emotionally charged, and often more extreme in nature. Thus, the algorithm optimizes not for diversity but for depth of engagement [12, p. 115].

In Instagram, the "social graph" - a network of subscriptions, interactions, and connections between users - plays a central role [5]. The algorithms behind Feed, Explore, and Reels analyze not only individual user behavior but also the activity of their social environment. This means that content engaged with by a user's close network is more likely to be recommended.

The Explore and Reels mechanisms further expand the information field while simultaneously reinforcing existing interests. The algorithm selects content similar to what the user has previously interacted with, while also considering its popularity among similar user groups [5]. As a result, a more stable "filter bubble" is formed, which evolves more slowly but more deeply reinforces existing perceptions, preferences, and stereotypes.

Within the system of mass communication, recommendation algorithms can be used as effective tools in advertising and PR activities. Through targeting and personalization, it becomes possible to disseminate verified information to specific audience segments. PR strategies may include the creation of trust-based content,

collaboration with opinion leaders, and the integration of fact-checking materials into digital platforms. Combined with algorithmic mechanisms, this approach enhances the effectiveness of countering disinformation and contributes to building a more resilient information environment.

Another important aspect of recommendation systems is their ability to amplify specific types of content through feedback loops. When a user interacts with a particular category of content, the algorithm interprets this behavior as a signal of relevance and increases the frequency of similar recommendations. This creates a self-reinforcing cycle in which certain narratives, including misleading or manipulative ones, can rapidly gain visibility.

This amplification mechanism is particularly significant in the context of disinformation. Content that triggers strong emotional reactions - such as fear, outrage, or curiosity - is more likely to generate engagement, and therefore more likely to be promoted by the algorithm. As a result, disinformation can spread not because of its credibility, but because of its ability to capture attention.

Moreover, the speed at which such amplification occurs differs across platforms. In TikTok, the rapid feedback loop based on micro-interactions allows content to go viral within a very short time frame. In contrast, Instagram's hybrid model leads to a slower but more stable diffusion process, where content spreads through both algorithmic recommendations and social connections.

The increasing reliance on algorithmically curated content has led to a growing dependency of users on recommendation systems. Instead of actively searching for information, users tend to passively consume content selected by algorithms. This shift significantly affects cognitive processes, including attention, perception, and decision-making. As users become more dependent on algorithmic feeds, their exposure to diverse information decreases. This not only limits their understanding of complex issues but also increases their vulnerability to manipulation. In such conditions, disinformation can be perceived as credible simply because it is repeatedly encountered within a personalized information environment.

Furthermore, the lack of transparency in algorithmic processes contributes to this dependency. Users are often unaware of why certain content appears in their feeds, which reduces their ability to critically evaluate the information they consume. This creates a situation where algorithms indirectly shape users' perceptions of reality.

A comparison of TikTok and Instagram algorithms reveals significant differences in the speed of information cycles and the ability to exit a "filter bubble." TikTok is characterized by a high rate of adaptation: the information cycle can become closed after just a few interactions [9, p. 73]. At the same time, this implies that if user behavior changes (for example, through active engagement with a new type of content), the algorithm can quickly adjust its recommendations.

In contrast, Instagram demonstrates a more inertial model. The social graph and accumulated interaction history slow down changes in content recommendations. This makes it more difficult to break out of an established filter bubble. Even when user interests change, the algorithm continues to rely on previous connections and preferences.

In summary, TikTok tends to create fast, dynamic, but potentially more unstable filter bubbles, whereas Instagram forms slower, more stable, and socially embedded information environments (Table 1).

Table 1. Characteristics of Information Environment Formation on TikTok and Instagram [4]

Parameter	TikTok	Instagram
Algorithm Type	Primarily content-based + behavioral signals	Hybrid (content-based + collaborative filtering + social graph)
Key Signals	Views, watch time, likes, swipes	Likes, comments, follows, profile interactions
Adaptation Speed	Very high (responsive to micro-interactions)	Moderate (requires more interaction history)
Content Source	Primarily unfamiliar accounts (For You feed)	Combination of familiar accounts and recommendations
Role of Social Connections	Minimal	High
Risk of Filter Bubble	High due to rapid narrowing of interests	Moderate but stable due to social connections
Mechanism of Isolation	Repetition of similar content based on short-term signals	Reinforcement of existing interests and social network connections
Vulnerability to Manipulation	High (emotionally engaging and viral content spreads rapidly)	Moderate (depends on social connections and interaction patterns)

The differences between TikTok and Instagram algorithms have important implications for information security. TikTok's fast adaptation model increases the risk of rapid disinformation spread, as harmful content can quickly reach a wide audience. However, the same mechanism also allows for faster correction if user behavior changes. In contrast, Instagram's reliance on the social graph makes disinformation more persistent within communities. Once misleading narratives become embedded in social networks, they are more difficult to eliminate. This highlights the need for platform-specific strategies to counter disinformation.

From a broader perspective, both platforms demonstrate that algorithmic design directly influences the resilience or vulnerability of the information environment. Therefore, addressing disinformation requires not only content moderation but also structural changes in recommendation systems (Table 2).

Table 2 – Comparison of Algorithmic Risks

Aspect	TikTok	Instagram
Speed of spread	Very high	Moderate
Stability of narratives	Low	High
Role of social influence	Limited	Strong
Risk of virality	High	Medium
Resistance to correction	Medium	Low

The conducted study confirms that the technical parameters of recommendation systems, particularly engagement metrics, directly influence the formation of "filter bubbles." Algorithms of platforms such as TikTok and Instagram are optimized to

maximize user interaction time with content. This leads to the prioritization of materials that provoke rapid emotional responses and repeated engagement, even if they do not ensure informational diversity or accuracy. As a result, the technical logic of these algorithms effectively contributes to isolating users within a narrow thematic environment (Table 3).

Table 3 – Algorithmic Factors Influencing Disinformation

Factor	Impact on Disinformation
Engagement metrics	Amplify emotional and viral content
Personalization	Limits exposure to diverse viewpoints
Social graph	Reinforces existing beliefs
Watch time	Prioritizes high-retention content

Based on the conducted analysis, the following recommendations can be proposed:

- implementation of algorithms oriented toward content diversity;
- increasing transparency of recommendation systems;
- integration of fact-checking into recommendation feeds;
- development of digital literacy among users;
- use of PR campaigns to promote verified information.

In the context of further automation of recommendation systems, this effect is likely to intensify. With the advancement of artificial intelligence and more accurate behavioral prediction models, algorithms will become even more effective in content personalization, potentially reducing randomness and diversity in information flows. This creates challenges for media literacy, as users will increasingly encounter fewer alternative viewpoints and may gradually lose the ability to critically evaluate information.

Future research and development prospects are associated with the creation of so-called “exploration-oriented algorithms.” Such approaches involve integrating mechanisms that deliberately expand users’ information environments, for example, by introducing random or diverse recommendations, balancing personalization with novelty, and increasing the transparency of algorithmic decision-making. The implementation of such models may become a key step toward reducing the filter bubble effect and improving the overall quality of the digital information environment.

The findings of this study highlight the growing importance of integrating algorithmic understanding into PR and strategic communication practices. In the digital environment, effective communication is no longer determined solely by message quality but also by its compatibility with platform algorithms. PR professionals must adapt their strategies to the logic of recommendation systems by creating content that is both credible and engaging. This includes the use of data-driven targeting, collaboration with trusted influencers, and the strategic timing of content distribution.

At the same time, ethical considerations should remain central to communication practices. The use of algorithms for influence must be balanced with responsibility, transparency, and a commitment to combating disinformation. In this context, PR can play a crucial role not only in promoting brands but also in strengthening the overall quality of the information environment.

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