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The Social Impact and Cross-cultural Analysis of Short-Video Recommendation Algorithms on TikTok

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Abstract: *As short-video platforms become deeply embedded in global digital life, recommendation algorithms have emerged as a core force shaping contemporary information dissemination and user cognition. From the perspective of communication studies, this paper adopts the narrative literature review method to systematically sort out the mechanism, social impact and cultural differences of short-video algorithms represented by TikTok/Douyin. The study finds that: firstly, the relationship between algorithms and users is not one-way control, but a two-way dynamic feedback loop of "data input - algorithm prediction - behavior adaptation"; secondly, while promoting the democratization of content production, economic empowerment and knowledge popularization, recommendation algorithms have also triggered profound social risks such as digital addiction, political polarization and algorithmic discrimination; thirdly, the large-scale application of generative AI is extending the power of algorithms from "content distribution" upstream to "content production", exacerbating the governance difficulty of copyright infringement and the proliferation of misinformation. Finally, a comparison based on Hofstede's cultural dimension theory shows that the algorithmic logic of Douyin and TikTok reflects deep cultural differences between the East and the West in collectivism/individualism and power distance. This paper argues that short-video algorithms are not value-neutral technical tools. Future algorithm governance needs to strike a balance in transparency, embedded pluralistic values and international collaboration, so as to rebuild users' digital subjectivity under the "algorithmic gaze".*

Keywords: *TikTok; recommendation algorithm; algorithm-user interaction; digital addiction; political polarization; generative AI; deepfake; copyright infringement; cross-cultural comparison*

1. Introduction

In 2024, TikTok's global monthly active users exceeded 2.1 billion, with an average daily video playback volume of over 34 billion times; the Chinese version Douyin has more than 700 million daily active users, deeply embedded in the daily life of hundreds of millions of people. Approximately 34 million videos are uploaded to TikTok every day, making it impossible for any human editorial team to conduct substantive screening of such content. It is algorithms that perform the function of information filtering. [1]

The history of media technology shows that the information dissemination paradigm has undergone a profound evolution from the "subscription model" (users hold high subjectivity), "social graph dissemination" (diffusion along interpersonal networks) to "algorithmic distribution". TikTok has pushed the third paradigm to the extreme. The classic "gatekeeper" theory in communication studies has been completely reconstructed in the algorithmic context: algorithms are divorced from traditional public accountability mechanisms, lack understanding of content meaning and social ethics, and only take quantifiable indicators such as maximizing user engagement as the sole optimization goal. This structural power shift constitutes a core hidden danger in contemporary digital society. Algorithms affect billions of people's access to information everywhere, yet are completely outside public accountability mechanisms, and have no ability to understand content meaning and social value, only optimizing quantifiable behavioral indicators. [2]

Entering 2025, the large-scale deployment of generative AI has further complicated this issue: AI-generated content accounts for more than 52% of the total Internet content (European Parliament Research Service, 2025), and algorithms are no longer just content conveyors, but deeply involved in content production itself. [3]

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Against this background, the communication structure of short-video platforms gradually presents a feedback loop among "algorithms, users and content": user behavior continuously trains algorithm models, and algorithms in turn shape users' attention and content production direction through recommendation mechanisms. It is in this circular mechanism that short-video platforms not only unleash unprecedented communication potential, but also breed new social risks. Therefore, understanding the social impact of the TikTok algorithm cannot be limited to technical description, but requires a comprehensive analysis from the dimensions of communication structure, social consequences and cultural differences.

Based on this thinking, this paper first analyzes how short-video platforms build a highly adaptive information distribution system through continuous data backflow and behavior prediction, starting from the two-way feedback loop between algorithms and users. On this basis, the second part sorts out the dual social effects brought by short-video recommendation algorithms: on the one hand, they promote the democratization of content production, create new economic opportunities, and expand the boundaries of educational communication; on the other hand, their logic centered on maximizing attention may also induce addictive use, political polarization and potential algorithmic discrimination. The third part extends the perspective to the technological frontier, combining the copyright disputes and personal data risks caused by ByteDance's generative video model Seedance 2.0, to explore how generative AI reshapes the short-video ecosystem under the blessing of algorithms and further strengthens the structural power of platform algorithms. Finally, taking Hofstede's cultural dimension theory as the analytical framework, this paper compares the algorithm governance and content distribution logic of Douyin and TikTok in Eastern and Western contexts, and explains the differentiated operation of the same technical system in different social environments from the level of cultural values.

Based on the above analysis, this paper finally concludes that: the recommendation algorithms deeply rooted in short-video platforms, as new Gatekeepers, have exerted a profound impact on social structure, cultural values and political economy. However, as algorithm creators, technology companies still prioritize profit incentives over user well-being, resulting in chaos such as copyright infringement and political polarization. This paper calls for collaborative reforms in technological design, regulatory systems and business models to truly make algorithms serve and benefit people.

2. Research Methods

This paper adopts the narrative literature review method to comprehensively sort out studies related to the TikTok recommendation algorithm. Literature is mainly sourced from Web of Science, Scopus and Google Scholar databases. Search keywords include "TikTok algorithm", "recommendation system", "algorithmic recommendation", "filter bubble", "algorithm awareness", "short-video platform", etc. The time range of literature is mainly 2019-2025, combined with some early classic theoretical literature as the theoretical background. In the screening process, peer-reviewed journal papers, systematic reviews and authoritative research reports are prioritized, and duplicate or low-evidence materials are excluded.

The selected literature covers recommendation architecture [4], generative AI and misinformation [3][5][6][7], problematic TikTok use and mental health [8][9], political communication [10][11][12], creator economy [1][13][14], filter bubbles and user awareness [2][15][16][17][18][19][20][21][22][23], educational communication [24], surveillance capitalism [25], cultural dimensions [26], and online public opinion governance [27].

3. The Mutual Influence Between Algorithms and Humans: A Two-Way Dynamic Feedback Loop

A common misconception among some people is to describe the impact of algorithms on users as a one-way manipulation relationship. However, a large number of empirical studies reveal a complex two-way dynamic picture: user behavior continuously shapes algorithms, and changes in algorithms in turn reshape user behavior. The two form an inclusive and continuously evolving feedback loop. Understanding the complete structure of this loop is a theoretical prerequisite for grasping the social impact of algorithms.

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3.1. Operation Mechanism of Recommendation Algorithms and Their Impact on Users

The recommendation system of short-video platforms is usually operated based on a large-scale machine learning ranking system. The platform first constructs an individual interest profile through user behavior data (such as dwell time, likes, comments, reposts, follows, watch completion rate, etc.), and uses deep learning models to predict the user's engagement probability for candidate videos. The system then sorts massive content in real time according to the prediction score, and pushes the videos most likely to trigger interaction to the "For You Feed". Each time a user watches, swipes or dwells, it is instantly recorded and returned to the training data, thereby continuously updating model parameters and forming a dynamic loop of "behavior data - algorithm prediction - content distribution - behavior feedback". [4]

It is in this continuous self-optimizing circular mechanism that the impact of algorithms on users gradually penetrates from the behavioral level to the cognitive level, and then extends to the self-cognition level, presenting a three-layer penetration structure from the outside to the inside.

At the behavioral level, algorithms directly intervene in user behavior patterns through the Variable Intermittent Reinforcement (VIR) mechanism. The recommendation system does not guarantee that high-value content appears every time you swipe, but maintains users' continuous refreshing through probabilistic reward distribution. Each swipe down is similar to a bet with unknown reward probability, and this uncertainty constitutes the most powerful psychological driving factor for sustaining behavior. [20][21]

At the cognitive level, algorithms continuously narrow the scope of users' information exposure through the positive feedback loop of "interest reinforcement - interest confirmation". The recommendation model preferentially pushes content highly similar to the user's historical behavior, thereby gradually improving content homogeneity. A 2025 ScienceDirect study found that 42% of heavy TikTok users can perceive content repetition within five days, but still exhibit continuous addictive use even when aware of the "filter bubble". Researchers named this phenomenon "Algorithmic Fatigue": users are tired of repetitive content but cannot leave the platform. [2][15][18]

At the self-cognition level, the TikTok algorithm gradually participates in constructing the user's "Algorithmized Self" by continuously pushing content matching the user's existing interests and identity tags. A 2023 systematic review in MDPI Social Sciences pointed out that users' self-cognition and values gradually converge to "what you should like" as defined by algorithms; interviewed users stated that "they have never been able to fully control their digital selves". [16][23]

3.2. Users' Game and Shaping of Algorithms

However, users are not completely passively shaped by algorithms. Given that recommendation systems rely heavily on behavioral signals for model training, user behavior itself can reversely affect the algorithm's content judgment criteria.

At the content creator level, they optimize video structures for platform algorithms. For example, key information or plot climaxes are deliberately placed at the end to extend audience dwell time and improve video completion rate. Completion rate is an important indicator for short-video platforms to evaluate content quality, because a higher watch completion ratio is usually regarded by algorithms as a signal of high user engagement. [13]

At the ordinary user level, such algorithm game behaviors are mainly manifested in two typical strategies. First, some users will deliberately concentrate likes or watch a certain category of content for a long time to make the algorithm change the content of the recommendation feed. This behavior takes advantage of the recommendation system's dependence on engagement signal weights, that is, the algorithm continuously adjusts the interest prediction model according to the user's watch time, interaction frequency and click behavior. Second, ordinary users may use so-called "Algospeak" to avoid platform content review. Algospeak usually refers to expressions that replace sensitive words with homophones, abbreviations or symbols, such as using pinyin, emojis or number combinations instead of keywords that may be identified by the system, so as to reduce the probability of being detected by the automatic review system.

These strategies indicate that platform users are not mere algorithmic objects, but to a certain extent become influencers in the algorithmic environment.

However, this game relationship does not really weaken the structural power of platform algorithms.

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On the contrary, users' strategic behaviors often further provide new behavioral data for algorithms, thereby strengthening the training process of recommendation models and making algorithms more refined in understanding user behavior patterns. In other words, even if there are attempts to "manipulate algorithms" on the surface, the relationship between users and algorithms is still in a continuously self-reinforcing feedback loop.

3.3. Structure and Intervention Points of the Two-Way Loop

Synthesizing the above two directions, this paper summarizes existing research as the "spiral cycle between algorithms and users". This framework describes a three-stage dynamic closed loop (As shown in table 1) .

Table 1. Three-Stage Dynamic Feedback Loop between Algorithms and Users

Stage	Mechanism Description	Specific Performance
Stage 1: Behavioral Signal Input	Users' viewing, liking and commenting generate data signals in real time	Completion rate, replay times and swipe speed become core feature inputs
Stage 2: Algorithm Learning and Adjustment	Algorithms update interest models based on signals and adjust the next round of recommendations	Dynamic update of interest graph; preferences amplified and solidified
Stage 3: User Behavior Adaptation	Users receive adjusted content, and behavior patterns are further strengthened	Increased usage duration; narrowed interests; adjusted self-cognition

Source: Compiled from ScienceDirect (2025), UW News (2024), Concordia University (2024). [13][17][20]

The "breakthrough point" of this closed loop lies in external intervention. Experimental data (ScienceDirect, 2025) shows that after switching personalized recommendations from high to low personalization, users' average daily usage duration decreased by about 40%, sense of control score increased by 87%, and automatic use behavior and task procrastination both decreased significantly. This indicates that the effective means to break the closed loop is not to require users to exercise self-restraint (which has little effect under physiological driving), but to reduce the intensity of personalization at the algorithm design level or improve users' metacognitive ability through education. [17]

4. Advantages and Disadvantages of Short-Video Recommendation Algorithms and Their Social Impact

4.1. Advantages

The clear advantages of recommendation algorithms are: weakening the information gatekeeping structure of traditional media, shifting from traditional emphasis on the number of fans to content quality, increasing exposure opportunities for more ordinary content creators, and promoting the decentralization of information distribution; at the same time, a large number of high-quality content brought by emerging content creators further contributes to economic growth for regions or countries; in addition, algorithms have built-in special streaming mechanisms for educational and popular science content to promote knowledge popularization; in addition, algorithms help minority groups form a sense of belonging and provide personalized experiences for a wide range of users.

4.1.1. Decentralization of Content Distribution

Short-video recommendation algorithms are reshaping the power structure of traditional content distribution and information acquisition. In classic communication theory, information dissemination has long been controlled by "Gatekeepers": newspaper editors, TV producers or platform operation teams decide which content can enter the public communication space. This structure concentrates communication resources in a few media institutions and top creators.

However, TikTok's recommendation system has weakened this traditional gatekeeping structure to a certain extent. The platform's content distribution does not mainly rely on the user's existing social network or fan base, but is based on the real-time prediction of user interests by machine learning models. The system first pushes newly released videos to a limited initial traffic pool (usually about hundreds of users), and evaluates content quality according to key behavioral indicators such as completion rate, like rate and interaction rate. If these indicators reach a certain threshold, the video will be further pushed to a larger user group, thus forming a tiered distribution mechanism.

Under this logic, the core evaluation criterion for content communication has shifted from "number of fans" in traditional social media to "content performance". A zero-fan account can be continuously amplified by algorithms and eventually reach millions of users as long as it obtains a sufficiently high completion rate in the initial traffic pool. This mechanism significantly lowers the threshold for content to enter public communication space, enabling marginalized groups, niche cultures and emerging creators to gain more exposure opportunities. From the perspective of communication structure, this algorithm-driven distribution model reflects the combination of decentralized distribution and Long Tail distribution: a large number of "niche content" that was originally difficult to enter the mainstream media system finds their respective audiences through algorithm matching.

4.1.2. Economic Empowerment

The decentralization of content distribution provides employment opportunities for a large number of video creators and creates commercial value.

According to the 2025 Creator Economy Report, TikTok creators earned approximately US$4.1 billion in total revenue in 2024, and this figure is expected to rise to US$5.7 billion in 2025, with more than 1.5 million creators achieving professional development. The simultaneous growth in the number of creators and revenue scale confirms that the platform has indeed expanded the opportunity structure for creators to participate in the market at the content production end. [1]

In the commercial field, algorithm distribution has also created new market entrances for small and medium-sized enterprises. A report by Oxford Economics pointed out that small and medium-sized enterprises in the United States generated approximately US$14.7 billion in revenue through TikTok in 2023, the platform's contribution to the US GDP reached US$24.2 billion, and it indirectly supported nearly 5 million jobs. Survey data shows that 39% of small and medium-sized enterprises consider TikTok crucial to their business, and 69% of enterprises reported sales growth after using TikTok. [14]

These data confirm at the economic level that algorithms not only change the content production and distribution structure, but also reshape the paths for creators and small and medium-sized enterprises to enter the digital market. In other words, by shifting the content distribution logic from "relationship network" to "interest matching", short-video recommendation systems have weakened the traffic monopoly of traditional media and top accounts to a certain extent, thus promoting the relative democratization of the digital content ecosystem.

4.1.3. Educational Communication and Knowledge Popularization

TikTok has shown undeniable positive communication effectiveness in the educational field. Official platform data shows that educational content experienced explosive growth in 2024: STEM popular science creators achieved cross-circle knowledge dissemination through exclusive streaming mechanisms. For example, the teacher group has formed a strong resonance among Generation Z through the "TeacherTok" series of content, and influential teacher bloggers are using algorithms to reach a large number of young people aspiring to education. [24]

4.1.4. Personalized Entertainment Experience and Community Sense of Belonging

From the user experience perspective, highly personalized recommendations significantly improve content consumption satisfaction. A 2025 ScienceDirect experimental study confirmed that users' entertainment experiences in four dimensions—personal relevance, enjoyment, meaningfulness and time distortion—under highly personalized recommendations are significantly better than those under low-personalization recommendations. For specific groups such as overseas Chinese and ethnic minorities, native language and traditional custom content pushed by algorithms based on cultural tags are an important link for maintaining cross-regional cultural identity and have a practical community cohesion function. [17][19]

4.2. Disadvantages

The disadvantages are as obvious as the advantages. Algorithms increase user usage duration through Variable Intermittent Reinforcement (VIR), leading to addiction; in addition, filter bubbles caused by algorithms actively isolate users from opposing views, enhancing ideological polarization,

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which is obvious in the far-right; in addition, algorithms may reduce active streaming for marginalized groups due to biases intentionally or unintentionally implanted by developers or later learning, and strengthen the distribution of emotional content, leading to superficial, vulgar and emotional content.

4.2.1. Addiction Mechanism and Mental Health Damage

Addictive behavior induced by algorithms is the most criticized negative impact. With completion rate as the core optimization indicator, algorithms, together with the infinite scroll design, realize the complete replication of the VIR mechanism: the dopamine peak is triggered in the expected stage of "reward anticipation", making it difficult for users to stop using spontaneously driven by physiological levels.

Quantitative evidence is highly consistent. A 2024 meta-analysis published in PMC integrated data from 26 studies (11,462 participants) on the correlation coefficients between problematic TikTok use and various mental health indicators as shown in Figure 1. The key finding of the study is that problematic use (rather than mere usage duration) is a stronger predictor of mental health damage, indicating that the core problem lies not in "how long to use" but in "how to use". [8][9]

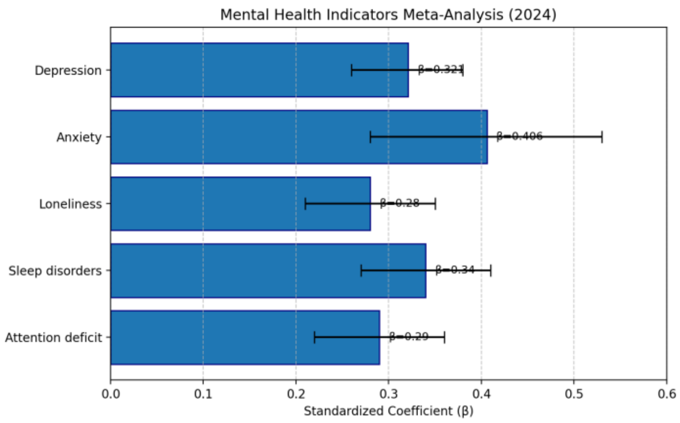

Figure 1. Correlations Between Problematic TikTok Use and Mental Health Indicators

Source: PMC meta-analysis (2024), integrating 26 studies; $p<0.001$.

Adolescents are particularly vulnerable. A joint Spanish study found that about 20% of adolescents use TikTok for more than two hours a day, the risk threshold, with girls (24.4%) significantly higher than boys (15.5%). A study including 1,346 adolescents with an average age of 14.97 years showed that problematic users performed significantly worse than non-problematic users in multiple dimensions such as depression, anxiety, loneliness, academic performance and sleep quality. The phenomenon of "Digital Dementia" recorded by Korean researchers is an extreme manifestation of this trend: some heavy Internet users aged 10 to 19 experience cognitive degradation such as inability to remember phone numbers.

4.2.2. Political Polarization

The impact of recommendation algorithms on ideology occurs through the "Filter Bubble" mechanism. Collaborative filtering, based on the assumption that "similar users like similar content", preferentially pushes content types that have historically triggered high interactions, gradually enclosing users in a homogeneous information environment. This limits content diversity, accelerates users' acceptance of a single viewpoint as truth, makes them more easily incited by emotional content, and ultimately forms extreme ideologies. [2][15]

Quantitative studies provide a clearer picture of political polarization. A computational study by Li et al. (2025) based on more than 160,000 TikTok accounts and 16 million videos found that right-leaning communities exhibit higher network isolation than other political groups; conservative users rarely follow accounts holding opposing views or mainstream media. An audit experiment for the 2024 German general election showed that the TikTok algorithm pushed users more and more content consistent with their initial political positions over time. The Harvard Kennedy School (2025) analyzed 51,680 political videos during the 2024 US presidential election and found that "toxic political content" containing insulting and harassing language consistently received higher interaction weights than non-toxic content. Algorithms reward political anomie speech at the structural level, providing a convenient channel for the spread of extremist narratives. [10][11][12]

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4.2.3. Algorithmic Discrimination

The personalization mechanism of algorithms creates inequality at the content level.

At the content dimension, content such as LGBTQ+ and specific ethnic cultures have been historically recorded to suffer from implicit traffic limiting or review bias; sample bias in training data and cognitive limitations of developers encode existing social biases in the real world into recommendation systems, forming a Matthew effect of algorithmic discrimination.

At the ecological level, the algorithmic logic centered on interaction rate creates a "bad money drives out good" effect: content with strong emotional stimulation naturally has higher completion rates and interaction rates, occupying an advantage in the traffic pool promotion competition; while in-depth analytical content is at a disadvantage in algorithm scoring due to requiring sustained attention. Algorithms cannot even distinguish positive comments from negative harassment, because both are "effective interaction signals" to the system. This lays a fundamental hidden danger for the algorithmic amplification of hate content. In the long run, the content ecosystem may drift towards superficiality, emotionality and vulgarity, exerting a profound cumulative negative impact on the quality of public discourse.

5. The Impact of Generative AI Under the Blessing of Algorithms

To date, ByteDance owns two technologies at the information production and distribution ends: recommendation algorithms and generative AI. Its potential vertical integration capability, that is, seamlessly injecting large-scale AI-generated synthetic content into TikTok's algorithmic recommendation pipeline, may crowd out the living space of real creators and form a platform ecological reversal of "AI content replacing human expression". Therefore, this section attempts to explore the advantages and disadvantages of generative AI Seedance under the blessing of algorithms. [4]

5.1. Positive Impact: Extending the Democratization of Creation

The positive impact of generative AI on the TikTok ecosystem is a technological extension of the algorithm's decentralized empowerment logic. AI video generation tools greatly reduce the technical threshold and capital cost of high-quality content production: no professional equipment is needed, and visually attractive short videos can be generated through text prompts, enabling more creators lacking technical resources to participate in content production.

5.2. Negative Impact

5.2.1. Negative Impact 1: Copyright Infringement

ByteDance's AI video generation model Seedance 2.0 was officially released in February 2026, triggering a collective backlash from the Hollywood film and television industry within days, becoming the most representative generative AI copyright crisis to date. Seedance 2.0 allows users to generate high-quality short videos through text prompts. After its release, a large number of user-generated content of strictly copyrighted IP images spread rapidly on social media. Algorithms became catalysts for promoting infringing content: since algorithms only focus on quantitative data rather than value judgments, many high-quality infringing videos continued to break through and gain widespread dissemination. Eventually, the massive production of AI content may crowd out the living space of real creators, forming a platform ecological reversal of "AI content replacing human expression". [5]

5.2.2. Negative Impact 2: Large-Scale Diffusion of Deepfakes

Deepfake is the most widely spread and threatening application form of generative AI in the TikTok ecosystem. Deepfake videos have increased by more than 550% since 2019: about 500,000 were spread on social media in 2023, and Deloitte predicts this number will rise to 8 million in 2025; AI-driven fraud losses are expected to increase from US$12.3 billion in 2023 to US$40 billion in 2027 (compound annual growth rate of 32%). TikTok's recommendation algorithm, which prioritizes highly emotionally stimulating content, is naturally highly compatible with deepfake content, promoting the large-scale diffusion of the latter. A Recorded Future study showed that AI-generated deepfake content was recorded in 30 countries holding national elections between July 2023 and July 2024, including a fake audio recording of President Biden calling on voters to abstain from voting (2024 New Hampshire

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primary, USA). [6][7]

5.2.3. Negative Impact 3: Personal Privacy and Surveillance Capitalism

The data collection logic of generative AI embodies the typical characteristics of surveillance capitalism. Referring to Shoshana Zuboff's theory of "Surveillance Capitalism", this process essentially transforms human subjective experience into predictable and manipulable behavioral commodities. Under this mechanism, individual attention and emotional responses are alienated into raw production materials for the platform, while users, as data subjects, have their right to know and control substantially weakened in the black-box operation of algorithms. The scope of data collected by the platform has significantly exceeded the functional boundaries required for video distribution, covering high-dimensional modalities such as precise GPS trajectories, biometrics (such as facial and voiceprints), device identifiers, and even keyboard input patterns. Through complex algorithm processing, these fragmented data are integrated into extremely accurate user profiles, which can not only reveal individuals' immediate consumption preferences, but also predict their political tendencies and psychological vulnerabilities. [25]

5.3. Differences in Short-Video Recommendations Under Different Cultural Backgrounds

5.3.1. Theoretical Framework: Hofstede's Cultural Dimensions

Algorithms are not value-neutral technical tools, but carriers of developers' cultural values and business logic encoded. Hofstede's cultural dimension theory is one of the effective ways to analyze the differences between Douyin and TikTok. [26]

Figure 2 illustrates the cultural-dimension comparison used to interpret the differences between the TikTok and Douyin recommendation contexts.

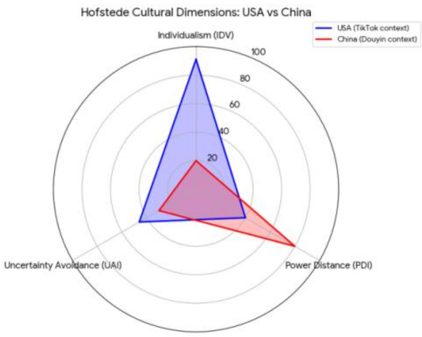

Figure 2. Hofstede Cultural Dimensions: USA vs. China

Source: Hofstede Cultural Dimensions Database; algorithm impact analysis synthesized from *Theoretical Exploration, Telematics and Informatics, International Journal of Communication*. [22][23][26][27]

Individualism vs. Collectivism (IDV) In China, under the collectivist culture emphasizing "group identity", the Douyin algorithm gives additional recommendation weights to group empathy content such as family emotions, festival folk customs and patriotic narratives. This is not just a passive reflection of user preferences, but a value preset actively embedded in the algorithm. In contrast, TikTok, facing the international community, has a recommendation logic centered on individual interests, with the optimization goal of personal immersion experience, so it tends to push niche subcultures, personal style display and other self-differentiated content.

Power Distance Index (PDI) In China's high power distance culture, users have a higher acceptance of the platform "choosing for me", and strong algorithmic intervention instead reduces decision-making anxiety. This provides a cultural soil for Douyin's design of forcibly injecting official media content into the recommendation stream. Users not only do not resist, but even regard it as a reflection of the platform "being responsible for me". In the low power distance Western context, the same design will immediately trigger public opinion backlash of "algorithmic manipulation", which is one of the most sensitive issues when TikTok faces regulatory pressure in Europe and the United

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States.

Uncertainty Avoidance Index (UAI) Low uncertainty avoidance means that users have a higher acceptance of "unknown content", which is highly compatible with Douyin's algorithm strategy of "strongly pushing cold content": Douyin will actively push content that users have never been exposed to into the recommendation stream to test potential interests. In the localized adaptation of TikTok in Western markets, it relies more on users' clear interest signals and reduces the proportion of "forced circle-breaking" recommendations, which is to a certain extent an adaptation to the higher uncertainty avoidance tendency of Western users.

5.3.2. TikTok vs. Douyin: Differences in Operation Strategies and Algorithmic Logic

Although TikTok and Douyin share the underlying recommendation algorithm framework developed by ByteDance, the two platforms show differences in content strategy, algorithm parameter tuning, social functions and business models. The following table aims to show a cross-sectional comparison of the global version and the Chinese version of TikTok in 8 different dimensions, demonstrating the localized characteristics of algorithms. Table 2 summarizes these cross-cultural differences in platform operation strategies and algorithmic logic.

Table 2. Cross-Cultural Comparison between TikTok and Douyin

Comparison Dimension	TikTok (Global Version)	Douyin (Chinese Version)
Main Cultural Orientation	Global diversity, openness and inclusiveness, cross-cultural interaction	Local priority, cultural adaptation, emotional identity
Content Ecology Orientation	Cross-cultural innovation, entertainment, self-expression	Local customs, practical information, family emotions, main theme
Core Algorithmic Logic	Personalized matching of global content diversity	Weighting of local cultural content, integration of official narrative guidance
Depth of Commercial Functions	Mainly entertainment and creativity, e-commerce functions gradually enhanced	Deep integration of entertainment, information, social interaction and e-commerce
Preference for Influencer Content	Music, entertainment, creative categories	Daily life, product recommendations, practical tips
Purchase Behavior Conversion Rate	Relatively low	Significantly higher (algorithms integrate e-commerce conversion goals)
Weight of Mainstream Media Content	Relatively low	Significantly higher (algorithms integrate publicity and guidance mechanisms)
User Participation Motivation	Self-expression, cultural exploration, entertainment	Community belonging, cultural identity, access to practical information

Source: Synthesized from *Theoretical Exploration* and Hofstede's cultural dimension framework.

5.3.3. Enlightenment of Cultural Comparison: Algorithms Are Both Mirrors and Shapers of Culture

There is a two-way causal relationship between algorithms and culture: algorithm design reflects cultural values (developers consciously or unconsciously encode cultural presets into the system when setting optimization goals); algorithms in turn continuously shape culture (users exposed to specific

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recommendation logic for a long time are subtly influenced in information contact patterns and value frameworks).

A particularly noteworthy intergenerational drift finding is that in a survey of young Douyin users in China, the individualism dimension score is higher than that of American peers, and the power distance dimension score is lower than that of American samples (CRISTIANO FELACO, 2025). This is completely contrary to the prediction of traditional Hofstede theory. This suggests that digital media algorithms themselves are participating in reshaping the cultural value system of young generations. Algorithms are not only passive recorders of cultural differences, but also active promoters of cultural changes. [23]

6. Conclusion

6.1. Core Findings

This paper conducts a systematic investigation on the social impact of the TikTok recommendation algorithm in multiple dimensions, and the core findings can be summarized as follows.

First, the relationship between algorithms and humans is two-way dynamic rather than one-way. While being shaped by algorithms, users also reversely train algorithms through conscious or unconscious behaviors. Second, the advantages of short-video algorithms are obvious: democratization of content empowerment, potential of educational communication, and improvement of personalized entertainment experience are all quantifiable real positive effects. However, the realization of these advantages is premised on the priority of the platform's commercial goal (maximizing engagement). Once personal well-being conflicts with the platform's commercial logic, algorithms invariably choose the latter. Third, the harm of algorithms is huge. The addiction mechanism intervenes in the dopamine circuit through the VIR principle, exerting an impact below the level accessible to user consciousness; political polarization narrows the information horizon through accumulation rather than single persuasion; algorithmic discrimination is produced by both training data bias and commercial logic. Fourth, the intervention of generative AI penetrates the algorithmic impact from the distribution layer to the production layer. Copyright infringement and deepfake content spread widely under the blessing of recommendation algorithms. Fifth, Eastern and Western algorithms reflect deep cultural values and power structure differences, and are continuously participating in reshaping the cultural value system of young generations through algorithms, forming an undeniable cultural geopolitical dimension.

6.2. Limitations

This paper's understanding of recommendation algorithms is still biased towards macro-functional description rather than technical essence. 2. This paper attempts to use Hofstede's cultural dimensions from the 1970s to explain 21st-century digital platforms, which carries the risk of theoretical obsolescence. 3. This paper attempts to analyze "surveillance capitalism" but ignores the ongoing competition for traffic stock. The drawbacks of algorithms (such as addiction) often stem from the growth pressure of the capital market. Without discussing the mandatory intervention of financial report pressure on algorithm parameters, this paper cannot touch the root cause of the problem. 4. This paper downplays the potential reasons behind the cultural differences reflected by algorithms: the great power game for digital sovereignty.

6.3. Epilogue: Rebuilding Humanistic Subjectivity in the Algorithmic Age

The position of this paper is not technological pessimism, but prudent critical intervention. Algorithms are products of human wisdom, and their optimization goals and value presets can be redesigned; regulatory frameworks are expressions of social contracts and can be continuously updated through democratic consultation; digital literacy is the foundation of cognitive sovereignty and can be cultivated through education. However, achieving these changes requires overcoming profound structural obstacles: the inherent contradiction between platform commercial incentives and users' long-term well-being, the institutional gap between the limitations of regulatory power and the global mobility of digital technologies, and the cognitive inequality caused by the uneven distribution of public algorithm awareness.

Perhaps the most fundamental proposition is not how to "restrict" algorithms, but how to redefine the goals that algorithms serve. When the core incentive of the platform is to maximize engagement

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rather than user well-being, all technical optimizations may yield to commercial logic. Promoting the shift of algorithms from "engagement maximization" to "user well-being maximization" requires collaborative reforms in three levels: technological design, regulatory systems and business models, which is a necessary path to place humans at the center of algorithm design beyond a single technologist perspective.

For media studies researchers, this requires maintaining a theoretical space between the precise description of technical mechanisms and the critical investigation of social impacts, so as to provide knowledge support for public policies beyond the "myth of algorithm neutrality". For every digital citizen, understanding how algorithms affect you and how you inadvertently participate in its construction is the first and most important step to maintain subjectivity under the algorithmic gaze.

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