

Analysis of the Psychological Mechanisms of Online Group Polarization from a Big Data Perspective

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Abstract: Recommendation algorithms use behavioural data to customise content delivery, reduce the diversity of information, strengthen the information cocoon effect, and drive group opinions towards the extremes. Psychologically, the demand for cognitive closure is systematically stimulated; Social comparison bias and deindividuation effects combine to form opinion resonance, and emotional contagion mechanisms accelerate the spread of extreme views. A BERT-LDA fusion model is introduced in this paper to conduct structured analysis of typical public opinion events on Weibo, a three-stage polarization evolution model of "Algorithm Reinforcement–Cognitive Shift–Emotional Resonance" is built, and the psychological mechanism is quantitatively verified. At the level of governance, a three-dimensional coordinated approach of algorithm optimisation, psychological intervention and institutional coordination is needed to address the root causes of generation and spread of online group polarisation.

Keywords: Online Group Polarization; Information Cocoon; Cognitive Closure; Emotional Contagion; BERT-LDA Model

1. Introduction

With the development of large-scale social media platforms and their application of big data technology, the processes of generation and dissemination of public opinion have changed significantly. Based on the behaviour data of users, the platform's recommendation algorithm continuously constructs a high-homogeneity information environment, confines individuals in a structural information enclosure, and promotes the convergence of group opinion towards the extremes. Online anonymity reduces the restrictions of social norms, increases the risk of deindividuation, and lowers the threshold for polarisation. Most of the previous research on online group polarisation has concentrated on

the path of spread and platform structure, failed to systematically explore the underlying psychological reasons^[1, 2], and only offered weak quantitative evidence. This paper integrates the core theories of cognitive and social psychology, introduces a BERT-LDA fusion model for empirical analysis, constructs a three-stage polarization evolution model of "Algorithm Reinforcement–Cognitive Shift–Emotional Resonance," and offers practical references for opinion governance on digital platforms.

2. Conceptual Definition and Big Data Characterization of Online Group Polarization

2.1 Reconstructing the Meaning of Group Polarization from a Big Data Perspective

In 1969, Moscovici and Zavalloni first put forward the idea of group polarisation to describe the phenomenon where, after a group discussion, the opinions of its members tend to move closer to the extremes. In the era of big data, polarisation is no longer only the result of face-to-face group interaction; rather, it is also caused by the combined effects of algorithmic logic, data environment and psychological mechanism. Platform recommendation systems collect users' behaviour data, and based on this information, continuously provide content that suits the user's interests and automatically promote opinion homogeneity in the technological system. This mechanism fundamentally changes the conditions for the occurrence of polarisation and provides new features of scalability, concealment and self-reinforcement that traditional theories of polarisation are no longer adequate to explain^[3].

2.2 Behavioral Characteristics and Data Patterns of Online Polarization

Political problems, public security cases and value-conflict contents are highly polarised and activating of topics. Generally speaking, the

main development of changes in polarisation occurs within 72 hours after a public opinion event, and this process follows a pattern of "rapid aggregation - sustained reinforcement". In terms of dissemination structure, polarised communities have dense, closed internal connections and very little cross-community information flow; they form what are known as "echo chambers" (see Figure 1).

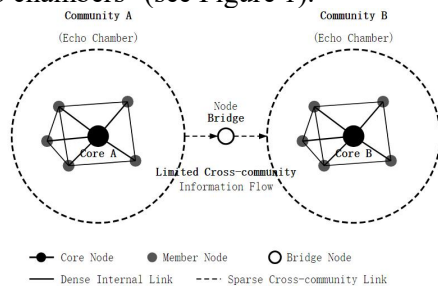


Figure 1. Schematic Diagram of Online Polarization Dissemination Structure

2.3 Limitations of Existing Research and Construction of an Analytical Framework

The three deficiencies of the current research are as follows: First, the explanation of psychological mechanisms is generally limited to single-variable analysis, and an integrated account of the interactive effects among algorithms, cognition, and emotion is lacking; Second, most of the research methods are content analysis and questionnaire surveys; Third, there is no systematic model that incorporates both psychological mechanisms and algorithmic logic in a unified theoretical system. In light of the above, this paper establishes the three-stage polarisation evolution model of "Algorithm Reinforcement–Cognitive Shift–Emotional Resonance" (see Figure 2) as the main analytical system for the following analysis to enable an all-encompassing understanding of the psychological reasons for polarisation.

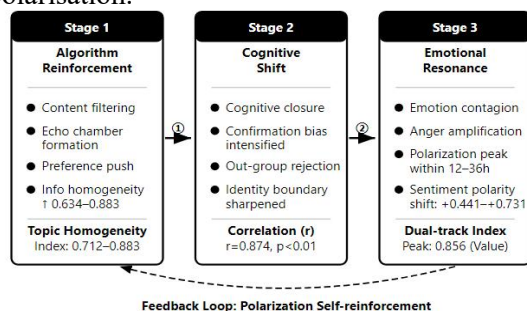


Figure 2. Three-Stage Polarization Evolution Model of Algorithm Reinforcement–Cognitive Shift–Emotional Resonance

3. Mechanisms of Polarization Generation Driven by Algorithms and Cognitive Psychology

3.1 Pathways Through Which Recommendation Algorithms Reinforce the Information Cocoon

The main goal of a recommendation algorithm is to increase a user's time spent on the platform and interaction frequency; thus, it may conflict with the desire for diverse information. Algorithms use users' behaviour data to map preferences with collaborative filtering and deep-learning models, continuously recommend highly similar content, form a closed feedback loop of "preference input - content reinforcement - preference fixation", and restrict the scope of information exposure over time. The attenuation pattern can be shown by the formula:

$$D(t) = D_0 \cdot e^{-\lambda t} \quad (1)$$

$D(t)$ is the information diversity index for a user in week t , D_0 is the baseline information diversity before personalised recommendation, λ is the algorithm-driven diversity decay coefficient ($\lambda > 0$), and t is the time (in weeks) the user has been exposed to the personalised recommendation environment. According to research, the average number of opinion types that users encounter in a personalised recommendation environment decreases by about 34% after six weeks, and the systematic erosion of information diversity provides the structural soil for the formation of cognitive biases (see Table 1).

Table 1. Quantitative Features of Recommendation Algorithm Reinforcement for Information Cocoon

Indicator	Non-Personalized Recommendation	Personalized Recommendation (After 6 Weeks)	Change
User Opinion Contact Diversity Index	0.78	0.51	↓34.6%
Cross-Stance Content Exposure Rate	42.3%	18.7%	↓55.8%
Homogeneous Content Repetition Rate	23.1%	61.4%	↑165.8%
User Opinion Polarization Score (1–10)	4.2	6.8	↑61.9%

3.2 Positive Coupling Between the Need for Cognitive Closure and Group Polarization

Kruglanski's concept of the Need for Cognitive

Closure (NCC) in 1989 is the psychological desire people have to find a simple answer and avoid uncertainty in life. In a homogeneous information environment constructed by algorithms, high-NCC users are more likely to believe the one-way dissemination of information from the system without verification, develop closed-minded views rapidly, and ignore contradictory data. Neurocognitive research shows that people who are repeatedly exposed to the same type of information have reduced activation of the prefrontal cortex during processing of different views, and as a result, show structural changes in cognition. Algorithms limit the scope of information, and NCC-driven avoidance of heterogeneous content thus forms a mutually reinforcing positive feedback loop that exacerbates the problem of polarisation^[4].

3.3 The "Algorithm–Cognition" Dual-Drive Polarization Generation Model

The working mechanism of the "algorithm–cognition" dual-drive model is as follows: Recommendation algorithms continuously reduce the diversity of information through technical means (external drive), thus activating and strengthening users' need for cognitive closure (internal drive); the two are interconnected and work together to push group opinions towards the extremes. This model shows the dual mechanism of polarisation generation: with only algorithmic drive and no cognitive bias, the polarisation effect would be countered by individual rational correction; with only high-NCC individuals and no algorithmic reinforcement, the extent of polarisation would be limited by the diversity of real-world social networks. It is precisely because of the joint action of both that online polarisation has exceeded the intensity and speed predicted by previous studies^[5].

4. Analysis of Social-Psychological Mechanisms in the Evolution of Group Polarization

4.1 The Superimposed Effects of Social Comparison and Deindividuation

According to Festinger's theory of social comparison, when people are unsure of their own opinions, they will observe what other people think. In the context of online polarisation, the homogenous communities

created by algorithms provide a very consistent reference system for comparison; therefore, individuals are inclined to align with and moderately exceed the position of the main group in the comparison process, resulting in a gradual change in opinion. The deindividuation effect is further promoted by the anonymity of the Internet; reduced individual responsibility lowers the psychological cost of extreme behaviour, and thus, the group norm's tolerance for such speech is extended. The two mechanisms work together to provide structural support for the outer end of the group, and as a result, the entire position of the group can quickly move to the far-end anchor point^[6].

4.2 Emotional Contagion Mechanisms and the Logic of Extreme Opinion Diffusion

Hatfield et al. systematically presented the concept of emotional contagion in 1993, which refers to the spread of emotions among people through social interaction. Algorithms have significantly enhanced the traffic amplification effect in the online environment to some extent. Platform recommendation logic favours the distribution of high-emotion-intensity content, and anger-type information spreads about 2.7 times faster than neutral information; this has been verified by many studies in computational communication. With the rapid spread of emotions, what was once a difference of rational thought has become an emotional group division; cognitive judgment has yielded to emotion-driven stance identification, and thus, extreme views have been widely disseminated by bypassing rational scrutiny^[7].

4.3 Empirical Verification of Polarization Mechanisms Using the BERT-LDA Model

To quantify the above psychological mechanisms, a BERT-LDA fusion model was used to conduct structured analysis of six representative public opinion events on Weibo from 2022 to 2023 (a total of about 3.2 million text data entries). LDA topic modelling is used in the model to extract the distribution of discussion topics, and BERT performs fine-grained annotation of the emotional polarity and stance orientation of the text; the two-level outputs are cross-validated to generate a dual-track polarisation index that covers both the cognitive dimension (topic homogeneity) and the emotional dimension (distribution of sentiment polarity) (see Table 2). Based on empirical

results, value-conflict and social-equity events have relatively higher composite polarisation indices (0.856 and 0.839, respectively), and there is a significant positive correlation between topic homogeneity and sentiment polarity shift ($r = 0.874$, $p < 0.01$); thus, both reinforcement of cognitive closure and emotional resonance drive change simultaneously.

Table 2. Quantitative Analysis Results of Polarization for Six Representative Public Opinion Events (BERT-LDA Model Output)

Event Type	Topic Homogeneity Index	Sentiment Polarity Shift	Composite Dual-Track Polarization Index	Time of Peak Polarization
Political Controversy	0.847	+0.693	0.821	18h after incident
Public Safety	0.791	+0.612	0.764	24h after incident
Value Conflict	0.883	+0.731	0.856	12h after incident
Celebrity Controversy	0.634	+0.441	0.598	36h after incident
Technology Ethics	0.712	+0.528	0.681	30h after incident
Social Equity	0.856	+0.702	0.839	15h after incident

Note: Results are based on the computational analysis of 2022-2023 Weibo public opinion data using the BERT-LDA model.

5. Collaborative Governance Pathways for Online Group Polarization

5.1 Information Diversification Interventions at the Algorithm Level

At the level of algorithms, governance can be achieved by modifying the objective function of recommendation to include constraints for information diversity. A "viewpoint diversity penalty term" can be added to the collaborative filtering model: if the system determines that the degree of homogeneity in a user's information exposure exceeds a predetermined limit, it will automatically activate a mechanism for mandatory cross-stance content exposure, and at the same time, an emotional intensity filtering module can be set up to reduce the transmission rate of content with strong emotions. The first

type of solution is to substitute the single objective of 'maximising platform participation' with a multi-objective balancing function of 'participation-diversity-emotional stability', and rebuild structural pluralism in the information ecosystem at the technical architecture level^[8].

5.2 Fostering Psychological Resilience and Correcting Cognitive Biases

Governance at the psychological level aims to improve the public's media literacy regarding algorithmic logic and enhance their own recognition of cognitive biases. According to research, users who have participated in algorithmic literacy training show a reduction of about 22% in their cognitive closure tendency scores and a corresponding increase in proactive cross-stance information-seeking behaviour. Critical Information Consumption Skills can be integrated into the system of media literacy education in educational practice to cultivate metacognitive abilities that help individuals recognise confirmation bias and emotion-driven judgments. Inoculation theory has shown excellent practical results in this area: by exposing people to a weakened form of polarised content in advance and teaching them counter-argument strategies, their psychological defence against polarisation can be strengthened effectively.

5.3 A Three-Dimensional Collaborative Governance Framework: "Technology-Psychology-Institution"

All single-dimension governance methods have defects: algorithm intervention without institutional constraints can be easily reversed due to commercial interests, and psychological intervention without technical support cannot reach highly polarised users. Therefore, a three-dimensional cooperative system of "Technology-Psychology-Institution" should be established: the technology dimension will promote mandatory disclosure of platform algorithm transparency and set up a third-party audit mechanism; the psychology dimension will institutionalize media literacy education in the national education system; and the institutional dimension will create a pluralistic collaborative regulatory system involving platforms, governments and civil society, with clear division of responsibilities for each party. Together, the three dimensions form a closed-loop governance system for the whole

chain of "technological infrastructure - individual cognition - institutional norms".

6. Summary

Online group polarisation is an intricate social phenomenon that results from the combination of algorithmic logic and psychological factors. According to the construction of the "algorithmic reinforcement → cognitive shift → emotional resonance" three-stage polarisation evolution model, this paper systematically reveals the path through which recommendation algorithms strengthen information cocoons, the positive coupling mechanism between the need for cognitive closure and algorithms, and the collaborative logic of three social-psychological mechanisms: social comparison, deindividuation, and emotional contagion. Empirical verification by means of the BERT-LDA fusion model shows that value conflict issues have the highest composite polarisation index, and the synergistic effect of the emotional and cognitive dimensions is significant; thus, a replicable methodological framework for quantitative research on the psychological mechanisms of polarisation has been provided. At the level of governance, the three-dimensional cooperative framework of "technology-psychology-institution" is employed to determine the type of intervention at the three levels—algorithmic structure, individual cognition, and institutional constraints—and is highly feasible in practice. Looking ahead, the application of generative artificial intelligence will drive down the cost of producing divisive content to almost nothing and thus worsen the problems of polarisation governance. In the future, research can be conducted to explore construction paths for real-time polarization early-warning systems and deepen cross-cultural comparative studies to offer more forward-looking theoretical support for the governance of the digital age.

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