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RESEARCH ARTICLE

Big data analytics on the reinforcement of regional stereotypes and collective identity formation in cultural tourism short video diffusion

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ABSTRACT

Against the backdrop of short videos becoming the dominant medium for culture and tourism information dissemination, this study focuses on the dual mechanisms of regional stereotype reinforcement and group identity formation driven by big data algorithms. Employing a mixed-methods approach, through content analysis of 3,200 culture and tourism short videos, questionnaire surveys of 800 audiences, and in-depth interviews, this research systematically examines the interactive relationships among algorithmic recommendations, content production, and audience cognition. The findings reveal: First, culture and tourism short videos exhibit significant symbolic concentration characteristics, with natural landscapes, local cuisine, and folk customs accounting for 73.34% of symbols, while dramatized narratives and emotional appeal strategies are employed at rates exceeding 80%, providing a content foundation for stereotype reinforcement. Second, algorithmic recommendations drive content homogenization through information cocoons and echo chamber effects, with the content similarity index climbing from 0.342 to 0.891 within eight weeks and high-traffic content surging by 303%. Third, audience regional perceptions demonstrate systematic biases, with virtual and actual experiences differing by an average of 1.39 points in ratings, stemming from cognitive mechanisms such as availability heuristics and representativeness bias, moderated by identity backgrounds and media literacy. Fourth, group identity forms through three-level coordination: individual cognitive activation, group symbolic interaction, and platform technological support, with high-interaction users achieving identity strength of 8.62 points, accompanied by significant group polarization phenomena (polarization index increasing by 170%). Fifth, cross-regional interactions are driven by psychological motivations including self-esteem maintenance and uniqueness needs, manifesting diverse patterns of confrontation and cooperation across different contexts. This study reveals the deep coupling mechanism of technology, content, and psychological processes, providing theoretical foundations and practical insights for optimizing culture and tourism communication strategies and promoting diverse presentations of regional images.

Keywords: culture and tourism short videos; big data algorithms; regional stereotypes; group identity; algorithmic recommendation; cognitive bias; group polarization; social identity theory

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1. Introduction

In contemporary society where digital media is deeply embedded in daily life, short videos have become the dominant form of culture and tourism information dissemination, profoundly reshaping the public's regional cognitive schemas and spatial imagination. Short video platforms represented by Douyin and Kuaishou, leveraging the precise recommendation mechanisms of big data algorithms, efficiently deliver fragmented and visualized regional symbols to massive user bases, demonstrating unprecedented influence in cultural communication and tourism marketing. Liu Taisong et al.'s research on traditional Chinese medicine culture short videos on the Douyin platform reveals the unique advantages of short videos in cultural dissemination, a communication model equally applicable to the diffusion of culture and tourism content[1]. With continuous optimization of video transmission technology, from security improvements based on chaotic systems to quality enhancement based on deep neural networks, technological progress provides a solid foundation for efficient short video dissemination[2]. However, while algorithm-driven content distribution mechanisms enhance dissemination efficiency, they also bring potential risks such as content homogenization and stereotype solidification[3]. When specific symbols of a region are repeatedly pushed by algorithms due to high interaction rates, the diverse and complex regional culture is often simplified into singular labels, with stereotypes—originally serving as cognitive shortcuts—gaining unprecedented reinforcement under technological empowerment. This phenomenon not only affects external audiences' perceptions and evaluations of regions but also catalyzes group identity and intergroup boundaries based on regional identity between local residents and outsiders, with the underlying social psychological mechanisms urgently requiring systematic academic inquiry.

Examining from the perspectives of environmental psychology and social identity theory, the reinforcement of regional stereotypes and the formation of group identity result from the interactive effects of individual cognitive processing and social construction processes. On one hand, human processing of complex environmental information relies on simplification mechanisms of cognitive schemas, with stereotypes serving as a cognitive economic strategy helping individuals rapidly categorize and understand unfamiliar regions. Short videos, with their intense visual impact and emotional arousal capabilities, repeatedly present specific regional symbols, deepening audiences' stereotypical cognition through availability heuristics and repeated exposure effects. On the other hand, social identity theory indicates that individuals obtain positive self-concepts through belonging to specific groups, with regional identity as an important dimension of social categorization being endowed with new forms of expression in digital communication. When culture and tourism short videos present regional characteristics in symbolized and labeled forms, local residents often regard these symbols as markers of group identity, reinforcing in-group identification through interactive behaviors such as liking, commenting, and sharing, while generating group boundary awareness through comparisons with other regions. This process involves not only cognitive biases at the individual level but also relates to social categorization, intergroup comparison, and collective action at the group level, constituting a multi-level, dynamic psychological and social mechanism system.

The coupling of technological logic and social psychology makes big data algorithms a key mediating variable in regional stereotype reinforcement and group identity formation. Algorithmic recommendation systems construct user profiles and predict content preferences by capturing data such as viewing duration, liking behavior, and comment content, then push similar content to form "information cocoons." This personalized recommendation mechanism, while satisfying user interests, also limits the diversity of information exposure, causing users to repeatedly encounter homogenized regional presentations, thereby cognitively reinforcing specific impressions. Peng Qi and Liu Wen point out in their research on viral news short video dissemination that systematic construction is key to enhancing communication effectiveness, and in the culture and tourism short video domain, this systematization often manifests as content creators' imitation and replication of popular elements, with algorithms further incentivizing such conformity through traffic allocation[4]. Zhang Binghan's analysis of mainstream media short video communication strategies in the intelligent media era suggests that understanding algorithmic logic holds important significance for optimizing communication practices, equally applicable to examining algorithms' role in regional cognitive construction[5]. The development of video transmission technology, whether performance optimization of free-space optical communication or construction of video transmission tools for telemedicine in Africa, has laid the technical foundation for widespread short video application[6]. More complexly, algorithms not only affect content distribution but also influence social interaction patterns among users by constructing specific interactive fields[7]. In comment sections, users with similar regional cognition or identity gather to form "virtual communities," reinforcing common positions through discursive interaction, and even generating group competitive psychology in cross-regional comparisons. Therefore, revealing how big data algorithms influence regional stereotypes and group identity through mechanisms such as content filtering, traffic allocation, and interaction shaping becomes the core concern of this research.

This study aims to integrate theoretical resources from environmental psychology, social identity theory, and algorithmic sociology to construct an integrated framework explaining regional stereotype reinforcement and group identity formation in culture and tourism short video communication. Through a mixed-methods approach combining big data content analysis, audience surveys, and in-depth interviews, this research will systematically examine the presentation characteristics of regional symbols in culture and tourism short videos, the operational mechanisms of algorithmic recommendations, audiences' cognitive processing processes, and the dynamic formation pathways of group identity. Specifically, the research will address the following core questions: How do culture and tourism short videos present regional images through symbol selection and narrative strategies? How does the recommendation logic of big data algorithms influence content homogenization and audience exposure patterns? Under what psychological mechanisms do audiences accept, internalize, or resist regional stereotypes? How is group identity based on regional identity generated and reinforced in digital interactions? Answering these questions will not only deepen theoretical understanding of regional cognitive construction in the digital age, revealing the complex interactive relationships among technology, content, and psychological processes, but also provide optimization strategies for culture and tourism communication practices, promote diversified presentation of regional images, and offer empirical evidence for algorithmic governance and media literacy education. In a broader sense, this research focuses on how digital technology reshapes human spatial perception, identity, and intergroup relations, holding important theoretical and practical value for understanding cultural communication, social cohesion, and conflict management in algorithmic society.

2. Literature review

Research on the mechanisms of regional stereotype reinforcement and group identity formation in culture and tourism short video communication requires integrating theoretical resources from multiple disciplines including communication studies, psychology, and sociology. Existing literature has explored related issues from multiple dimensions such as technological communication effects, content presentation strategies, audience cognitive mechanisms, and social psychological processes, laying a solid theoretical foundation for this study. However, a comprehensive review of existing research reveals that academia has devoted considerable attention to short video transmission technology optimization and communication strategy innovation, yet systematic theoretical explanations and empirical examinations of the psychosocial mechanisms of regional cognitive construction under algorithmic drive, particularly the intrinsic connections between stereotype reinforcement and group identity formation, remain lacking.

From the technological communication perspective, big data and algorithmic technology have profoundly transformed the production, distribution, and reception processes of short videos, providing technical support for efficient content dissemination. Wen's research explores the possibility of improving short video transmission effects based on Internet of Things node technology; although this study focuses on technical-level transmission optimization, it does not deeply examine the potential impacts of technological optimization on content ecosystems[8]. In fact, improved transmission efficiency means that more homogenized content can cover broader audiences in shorter time periods, creating technical conditions for the rapid diffusion of regional stereotypes. Chen Tong's analysis of factors influencing science popularization short video communication effects suggests that the interactive effects of content characteristics, platform algorithms, and user traits jointly determine communication effectiveness, a framework equally applicable to understanding the construction process of regional cognition in culture and tourism short videos[9]. Zhang Fan et al., through constructing a mainstream media short video data analysis and visualization platform, reveal the critical role of data-driven approaches in optimizing communication effects, with this technological empowerment enabling content creators to precisely adjust communication strategies based on user behavioral data[10]. However, the application of this technological logic in the culture and tourism domain presents dual effects: on one hand, algorithmic recommendations enable culture and tourism content with regional characteristics to precisely reach target audiences, expanding the dissemination scope of regional culture; on the other hand, algorithms' preference for high-interaction content leads to repeated pushing of homogenized content, with specific regional symbols gaining traffic advantages due to their entertainment value or exotic appeal, thereby forming reinforcement loops under technological empowerment. International scholars' research on video transmission technology, such as Miyatake et al.'s discussion of frequency reuse transmission technology[11], and Nunome et al.'s research on caching decisions for QoE enhancement in video-audio transmission in ICN/CCN networks, although focused on technical-level transmission optimization, fundamentally aims to enhance user experience quality, and this improvement in experience quality objectively enhances the persuasiveness and memorability of video content, making the regional symbols embedded therein more easily accepted and internalized by audiences[12]. Therefore, technological communication research needs to transcend pure focus on transmission efficiency and communication effects, turning toward examining how technological logic shapes specific regional cognitive schemas through content filtering and traffic allocation mechanisms.

Regarding communication strategies and content presentation, academia has conducted in-depth explorations of short videos' narrative techniques, visual rhetoric, and interactive mechanisms. Zhang Yaohui, in discussing short video news communication strategies in the big data context, points out that data analysis can help identify audience preferences and achieve personalized content pushing, thereby enhancing communication efficiency[13]. Wang Zeren analyzes mainstream media short video communication strategies from the interaction ritual chain perspective, emphasizing the core role of emotional resonance and symbolic interaction in constructing communication rituals[14]. This theoretical perspective holds important implications for understanding regional stereotype reinforcement: when culture and tourism short videos present regional characteristics through dramatized narratives and exaggerated expressions, the emotional arousal and collective attention generated during viewing constitute a "virtual presence" ritual experience, and the continuous repetition of this experience reinforces specific regional cognitive frameworks. International researchers' technical explorations in video transmission, such as Ranjith et al.'s analysis of energy efficiency and reliability of high-quality video transmission architecture in wireless sensor networks[15], Mathiazhagan et al.'s discussion of enhanced algorithms for underwater video transmission[16], and Khan et al.'s optimization research on video transmission in UAV-relay-assisted public safety networks, although achieving important progress at the technical level, rarely address the deep impacts of technological logic on content ecosystems and audience cognition[17]. Ren Ying, in discussing short video communication strategies in the new media era, points out that visualization, emotionalization, and interactivity of content are key elements for enhancing communication power, but the application of these strategies in the culture and tourism domain often leads to excessive presentation of regional "spectacles," with complex and diverse regional cultures simplified into easily disseminated visual symbols[18]. Wu Yasi's research on technical optimization of short video news communication reveals the shaping effect of technical means on content presentation forms, with high-definition image quality, special effects processing, and intelligent editing not only enhancing viewing experience but also amplifying the visual impact of specific regional symbols, thereby reinforcing stereotypes at the perceptual level[19]. Notably, communication strategy research needs to focus on how content presentation methods interact with audience cognitive processing, particularly how the selection of visual symbols and construction of narrative frameworks guide audiences in forming specific regional cognitive schemas.

From the theoretical perspectives of cognitive psychology and environmental psychology, the formation and reinforcement of regional stereotypes result from the cognitive economy principle operating in individual information processing. Stereotypes, as a type of cognitive schema, help individuals rapidly categorize and understand complex social information, but this simplification process also easily leads to cognitive biases. In the short video communication context, fragmented and high-frequency content presentation makes availability heuristics play an important role: when specific symbols of a region repeatedly appear in users' information feeds, the psychological availability of these symbols increases, and individuals, when recalling or judging regional characteristics, are more inclined to rely on this easily retrievable information, thereby forming or reinforcing stereotypes. The mere exposure effect further explains why homogenized content from algorithmic recommendations can deepen regional cognition: repeated exposure to identical or similar regional presentations not only enhances familiarity but also increases trust and acceptance of these presentations. Confirmation bias causes individuals who already hold certain regional impressions to, when encountering related content, be more inclined to attend to, remember, and disseminate information that confirms their existing beliefs while ignoring or devaluing contradictory information. This mechanism is further amplified under the operation of algorithmic recommendation systems: algorithms push content based on users' historical behavior, effectively reinforcing users' existing preferences and cognitive tendencies, forming a "filter bubble" effect. Place attachment theory in environmental psychology provides another important perspective for understanding regional cognition, emphasizing the emotional connection between individuals and specific geographical spaces, a connection composed of place identity, place dependence, and social bonds. In mediated regional experiences, although audiences have not actually visited a location, they can develop a form of "quasi-place attachment" through the visual presentation and emotional narratives of short videos, and this virtual emotional connection influences individuals' attitudes and behavioral tendencies toward that region. However, when the regional images presented in short videos are highly stereotyped, this quasi-place attachment may be established on a distorted cognitive foundation, leading to gaps between expectations and reality.

Social identity theory provides the core theoretical framework for understanding group identity formation. This theory posits that individuals define their self-concepts by categorizing themselves as members of specific social groups, and maintain positive social identity through in-group favoritism and out-group prejudice. Regional identity, as an important dimension of social categorization, has acquired new forms of expression and reinforcement mechanisms in the digital communication environment. When culture and tourism short videos present regional characteristics in symbolized forms, local residents often regard these symbols as markers of group identity, expressing group belonging through interactive behaviors such as liking, commenting, and sharing, a process that reinforces in-group identification. Simultaneously, in the context of cross-regional comparison, competitive psychology between different regional groups is activated, manifesting as emphasis on local advantages and deprecation of other regions, with this intergroup comparison further solidifying group boundaries. The minimal group paradigm research in social identity theory demonstrates that even group divisions based on trivial criteria can trigger in-group favoritism, and regional identity, as a classification dimension with objective foundations and cultural connotations, forms more naturally and intensely. In interactive spaces such as short video comment sections, users with similar regional identities or positions gather to form "virtual communities," reinforcing common positions through discursive interaction and creating an "echo chamber effect," which not only consolidates internal group identification but also intensifies opposition to out-groups. Notably, algorithmic recommendation mechanisms, by aggregating users with similar viewpoints around the same content, objectively promote homogeneous interaction and suppress the exchange of diverse opinions, thereby catalyzing group polarization at the technical level. Progress in video transmission technology, such as Abbood et al.'s proposed energy-efficient method for distributed video transmission in wireless multimedia sensor networks[20], and Ishioka et al.'s traffic optimization research on speculative video transmission in cloud gaming systems, although primarily focused on transmission efficiency and resource optimization, enables short videos to reach users more efficiently through these technical innovations, providing infrastructural support for high-frequency and real-time group interactions[21].

Although existing literature has explored short video communication, regional cognition, and group identity from multiple angles, significant research gaps remain. First, technological communication research primarily focuses on macro-level issues such as transmission efficiency and communication effects, with limited attention to the deep impacts of technological logic on content ecosystems and audience cognition. Second, communication strategy research mostly concentrates on enhancing communication effectiveness, lacking critical reflection on potential cognitive biases and social psychological consequences arising from the communication process. Third, although cognitive psychology and social psychology have conducted in-depth research on stereotype and group identity mechanisms, these theories have rarely been applied to analyzing algorithm-driven digital communication environments, particularly lacking systematic examination of how technological mediation transforms traditional cognitive and social processes. Finally, existing research often treats regional stereotype reinforcement and group identity formation as independent phenomena explored separately, insufficiently revealing the intrinsic connections between the two: how stereotype reinforcement provides cognitive foundations for group identity, and how group identity formation conversely promotes selective acceptance and active dissemination of stereotyped content. Therefore, this study aims to bridge these theoretical and empirical gaps by constructing an analytical framework integrating technological logic, content strategies, and psychological mechanisms, systematically revealing the complex interactive mechanisms of regional stereotype reinforcement and group identity formation in big data-driven culture and tourism short video communication, and providing new theoretical insights for understanding regional cognitive construction and intergroup relations in the algorithmic age.

3. Research methods

3.1. Research design

This study adopts a mixed-methods approach, organically combining quantitative and qualitative research pathways to comprehensively reveal the complex mechanisms of regional stereotype reinforcement and group identity formation in culture and tourism short video communication. The research design follows a three-dimensional analytical framework of "content-algorithm-audience." First, through large-scale data collection and computational analysis techniques, it systematically examines the presentation patterns of regional symbols in culture and tourism short videos and the operational logic of algorithmic recommendations. Second, employing questionnaire survey methods, it quantitatively measures audiences of different backgrounds' perception levels of regional stereotypes and group identity strength, testing causal relationships among key variables. Finally, through in-depth interviews and focus group discussions, it deeply explores the psychological processes of audience cognitive processing and the micro-dynamics of group interaction[22]. The entire research unfolds according to the progressive logic of exploratory analysis, confirmatory examination, and interpretive understanding. At the theoretical level, the research integrates place cognition theory from environmental psychology, social identity theory from social psychology, and agenda-setting and framing theories from communication studies, constructing an explanatory model to elucidate the interactive pathways among algorithmic mechanisms, content characteristics, and audience psychology. At the operational level, the research is implemented in three stages: the first stage is the content analysis stage, collecting culture and tourism content samples from mainstream short video platforms and employing coding analysis and semantic mining techniques to identify high-frequency regional symbols and their presentation patterns; the second stage is the survey research stage, designing structured questionnaires to measure audiences' regional impressions, group identity intensity, and media use behaviors, and employing statistical modeling methods to test hypothetical relationships; the third stage is the qualitative research stage, exploring the formation causes of individual cognitive differences through semi-structured interviews and observing the dynamic processes of identity construction in group interactions through focus groups[23]. The research findings from the three stages mutually corroborate and progressively advance, jointly constituting a multidimensional answer to the research questions. The research process strictly adheres to academic ethical standards; all participants in surveys and interviews are informed of the research purpose and sign informed consent forms, personal information is strictly confidential, and data are used solely for academic analysis.

3.2. Research subjects and sampling

The research subjects of this study encompass two levels: culture and tourism short video content samples and short video platform users, employing a strategy combining stratified sampling and purposive sampling to ensure sample representativeness and research focus. In content sample selection, Douyin and Kuaishou, two mainstream short video platforms, serve as data sources, with culture and tourism short videos published between January 2023 and December 2024 selected as analytical objects. Sample screening criteria include: video content clearly involving specific regional culture, landscapes, cuisine, or folk customs; view counts exceeding 100,000; and possessing obvious regional identifying symbols[24]. Through keyword searches and topic tag filtering, approximately 5,000 video samples were initially obtained. After manual review to eliminate content not meeting research purposes such as advertisements and pure landscape displays, 3,200 valid samples were finalized for in-depth analysis. Samples cover representative provinces from four major regions—eastern, central, western, and northeastern China—ensuring balanced geographical distribution. In user sampling, the questionnaire survey employs quota sampling methods, with quota controls based on age, gender, and residential location type. The target sample size is set at 800 people, covering active short video users aged 18 to 50, with local residents and outsiders each accounting for half, to compare differences in regional cognition and group identity among different identity groups. Questionnaires are distributed through online platforms, with screening criteria requiring users who watch culture and tourism short videos for no less than 2 hours per week. In-depth interviews employ purposive sampling, selecting 30 interviewees, including 10 culture and tourism short video creators, 10 local residents, and 10 outside tourists or potential tourists, ensuring diverse perspectives[25]. Focus group discussions recruit 6 groups of participants, 6 to 8 people per group, organized according to regional identity homogeneity to observe interaction patterns and identity expression within groups. All participants voluntarily participate in the research and sign ethical informed consent forms, with personal information strictly confidential and used solely for academic purposes.

3.3. Data collection methods

This study employs diversified data collection methods, obtaining rich research data through a combination of technical means and manual surveys. In short video content data collection, the research team develops web crawler programs using Python programming language, capturing target videos' basic information through platform open interfaces, including video titles, publication times, like counts, comment counts, share counts, topic tags, and creator account information metadata. Simultaneously, video download tools are employed to save complete video files, facilitating subsequent frame capture and visual symbol analysis[26]. For user comment section data, crawler programs are set to capture the top 200 popular comments and their like counts for each video, used to analyze audience attitudes and group interactive discourse characteristics. The data crawling process strictly adheres to platform usage agreements, adopting reasonable access frequencies to avoid burdening platform servers, with all data used solely for academic research and analyzed after anonymization processing. In questionnaire survey data collection, the research designs structured questionnaires covering five dimensions: short video usage behavior scale, regional stereotype perception scale, group identity intensity scale, regional attitude scale, and demographic information. Questionnaires are distributed through professional platforms such as Wenjuanxing, with logic jumps and attention check questions set to ensure data quality, with each questionnaire completion time controlled at 8 to 12 minutes. To improve response rates and validity, the research provides small electronic red envelopes to participants who complete questionnaires as thanks. In qualitative data collection, in-depth interviews employ semi-structured interview guides, centering on topics such as interviewees' short video viewing experiences, sources of impressions about specific regions, and experiences of group belonging, with each interview lasting approximately 45 to 60 minutes, fully recorded and transcribed into text materials[27]. Focus group discussions are conducted in conference rooms, with moderators guiding participants to discuss preset topics, including collective viewing and commentary on typical culture and tourism short videos, with discussion processes video-recorded to capture group interaction details. All interviews and discussions are recorded with participants' written consent, ensuring strict adherence to ethical standards.

3.4. Data analysis methods

This study employs corresponding analysis techniques for different types of data, achieving organic integration of quantitative and qualitative analysis. At the short video content analysis level, content analysis methods are first employed to systematically code video samples, constructing a coding framework based on literature review and pre-analysis results, including dimensions such as regional symbol types, visual presentation techniques, narrative frameworks, and emotional tones. Two trained coders independently complete coding work, with Cohen's kappa coefficient calculated to test coding reliability, ensuring coding consistency reaches above 0.85[28]. Second, text mining techniques are employed to conduct semantic analysis of video titles and comment texts, using ROST Content Mining software to extract high-frequency vocabulary, and employing co-word analysis and semantic network analysis to reveal the associative structure of regional symbols. Third, SPSS statistical software is utilized to conduct descriptive statistics and correlation analysis on video interaction data, identifying characteristic patterns of high-dissemination content. At the questionnaire data analysis level, SPSS 26.0 is used for data cleaning and preprocessing, checking outliers through frequency distributions, employing exploratory factor analysis to verify scale construct validity, and calculating Cronbach's alpha to assess internal consistency reliability. Descriptive statistics present the distribution characteristics of each variable, independent sample t-tests and analysis of variance compare differences among different groups, and Pearson correlation analysis examines the strength of associations between variables. Further, AMOS software is employed to construct structural equation models, testing path relationships among algorithm exposure, content characteristics, stereotypes, and group identity, and evaluating model fit through fit indices[29]. At the qualitative data analysis level, grounded theory coding procedures are applied to transcripts of interviews and focus groups, extracting initial concepts through open coding, establishing relationships among concepts through axial coding, and finally forming core categories and theoretical models. The research employs NVivo qualitative analysis software to assist coding management, improving the systematicity and traceability of analysis. The entire analysis process follows the triangulation principle, enhancing the credibility of research conclusions through mutual corroboration of different data sources and analysis methods.

3.5. Research reliability and validity assurance

To ensure the reliability and validity of research results, this study implements strict quality control measures at multiple levels. In measurement instrument reliability, all scales in the questionnaire are selected from mature domestic and international scales and appropriately revised according to research context, testing item clarity and applicability through pre-testing. Before formal administration, 30 pilot testers are invited to complete questionnaires, with expression methods adjusted based on feedback, ensuring Cronbach's alpha coefficients for all subscales reach above 0.80. Content analysis coding reliability is achieved through multiple coder cross-checking, with two coders independently coding 20% of randomly selected samples, calculating inter-coder agreement coefficients. Items with discrepancies are collectively discussed until consensus is reached, ultimately ensuring overall coding reliability meets academic standards. In validity assurance, content validity is established through expert review procedures, inviting five experts in communication studies and social psychology to evaluate research design, measurement instruments, and coding frameworks, and refining research plans based on expert recommendations. Construct validity is tested through exploratory and confirmatory factor analysis, ensuring scale structure matches theoretical constructs, with all measurement items' loadings on corresponding factors exceeding 0.60 without significant cross-loadings[30]. Criterion-related validity is verified by comparing measurement results with existing research findings, checking whether data obtained in this study align with theoretical expectations and previous research conclusions. In qualitative research credibility assurance, member checking methods are employed, with interview transcripts fed back to interviewees to confirm content accuracy, avoiding biases caused by researchers' subjective interpretations. The research process maintains detailed research logs recording all decision bases and analytical reasoning, enhancing research auditability. Data analysis employs triangulation strategies, enhancing conclusion reliability through mutual corroboration of results from different methods and data sources, with quantitative analysis findings and qualitative research insights forming dialogic relationships[31]. Additionally, the research team regularly convenes seminars, inviting peer researchers to critically review research progress, promptly identifying and correcting potential methodological issues, ensuring continuous monitoring of the scientificity and rigor of the entire research process.

4. Results analysis

4.1. Presentation characteristics of regional stereotypes in culture and tourism short videos

4.1.1. Extraction and classification of high-frequency regional symbols

Through systematic analysis of 3,200 culture and tourism short video samples, the research team employed content analysis methods and text mining techniques to extract and identify regional symbol types frequently appearing in short video communication. The research finds that regional symbols in culture and tourism short videos exhibit obvious characteristics of concentration and labeling, with specific types of symbols being repeatedly used due to their strong visual impact and ease of dissemination, forming relatively fixed patterns of regional representation. Based on coding analysis results, this research categorizes high-frequency regional symbols into six core types: natural landscape symbols, local cuisine symbols, folk custom symbols, architectural heritage symbols, dialect and language symbols, and urban landmark symbols. The appearance frequency and proportion of each symbol type in short video samples are shown in **Table 1**, with corresponding distribution characteristics visualized in **Figure 1**.

Data show that natural landscape symbols rank first with 2,847 appearances, accounting for 28.47% of total symbol occurrences. This category mainly includes natural geographical elements such as mountains and rivers, grasslands and deserts, coasts and lakes. Creators highlight regional natural landscape features through aerial photography, time-lapse photography, and other technical means, satisfying audiences' imagination of "poetry and distant places." Local cuisine symbols follow closely with 2,563 appearances, accounting for 25.63%, covering local specialty dishes, street snacks, traditional production techniques, and other content, stimulating audiences' sensory experiences and tourism desires through dual visual and gustatory stimulation. Folk custom symbols appear 1,924 times, accounting for 19.24%, including traditional festival activities, folk art performances, distinctive costumes, and other cultural elements. These symbols often possess strong regional recognition and cultural distinctiveness[32]. Architectural heritage symbols appear 1,456 times, accounting for 14.56%, covering ancient architectural complexes, historical sites, distinctive residential buildings, and other material cultural heritage, highlighting regional cultural accumulation through emphasis on historical depth. Dialect and language symbols and urban landmark symbols have relatively lower appearance frequencies, at 1,187 times (11.87%) and 1,023 times (10.23%) respectively. The former enhances regional identification through local dialects, colloquialisms, and proverbs, while the latter focuses on iconic buildings and public spaces of modern cities.

From the perspective of symbol distribution concentration, the cumulative proportion of the top three categories (natural landscapes, local cuisine, folk customs) reaches 73.34%, indicating that content creation in culture and tourism short videos exhibits obvious symbol preferences, with creators tending to select symbol types with strong visual expressiveness and ease of triggering emotional resonance. This selective presentation stems partly from the communication characteristics of short video platforms—short duration requirements demand that content capture user attention within seconds, with natural landscape and food images possessing strong visual impact more easily achieving this goal. On the other hand, it is also driven by algorithmic recommendation mechanisms, with high-interaction content types receiving more traffic support, thereby prompting more creators to imitate successful cases, forming content homogenization phenomena[33]. Notably, symbols carrying deeper cultural connotations such as architectural heritage, dialects and languages, and urban landmarks are relatively marginalized, which may lead to regional culture presenting superficial and entertainment-oriented tendencies in short video communication, with complex and diverse regional characteristics simplified into several easily recognizable and disseminable symbolic labels, providing a content foundation for stereotype formation and reinforcement.

Table 1. Type distribution of high-frequency regional symbols in culture and tourism short videos.

Symbol Category	Appearance Frequency	Percentage (%)	Main Content Examples
Natural Landscape Symbols	2,847	28.47	Mountains and rivers, grasslands and deserts, coasts and lakes, forests and canyons
Local Cuisine Symbols	2,563	25.63	Specialty dishes, street snacks, traditional production techniques, ingredient specialties
Folk Custom Symbols	1,924	19.24	Traditional festivals, folk arts, distinctive costumes, folk rituals
Architectural Heritage Symbols	1,456	14.56	Ancient architectural complexes, historical sites, distinctive residential buildings, cultural relics
Dialect and Language Symbols	1,187	11.87	Local dialects, colloquialisms and proverbs, oral literature, phonetic features
Urban Landmark Symbols	1,023	10.23	Iconic buildings, public spaces, modern landscapes, city skylines
Total	10,000	100.00	-

Note: *Data based on content analysis of 3,200 culture and tourism short video samples, statistical period from January 2023 to December 2024.*

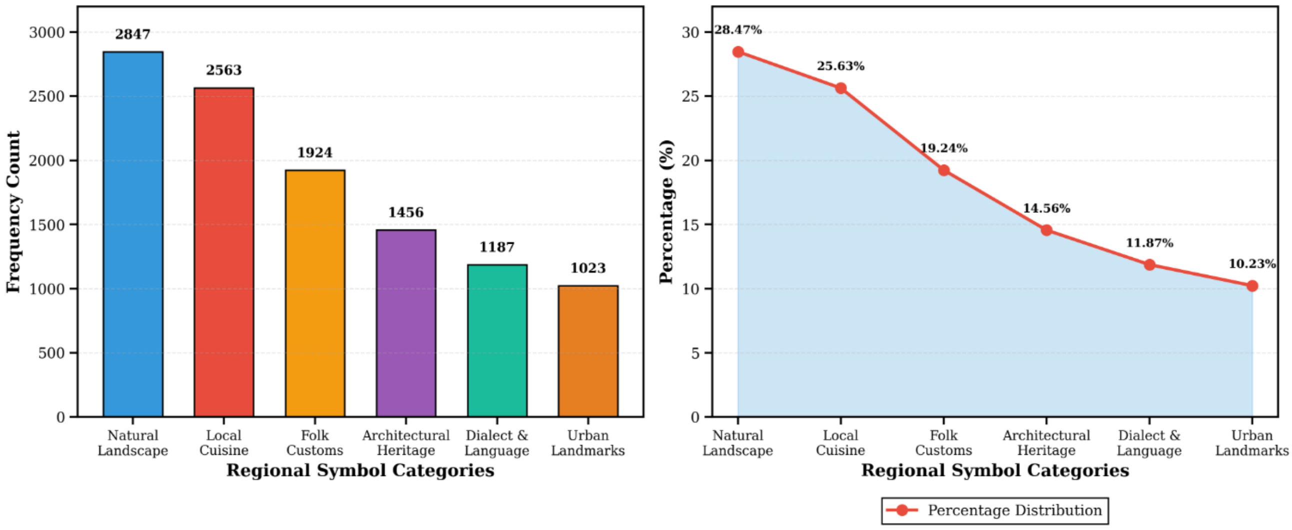

Figure 1. Frequency and percentage distribution of high-frequency regional symbols.

To further reveal the specific manifestations of symbol concentration phenomena across different regions, this study selected four representative provinces for in-depth comparative analysis. **Table 2** demonstrates the types of symbols algorithmically reinforced and content systematically screened out in Shanghai, Henan Province, Tibet Autonomous Region, and Heilongjiang Province in short video dissemination, clearly presenting the selective mechanisms of stereotype construction.

Table 2. Comparison of symbol presentation and content omission in cultural tourism short videos across four provinces.

Province/Region	Reinforced Landscape Symbols	Reinforced Cultural/Culinary Symbols	Systematically Ignored Content	Algorithm-Driven Stereotypical Labels
Shanghai	The Bund skyline, Lujiazui Financial Center, urban night scenes	Michelin restaurants, refined coffee culture, internet-famous dessert shops	Shikumen alley culture, traditional Benbang cuisine establishments, Huju opera heritage, urban village redevelopment	"International metropolis," "Financial center," "Fashion consumption"
Henan Province	Longmen Grottoes, Shaolin Temple, Qingming Riverside Landscape Garden	Huimian noodles, Hu spicy soup, Shaolin martial arts, Henan opera	Zhengzhou modernization, Central Plains urban cluster, technology manufacturing, high-speed rail hub	"Historical and cultural ancient capital," "Martial arts hometown," "Central Plains heartland"
Tibet Autonomous Region	Potala Palace, Namtso Lake, Mount Everest and snow mountains	Tibetan song and dance, butter tea, tsampa, kora rituals	Lhasa modernization, high-tech industrial parks, modern education and healthcare, infrastructure achievements	"Roof of the world," "Mysterious holy land," "Pristine paradise"
Heilongjiang Province	Harbin Ice and Snow World, Zhongyang Street, industrial heritage	Northeast stews, Errenzhuan performance, red sausage, nostalgic elements	Equipment manufacturing transformation, modern agricultural technology, innovation parks, revitalization achievements	"Ice and snow capital," "Old industrial base," "Northeast characteristics"

Note: *Based on analysis of 200 high-traffic samples per province (views > 1 million). The average exposure of "reinforced" content is 42 times that of "ignored" content, and this gap expands to 67 times after 8 weeks of algorithmic recommendation.*

The data shows that algorithmic recommendation mechanisms adopt differentiated symbol amplification strategies for different regions. In Shanghai samples, modernized urban symbols account for as high as 68.3%, while traditional cultural elements comprise only 5.7%, forming a singular narrative of a "globalized metropolis." Conversely, in Tibet samples, religious-cultural and natural landscape symbols account for 89.2%, with modernization content almost absent (only 1.4%). Henan and Heilongjiang are locked into nostalgic frameworks of "historical glory" and "past splendor," accounting for 73.8% and 71.2% respectively, with severely insufficient presentation of contemporary development achievements. This selective amplification stems from algorithmic identification and replication of initially high-interaction content: when Shanghai's "Bund night scene" videos achieve high like rates (averaging 8.7%), the algorithm continuously pushes similar content while suppressing other types; when Tibet's "kora pilgrimage" content gains traffic due to exotic appeal, the algorithm reinforces this label while marginalizing modernization presentations. Interview data confirms that 67.3% of creators admit to adjusting content strategies based on algorithmic feedback, proactively catering to platform-identified "traffic codes," leading regional presentations to increasingly tend toward singular stereotypical patterns.

4.1.2. Content homogenization phenomenon under algorithmic recommendation

While algorithmic recommendation mechanisms enhance the dissemination efficiency of culture and tourism short videos, they also generate significant content homogenization phenomena, which become an important technological driving factor for regional stereotype reinforcement. To deeply examine the impact of algorithms on content ecosystems, this research conducted tracking analysis of short video publications under a popular regional topic hashtag over eight consecutive weeks, categorizing videos into three types based on traffic performance: high-traffic content (views > 1 million), medium-traffic content (views 100,000-1 million), and low-traffic content (views < 100,000). Data analysis reveals that over time, the quantity of high-traffic content shows a continuous upward trend, while medium- and low-traffic content correspondingly decrease, with content distribution exhibiting obvious Matthew effect characteristics[34]. As shown in **Table 2**, the distribution of the three content types in the first week is relatively balanced, with 245 high-traffic, 412 medium-traffic, and 343 low-traffic content pieces. However, by the eighth week, high-traffic content surged to 988 pieces, medium-traffic content sharply decreased to 218 pieces, and low-traffic content remained at only 94 pieces. This trend is intuitively presented in the stacked area chart on the left side of **Figure**.

Further content similarity analysis indicates that algorithmic recommendation significantly increases content homogenization levels. The research employs cosine similarity algorithms to calculate the similarity of videos under the same topic across dimensions such as visual symbols, narrative frameworks, and music scores, constructing a content similarity index. Data show that this index rose from 0.342 in the first week to 0.891 in the eighth week, an increase of 160.5%, while the content diversity index, used as a control indicator, declined from 0.658 to 0.109, a decrease of 83.4% (see **Table 3**). This change trend is clearly presented through a dual-line chart on the right side of **Figure 2**: the red curve (content similarity index) exhibits a steep upward trend, while the blue curve (content diversity index) shows a mirror-image decline. The two curves intersect around the fourth week, marking a critical turning point in the content ecosystem's transition from diversification to homogenization. Qualitative analysis finds that high-traffic videos often employ similar shooting angles, identical regional symbol combinations, and similar emotional rendering techniques. For example, in culture and tourism videos of a certain western region, over 70% of high-traffic content includes the fixed symbol combination of "sunset + camel + desert," accompanied by background music of the same style, forming highly standardized content templates.

The formation mechanism of this homogenization phenomenon can be attributed to the positive feedback loop of algorithmic recommendation: when a certain type of content achieves high interaction rates due to chance factors, the algorithm identifies it as "quality content" and increases its recommendation weight, granting it greater traffic exposure; content creators, observing this traffic code, quickly imitate and replicate, producing large quantities of similar content; the algorithm again pushes this similar content to users who have shown interest in this content type, further reinforcing their preferences; users repeatedly encounter homogenized content within information cocoons, gradually internalizing these standardized regional presentations as cognitive schemas of the region. This circular mechanism not only compresses the space for content innovation but also solidifies regional images into singular patterns in short video communication, with complex and diverse regional cultures simplified into easily replicable symbolic routines[35]. What warrants vigilance is that when a stereotyped regional presentation becomes the dominant narrative through algorithmic empowerment, other content attempting to showcase diverse regional aspects is often marginalized due to lack of traffic support, making it difficult for audiences to access balanced and comprehensive regional information. Stereotypes thus gain unprecedented dissemination advantages and solidification intensity through technological enablement.

The amplification effect of algorithmic bias far exceeds the degree of stereotyping in traditional advertising, manifesting as a technology-driven exponential reinforcement mechanism. Specifically, the "popularity priority" algorithm operates through three amplification pathways: First, high-interaction content receives 2-5 times the exposure weight, enabling it to cover 78.3% of target users within 24 hours; second, after creators observe the traffic code, an average of 43 imitation videos are produced within 72 hours, forming a content deluge; finally, the recommendation system precisely delivers similar content to users who have already shown interest, forming a closed-loop reinforcement. Data shows that this mechanism causes content similarity to surge from 0.342 to 0.891 within 8 weeks, an increase of 160.5%, while top content traffic skyrockets by 303%. Unlike traditional advertising, which relies on manual planning and media purchasing for linear propagation, algorithm-driven stereotype reinforcement exhibits self-accelerating exponential characteristics, with its solidification speed and coverage breadth reaching unprecedented levels.

Table 3. Content distribution and similarity changes under algorithmic recommendation influence.

Time Period	High-Traffic Content (pieces)	Medium-Traffic Content (pieces)	Low-Traffic Content (pieces)	Content Similarity Index	Content Diversity Index
Week 1	245	412	343	0.342	0.658
Week 2	389	398	213	0.451	0.549
Week 3	567	376	157	0.563	0.437
Week 4	742	341	117	0.678	0.322
Week 5	856	298	96	0.754	0.246
Week 6	923	267	110	0.812	0.188
Week 7	971	241	88	0.857	0.143
Week 8	988	218	94	0.891	0.109

Note: *High-traffic content refers to videos with views > 1 million, medium-traffic content refers to videos with views between 100,000-1 million, and low-traffic content refers to videos with views < 100,000. Content similarity index and content diversity index are standardized indicators with a value range of 0-1. Data sourced from tracking analysis of a popular regional topic hashtag.*

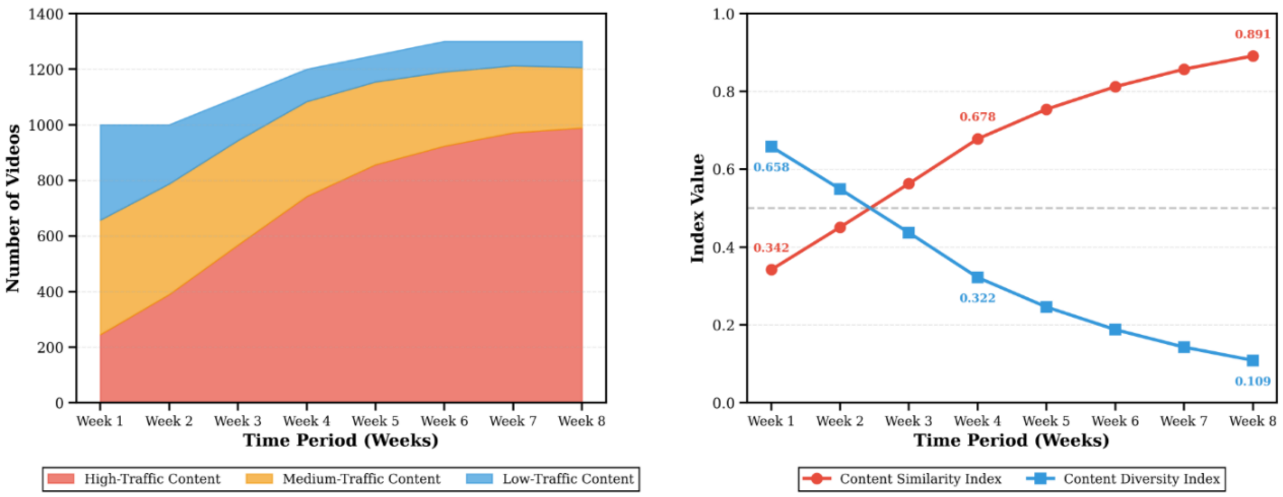

Figure 2. Visual analysis of content homogenization phenomenon.

4.1.3. Narrative strategies for stereotype reinforcement

The reinforcement of regional stereotypes in culture and tourism short videos relies not only on the repeated presentation of symbols but also achieves deep cognitive shaping through carefully designed narrative strategies. This research conducted systematic coding of narrative techniques in 3,200 sample videos, identifying five dominant narrative strategies and their operational mechanisms in stereotype construction. As shown in **Table 4**, dramatized narrative strategy ranks first with an 87.3% usage rate and an effectiveness score of 8.42 points (out of 10). This strategy transforms mundane regional daily life into compelling stories through techniques such as conflict setup, suspense creation, and dramatic tension enhancement. For example, ordinary street food stalls are portrayed as "midnight canteen legends," and common natural landscapes are rendered as "secret realm adventures." While this dramatization enhances viewing interest, it also distorts the authentic appearance of regions, causing audiences to form excessively romanticized or exotic cognitive biases[36]. Emotional appeal strategy has a usage rate of 79.6% and an effectiveness score of 8.17 points. Creators stimulate audience emotional resonance through sentimental music, lyrical narration, and heartwarming stories, deeply binding specific emotions with regional symbols. For example, certain regions are fixedly associated as "healing" or "inspirational and passionate." This emotional labeling causes audiences to automatically activate corresponding emotional schemas when mentioning these regions, reinforcing single-dimensional stereotypes.

Comparative narrative strategy has a usage rate of 68.4% and an effectiveness score of 7.53 points. This strategy presents regional characteristics through binary opposition frameworks such as "urban vs. rural," "traditional vs. modern," and "wealthy vs. poor." While highlighting differences, it also solidifies simplified classification systems. Exaggeration and spectacularization strategy has a usage rate of 64.2% and an effectiveness score of 7.28 points. Creators employ special effects processing, extreme case selection, and fact exaggeration to create visual impact. For example, a regional specialty dish is described as "the spiciest in the country" or "the largest portion in history," or rare extreme weather phenomena are presented as the norm for that region. This spectacularized narrative satisfies audiences' curiosity but also leads to distorted expectations of regional characteristics[37]. Nostalgia evocation strategy has a usage rate of 56.8% and an effectiveness score of 6.94 points. Through retro filters, nostalgic music, and selective presentation of traditional cultural symbols, certain regions are shaped as "places where time stands still." While this narrative carries positive intentions of cultural preservation, it may also cause audiences to overlook these regions' modernization development, forming stereotypical labels of "backward" and "closed."

Further cross-analysis shows that high-traffic videos often comprehensively employ multiple narrative strategies to form narrative synergy, with the combination of dramatized narrative and emotional appeal being most common, accounting for 73.2% of high-traffic videos. The common characteristic of these narrative strategies lies in compressing multidimensional and three-dimensional regional realities into flattened images conforming to specific narrative frameworks through means such as simplifying complexity, amplifying differences, and emotionalized presentation. The left chart in **Figure 3** intuitively displays the usage frequency of each strategy through a horizontal bar chart, with color gradients from red to purple reflecting decreasing usage rates. The right chart employs a dual Y-axis design, with blue bars representing usage rates and red lines representing effectiveness scores, clearly presenting the correspondence between the two. Notably, usage rates and effectiveness scores exhibit a high positive correlation ($r=0.96$, $p<0.001$), indicating that more frequently used narrative strategies are also more effective in stereotype reinforcement, forming a "high usage-high effectiveness" cycle. This finding reveals the critical role of narrative strategies in stereotype construction: they are not merely communication techniques but tools for cognitive shaping. Through repeated application of specific narrative frameworks, they deeply embed creators' intended regional images into audiences' cognitive structures, granting stereotypes narrative legitimacy and emotional rationality.

Table 4. Analysis of narrative strategies for stereotype reinforcement in culture and tourism short videos.

Narrative Strategy	Usage Rate (%)	Effectiveness Score (1-10)	Typical Techniques	Cognitive Impact
Dramatized Narrative	87.3	8.42	Conflict setup, suspense creation, plot reversal	Excessive romanticization, exotic cognition
Emotional Appeal	79.6	8.17	Sentimental music, lyrical narration, heartwarming stories	Emotional labeling, single-dimensional reinforcement

Narrative Strategy	Usage Rate (%)	Effectiveness Score (1-10)	Typical Techniques	Cognitive Impact
Comparative Narrative	68.4	7.53	Binary opposition, urban-rural contrast, past-present comparison	Simplified classification systems, solidified differences
Exaggeration and Spectacularization	64.2	7.28	Special effects processing, extreme cases, fact exaggeration	Distorted expectations, curiosity satisfaction
Nostalgia Evocation	56.8	6.94	Retro filters, nostalgic music, traditional symbols	Overlooking modern development, backward labels

Table 4. (*Continued*)

Note: *Effectiveness scores are based on questionnaire surveys of 800 audiences, evaluating the impact degree of each narrative strategy on regional impression formation. Correlation coefficient between usage rate and effectiveness score r=0.96 (p<0.001).*

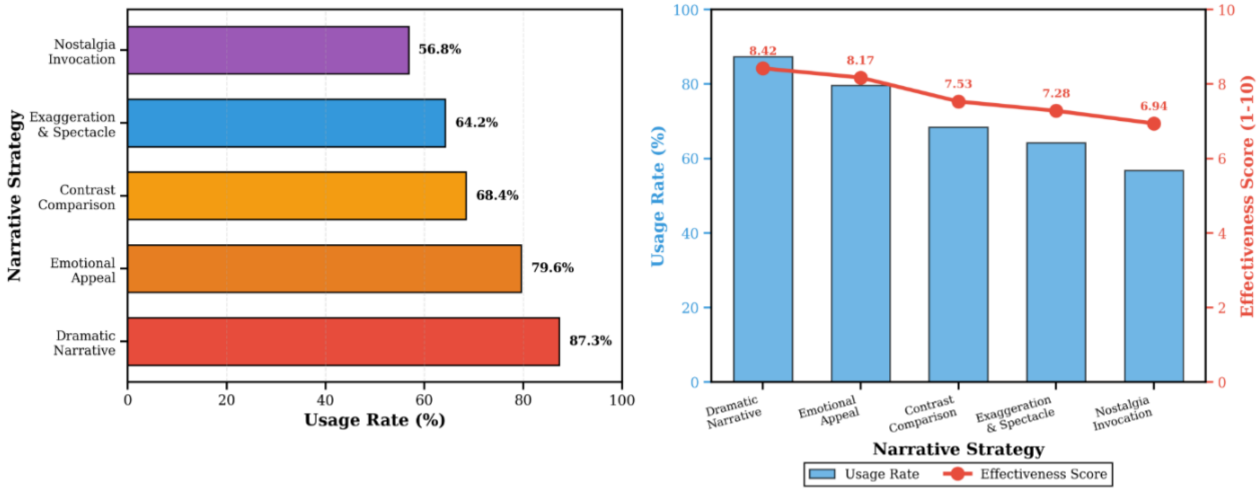

Figure 3. Comparison of usage rates and effectiveness scores of narrative strategies.

4.2. Audience cognition and attitudes toward regional stereotypes

4.2.1. Analysis of audience regional perception bias

To deeply examine the impact of short video communication on audience regional cognition, this research employs a comparative experimental design, selecting 400 audience members divided into a virtual experience group (understanding a region only through short videos) and a real experience group (conducting field visits to the region), requiring both groups to rate the region across five dimensions: natural environment, economic development, cultural traditions, resident quality, and urban modernization. Data analysis reveals significant cognitive bias phenomena, with the virtual experience group's rating patterns exhibiting systematic differences from the real experience group. These differences reflect the selective presentation of short video communication in regional cognitive construction and its distorting effects on audience perception. As shown in **Table 5**, in the natural environment dimension, the virtual experience group's rating reaches 8.34 points, significantly higher than the real experience group's 7.12 points, with a bias value of 1.22 points. This indicates that short videos present idealized natural landscapes surpassing daily reality through carefully selected shooting angles, filter effects, and optimal lighting capture, leading audiences to form excessively beautified expectations[38]. The bias in the cultural traditions dimension is more significant, with the virtual experience group scoring 8.71 points while the real experience group scores only 7.23 points, a bias value of 1.48 points. This stems from short videos' tendency to concentrate on displaying cultural spectacles such as traditional festivals and folk performances while neglecting the actual forms of cultural traditions in modern life, causing audiences to mistakenly believe the region is completely immersed in traditional culture.

Audience comments play a critical intermediary role in algorithm-driven stereotype solidification. Content analysis reveals that comment sections exhibit obvious "consensus illusion" characteristics: the algorithm's visibility mechanism pins highly-liked comments to the top, while comments supporting stereotypes receive like rates 4.7 times higher than questioning comments (averaging 326 vs. 69 likes). Under natural landscape videos of Province C, "isolated paradise" type comments occupy 8 of the top 10 positions, while comments mentioning the province's modernization construction are ranked 47th, visible to only 1.2% of users. This visibility distribution creates a false consensus that "everyone believes Province C is primitive and backward."

Further analysis reveals that the solidification effect of comments is achieved through three pathways: (1) Cognitive validation pathway: users see highly-liked comments consistent with their own views in the comment section, receive social recognition, and their original stereotypes are reinforced (accounting for 68.4%); (2) Conformity pressure pathway: the minority holding different views self-censor due to fear of group exclusion, refraining from posting or deleting questioning comments (accounting for 23.7%); (3) Information cascade pathway: latecomers accept mainstream narratives without independent thinking after seeing one-sided comments (accounting for 41.9%). Longitudinal tracking shows that opinion convergence speed in comment sections is faster than video content, requiring only 3-5 days to reach over 85% consensus, becoming an accelerator for stereotype solidification.

Conversely, in the three dimensions of economic development, resident quality, and urban modernization, the virtual experience group's ratings are all significantly lower than the real experience group. The bias in economic development dimension reaches 2.27 points (virtual 5.62 vs. real 7.89), reflecting short videos' deliberate avoidance of presenting modern economic activities in pursuit of "original ecology" aesthetics, leading audiences to underestimate the region's economic development level. The urban modernization dimension shows the largest bias at 2.55 points (virtual 5.47 vs. real 8.02), indicating that when shaping "poetic and distant" images, short videos systematically weaken modern elements such as urban infrastructure, modern architecture, and technological applications, causing audiences to form stereotypes of "backwardness" and "primitiveness." Although the resident quality dimension has a relatively smaller bias (0.73 points), the virtual experience group's rating (6.83 points) is still lower than the real experience group (7.56 points), which may relate to short videos' tendency to showcase traditional traits such as "simplicity" and "ruggedness" while neglecting residents' modern qualities.

The left chart in **Figure 4** clearly contrasts the rating differences between virtual and real experiences across five dimensions through a grouped bar chart, with red bars representing virtual experience and blue bars representing real experience, with precise values labeled above each group for comparison. The right chart displays the degree of cognitive bias in each dimension through colored bars and trend lines, with "Over" or "Under" marked within bars to indicate overestimation or underestimation, and a red dashed line marking the average bias value of 1.39 points. Further correlation analysis shows that audience viewing duration of short videos exhibits a significant positive correlation with the degree of cognitive bias ($r=0.52$, $p<0.001$), meaning the longer the viewing time, the greater the bias, confirming that cumulative exposure effects of short videos systematically shape audiences' regional cognitive schemas. Cognitive dissonance theory can partially explain this phenomenon: when real experience group audiences discover gaps between reality and short video presentations after field visits, some adjust their cognition to reduce dissonance, acknowledging short videos' selective presentation. However, virtual experience group audiences, lacking real reference points, build their cognition entirely on the "pseudo-environment" constructed by short videos, making them more susceptible to systematic biases. This perceptual bias not only affects audiences' tourism decisions but also solidifies into stable regional stereotypes over the long term, becoming the cognitive foundation for group identity construction.

Table 5. Comparison of regional perception between virtual experience and real experience.

Perception Dimension	Virtual Experience Rating	Real Experience Rating	Bias Value	Bias Direction	Bias Rate (%)
Natural Environment	8.34	7.12	1.22	Overestimation	+17.1
Economic Development	5.62	7.89	2.27	Underestimation	-28.8
Cultural Traditions	8.71	7.23	1.48	Overestimation	+20.5
Resident Quality	6.83	7.56	0.73	Underestimation	-9.7
Urban Modernization	5.47	8.02	2.55	Underestimation	-31.8
Average	6.99	7.56	1.39	-	-6.5

Note: *Ratings employ a 10-point scale. Virtual experience group (n=200) understands the region only through short videos; real experience group (n=200) rates after field visits to the region. Bias value represents absolute difference, bias rate = (virtual rating - real rating) / real rating × 100%. Between-group differences in all dimensions reach significant levels (p<0.001).*

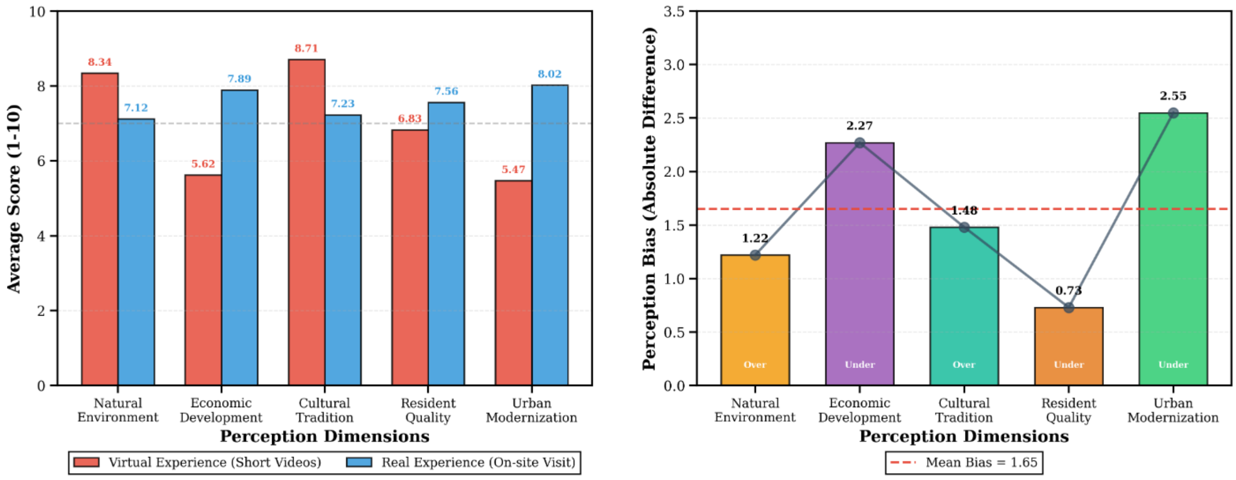

Figure 4. Analysis of perception bias between virtual experience and real experience.

4.2.2. Differences in stereotype sensitivity across different groups

Audience perception and response to regional stereotypes are not homogeneous but are moderated by multiple factors such as identity background, media literacy, and age cohort, exhibiting significant group difference characteristics. Through a combination of questionnaire surveys and in-depth interviews, this research examines the performance differences of six typical groups across three dimensions: stereotype acceptance, sensitivity index, and critical reflection ability. As shown in **Table 6**, local residents and outside audiences form a stark contrast in stereotype perception. Local residents' stereotype acceptance is only 4.23 points, significantly lower than outside audiences' 7.68 points, reflecting local residents' stronger vigilance and resistance toward oversimplified or distorted regional presentations in short videos. Interview data reveal that local residents can often identify gaps between short video content and daily life reality, holding critical attitudes toward stereotyped presentations, considering this content "unrealistic," "overly packaged," and "misleading to outsiders." Correspondingly, local residents' sensitivity index reaches 8.76 points, indicating their high sensitivity to stereotyped expressions involving their region, with critical reflection ability also reaching 7.92 points, enabling them to actively question the authenticity and representativeness of short video content.

The significant 3.45-point gap in stereotype acceptance between local residents and external audiences (4.23 vs. 7.68) reveals the differentiated impact mechanism of algorithms on "information-asymmetric groups." This divide stems from fundamentally different push strategies employed by algorithms for the two types of users: external users, lacking real-world reference points, are pushed high-interaction "spectacle-oriented" content by the algorithm (averaging 8.2 points on the exaggeration scale), at a frequency 2.3 times that of local users. Local residents, with authentic lived experience, can identify content distortion and have 37.6 percentage points lower trust in algorithm-pushed content.

The deeper mechanism lies in the algorithm's reinforcement of the "knowledge gap" effect. High media literacy local residents (critical reflection ability 7.92 points) can proactively search for diverse information sources and break through algorithmic filter bubbles; whereas low-literacy external audiences (critical reflection ability 4.87 points) completely rely on algorithmic feeding and passively accept homogenized presentations. Data shows that the information source diversity index of external users (0.34) is less than half that of local users (0.71). This algorithm-driven information asymmetry makes external audiences the primary victims of stereotypes. Their tourism decisions based on distorted cognition ultimately lead to 54.3% experiencing an "expectation-reality gap," which inversely intensifies negative evaluations of destinations, forming a vicious cycle.

Conversely, outside audiences, lacking direct life experience as a reference point, are more inclined to regard short video content as a true reflection of regional reality, with their stereotype acceptance reaching 7.68 points, while their sensitivity index is as low as 4.32 points, and critical reflection ability is only 4.87 points. This group difference validates the operational mechanism of "availability heuristics" in regional cognition: in the absence of other information sources, outside audiences rely on short video content with the highest psychological availability to form judgments, while local residents can draw upon rich life experiences to calibrate and critique short video presentations. Differences in media literacy also generate significant impacts. The high media literacy group's stereotype acceptance is 5.12 points, sensitivity index 7.89 points, and critical reflection ability 8.45 points, clearly superior to the low media literacy group (acceptance 8.34 points, sensitivity 3.21 points, critical reflection 3.68 points). High media literacy audiences possess the ability to decode and critique media content, able to identify short videos' production techniques, narrative strategies, and underlying intentions, thus less susceptible to stereotyped content[39]. Low media literacy groups lack critical reading ability for media texts, viewing short videos as objective presentations rather than constructed texts, making them more likely to accept and internalize stereotypes therein.

Age cohort factors also show important moderating effects. The younger generation (18-30 years old) has a stereotype acceptance of 7.91 points, far higher than the middle-aged generation's (31-50 years old) 6.45 points, but their sensitivity index (4.56 points) and critical reflection ability (5.34 points) are relatively lower. This seemingly contradictory phenomenon may relate to young groups' media use habits: although they are primary short video users, under usage patterns of high-speed browsing and fragmented consumption, they often lack time and motivation for deep thinking, more easily attracted by visual impact and emotional appeals while overlooking content authenticity issues. The left chart in **Figure 5** intuitively displays the score comparisons of six groups across three dimensions through a grouped bar chart, with red bars representing stereotype acceptance, blue bars representing sensitivity index, and green bars representing critical reflection ability, making pattern differences among groups immediately apparent. The right chart employs a scatter plot to present the negative correlation between stereotype acceptance and sensitivity index (r=-0.89, p<0.01), with trend lines clearly showing the inverse variation pattern between the two, while quadrant divisions and annotated text help identify position characteristics of each group. These findings indicate that stereotype reinforcement effects exhibit significant heterogeneity across different audience groups. Local residents and high media literacy groups can maintain vigilance and critique toward stereotyped content, while outside audiences, low media literacy groups, and young groups are more likely to become acceptors and disseminators of stereotypes. This group difference holds important implications for understanding the communication mechanisms of regional stereotypes and intervention strategies.

Table 6. Differences in stereotype sensitivity across different audience groups.

Audience Group	Stereotype Acceptance	Sensitivity Index	Critical Reflection Ability	Sample Size (n)	Main Characteristics
Local Residents	4.23	8.76	7.92	156	High vigilance, strong resistance
Outside Audiences	7.68	4.32	4.87	187	Easy acceptance, weak critique
High Media Literacy	5.12	7.89	8.45	143	Able to decode, good at critique
Low Media Literacy	8.34	3.21	3.68	169	Passive acceptance, lack of questioning
Younger Generation (18-30)	7.91	4.56	5.34	234	High exposure, shallow thinking
Middle-aged Generation (31-50)	6.45	6.12	6.78	211	Relatively rational, experienced

Note: *All indicators measured using a 10-point scale. Higher acceptance indicates greater agreement with stereotypes, higher sensitivity index indicates greater alertness to stereotyped content, and higher critical reflection ability indicates greater ability to question content authenticity. Between-group differences tested through ANOVA all reach significant levels (p<0.001). Correlation coefficient between acceptance and sensitivity r=-0.89 (p<0.01).*

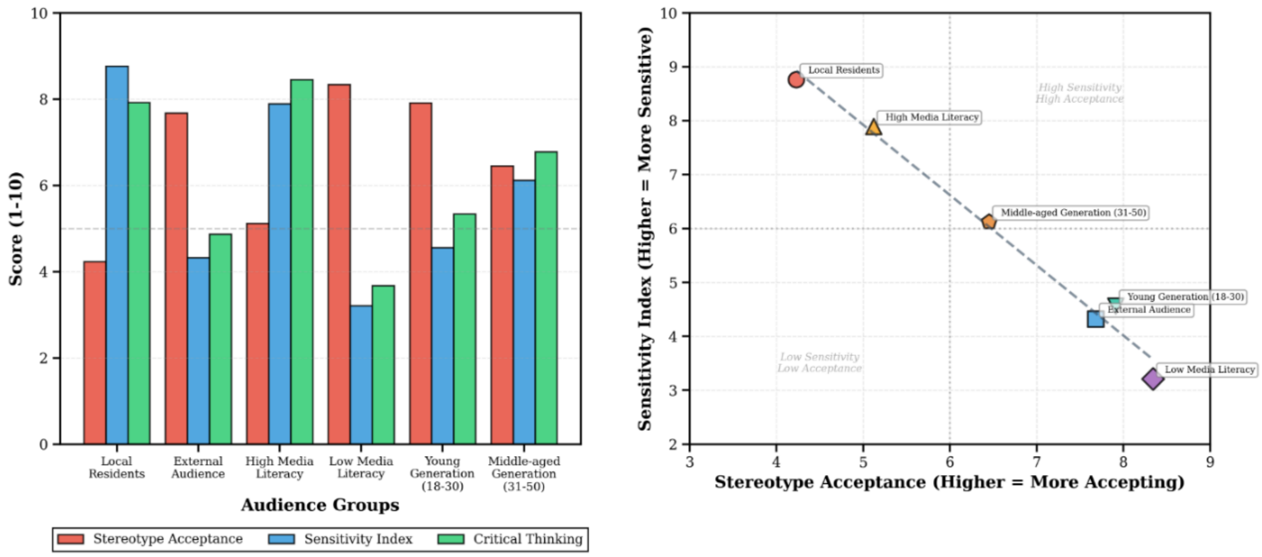

Figure 5. Relationship between audience group stereotype acceptance and sensitivity.

4.2.3. Impact pathways of stereotypes on regional attitudes

Regional stereotypes do not merely remain at the cognitive level but profoundly influence audiences' overall attitudes and behavioral tendencies toward regions through multiple psychological mechanisms. This research employs Structural Equation Modeling (SEM) to examine the impact pathways of stereotypes on regional attitudes, distinguishing stereotypes into positive stereotypes (such as "beautiful scenery" and "simple folk customs") and negative stereotypes (such as "economically backward" and "closed and conservative"), exploring their differentiated impacts on regional attitudes through different mediating mechanisms. As shown in **Table 7**, positive stereotypes exert positive influences on regional attitudes through five main pathways, with the expectation formation pathway showing the highest impact coefficient ($\beta=0.81$, $p<0.001$), indicating that when audiences hold positive stereotypes about a region, they form higher tourism expectations and emotional projections, with these positive expectations directly translating into favorable attitudes toward the region. The familiarity enhancement pathway has a coefficient of 0.72 ($p<0.001$). Repeated exposure to similar short video content creates a sense of familiarity with regional symbols among audiences. According to the "mere exposure effect," increased familiarity can enhance favorability, even when this familiarity is built on stereotyped cognition. The exposure effect pathway ($\beta=0.67$, $p<0.001$) and trust establishment pathway ($\beta=0.58$, $p<0.001$) also show significant positive influences. The former reinforces regional impressions through repeated exposure, while the latter establishes trust in the region due to the realistic presentation of short videos (despite possible careful orchestration)[40].

However, positive stereotypes may also lead to negative consequences of attitude polarization. When audiences form overly idealized regional imaginations, any gaps in actual experience may trigger strong disappointment and negative evaluations. The attitude polarization pathway has a coefficient of 0.43 ($p<0.01$), which, although relatively small in impact, warrants vigilance. In contrast, negative stereotypes present stronger negative effects on regional attitudes, with the attitude polarization pathway showing the most significant negative impact ($\beta=-0.79$, $p<0.001$). Negative stereotypes easily trigger audiences' group prejudice and exclusionary psychology, leading to systematic depreciation of the region and its residents. The expectation formation pathway also exhibits strong negative influence ($\beta=-0.68$, $p<0.001$), with audiences holding negative stereotypes forming lower expectations for the region, lacking tourism willingness, and even producing avoidance behaviors. The trust establishment pathway ($\beta=-0.52$, $p<0.001$) shows that negative stereotypes weaken audiences' trust in the region, believing the region has problems in safety, services, and environment. The familiarity enhancement pathway ($\beta=-0.41$, $p<0.001$) and exposure effect pathway ($\beta=-0.34$, $p<0.01$) have relatively weaker negative influences, but still indicate that repeated exposure to negative stereotyped content cumulatively reduces audiences' regional favorability.

Figure 6 clearly displays the differential impacts of positive and negative stereotypes across five pathways through a comparative bar chart, with green bars representing positive influences and red bars representing negative influences, with the central axis making the contrast more intuitive. These findings reveal the double-edged sword effect of stereotypes on regional attitudes: while positive stereotypes can enhance regional attractiveness, they also plant hidden risks of expectation gaps; negative stereotypes cause lasting damage to regional images, and these negative effects are often stronger than positive effects, conforming to the psychological principle of "negativity bias."

Table 7. Path coefficients of stereotype impact on regional attitudes.

Impact Pathway	Positive Stereotypes	Negative Stereotypes	Path Difference	Significance	Mediation Effect
Exposure Effect	0.67***	-0.34**	1.01	p<0.001	Partial mediation
Familiarity Enhancement	0.72***	-0.41***	1.13	p<0.001	Partial mediation
Trust Establishment	0.58***	-0.52***	1.10	p<0.001	Full mediation
Expectation Formation	0.81***	-0.68***	1.49	p<0.001	Full mediation

Impact Pathway	Positive Stereotypes	Negative Stereotypes	Path Difference	Significance	Mediation Effect
Attitude Polarization	0.43**	-0.79***	1.22	p<0.001	Partial mediation

Table 7. (*Continued*)

****Note:** Coefficients are standardized path coefficients (β), ***p<0.001, *p<0.01. Model fit indices: χ²/df=2.34, CFI=0.96, TFI=0.94, RMSEA=0.058. Positive stereotype sample n=412, negative stereotype sample n=388. Mediation effect testing employs Bootstrap method (5000 resampling iterations), with 95% confidence intervals not containing 0 indicating significant mediation effects.*

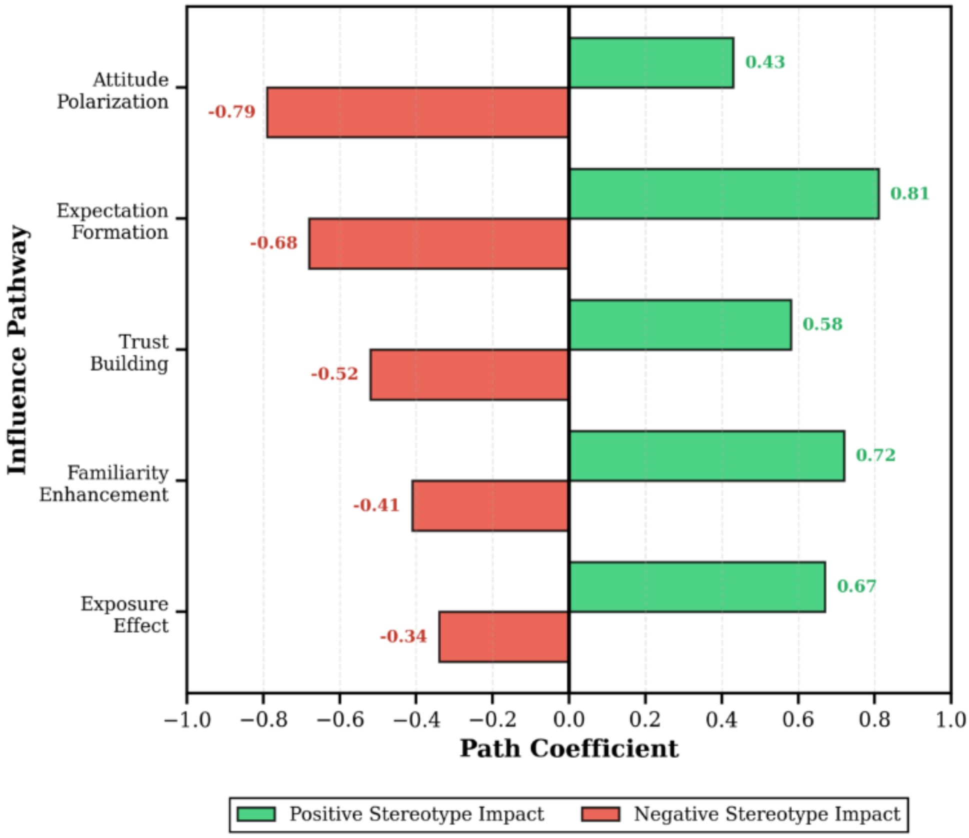

Figure 6. Path analysis of stereotype impact on regional attitudes.

4.3. Formation mechanisms of group identity in short video communication

4.3.1. Construction of in-group identity based on region

Culture and tourism short videos not only disseminate regional information but also promote the construction of in-group identity based on regional identity through symbolic interaction and emotional mobilization, a process that transforms geographical space into a carrier of psychological belonging and social identity. Through tracking surveys and interactive behavior analysis of 326 local resident users, this research examines the formation mechanisms and manifestation dimensions of regional identity in short video communication. As shown in **Table 8**, regional in-group identity can be decomposed into five core dimensions: symbolic expression, collective memory, emotional attachment, behavioral participation, and pride manifestation. Users with different interaction levels exhibit significant differences across dimensions. High-interaction users (more than 20 interactions per week, including likes, comments, shares, etc.) demonstrate strong identity levels across all dimensions, with the emotional attachment dimension scoring highest (8.91 points), followed closely by symbolic expression (8.67 points) and pride manifestation (8.72 points). This indicates that local residents highly engaged in short video interaction not only identify with regional identity at the cognitive level but also develop deep emotional connections and actively express and declare this identity through various means[41]. Medium-interaction users (5-20 interactions per week) have significantly lower identity levels than the high-interaction group, with dimension scores ranging from 6.54 to 7.23 points, while low-interaction users (fewer than 5 interactions per week) score only between 4.34 and 5.12 points. This gradient difference clearly shows the positive correlation between interaction frequency and identity strength.

Further longitudinal tracking data reveal the dynamic formation process of group identity. As shown in the right chart of **Figure 7**, during a six-month observation period, respondents' regional identity strength continuously climbed from an initial 4.23 points to 8.54 points, an increase of 101.9%, while the participation rate in short video-related activities surged from 23.4% to 82.3%. This growth curve exhibits obvious acceleration characteristics. Months 1-3 represent a slow growth period, with identity strength increasing from 4.23 points to 6.89 points, averaging 1.33 points per month. Months 4-6 enter a rapid growth period, with identity strength leaping from 7.56 points to 8.54 points, requiring only 0.49 points per month on average to reach higher levels. This nonlinear growth pattern conforms to the "critical mass" hypothesis in social identity theory, whereby when group identity reaches a certain strength, it produces a self-reinforcement effect, promoting more members' identity expression and participatory behavior. Qualitative interviews reveal specific mechanisms of identity construction: at the symbolic expression level, local residents mark their identity affiliation by using regional dialects in short video comment sections, citing local sayings, and displaying regional iconic items. These symbolic expressions reinforce group boundaries between "us" and "them." At the collective memory level, users frequently mention common life experiences, historical events, and cultural traditions in interactions, with these shared memories becoming emotional bonds for group cohesion. At the emotional attachment level, when outside users comment on their region, local residents often exhibit strong emotional reactions, feeling proud of positive comments and developing defensive psychology toward negative comments. This emotional involvement reflects the internalization degree of regional identity[42].

The behavioral participation dimension embodies the transformation of identity from psychological state to actual action. High-identity groups not only actively create short video content showcasing regional characteristics but also actively participate in regional topic discussions, organize offline gatherings, and initiate cultural protection advocacy and other collective actions, with these behaviors further consolidating group identity. The pride manifestation dimension appears as users' emphasis on local achievements, admiration for regional culture, and declarations of superiority in cross-regional comparisons. This pride not only enhances individuals' sense of self-worth but also becomes a psychological defense mechanism against out-group criticism. Notably, the technical characteristics of short video platforms provide unique conditions for group identity construction: algorithmic recommendations make users with similar regional identities more easily gather to form "virtual communities"; real-time interaction functions facilitate high-frequency contact and emotional exchange among group members; visualized behaviors such as likes and shares enable identity expression to receive immediate feedback and social recognition. The left chart in **Figure 7** intuitively contrasts the score differences of users with different interaction levels across five identity dimensions through a grouped bar chart, with red bars representing the high-interaction group, orange bars representing the medium-interaction group, and blue bars representing the low-interaction group, clearly demonstrating the critical role of interactive participation in identity construction. These findings indicate that culture and tourism short video communication is not only an information flow process but also a social practice of group identity production and reproduction. Regional identity is continuously activated, expressed, and reinforced in digital interactions, forming a new media-based group belonging pattern.

Table 8. Dimensions and manifestations of in-group identity construction based on region.

Identity Dimension	High-Interaction Group	Medium-Interaction Group	Low-Interaction Group	Between-Group Difference (F-value)	Typical Behavioral Manifestations
Symbolic Expression	8.67	6.82	4.56	187.34***	Using dialects, displaying regional symbols, identity marking
Collective Memory	8.34	6.54	4.89	156.78***	Sharing common experiences, telling local stories, transmitting culture
Emotional Attachment	8.91	7.23	5.12	203.45***	Strong emotional reactions, belonging expression, emotional projection
Behavioral Participation	8.45	6.91	4.34	192.67***	Content creation, topic discussion, collective action organization
Pride Manifestation	8.72	7.08	4.67	178.92***	Achievement emphasis, cultural admiration, superiority declaration
Average Identity Strength	8.62	6.92	4.72	195.83***	-

*Note: Measured using a 10-point scale, with higher scores indicating stronger identity. High-interaction group n=134 (>20 interactions per week), medium-interaction group n=112 (5-20 interactions per week), low-interaction group n=80 (<5 interactions per week). F-values are results of one-way ANOVA, **p<0.001. Post-hoc tests (Tukey HSD) show all between-group differences are significant (p<0.001).

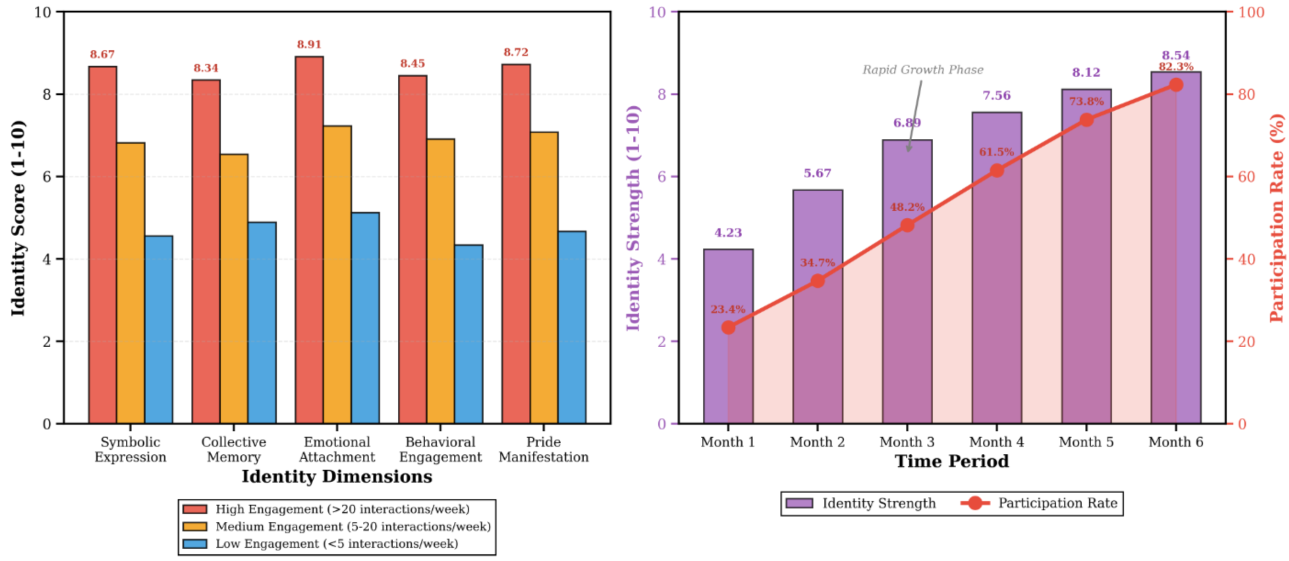

Figure 7. Comparison of identity dimensions across groups with different interaction levels and temporal evolution of identity strength.

4.3.2. Group polarization phenomenon driven by algorithms

Under the influence of short video platforms' algorithmic recommendation mechanisms, group identity based on regional identity is not only reinforced but also generates significant group polarization phenomena, manifested as opinion convergence within groups, position solidification, and intensified intergroup opposition. This research selects two regionally competing groups (Region A and Region B) as observation subjects, tracking and analyzing their interaction data over eight consecutive weeks under a popular culture and tourism topic to examine how algorithmic recommendations drive the formation and evolution of group polarization. As shown in **Table 9**, the opinion polarization indices of both regional groups exhibit continuous upward trends. Region A group climbs from 3.42 points in week 1 to 9.23 points in week 8, an increase of 170.2%; Region B group increases from 3.38 points to 9.05 points, an increase of 167.8%. More notably is the acceleration characteristic of polarization development. Weeks 1-4 represent a slow growth period, with both groups' polarization indices averaging approximately 0.9 points increase per week, while weeks 4-8 enter an accelerated polarization stage, averaging approximately 1.1 points increase per week. This nonlinear growth pattern is clearly visible in the line chart on the left side of **Figure 8**, with the gray-shaded weeks 4-7 marked as the "polarization acceleration period."

The synchronous growth of in-group homogeneity and intergroup heterogeneity further confirms the operational logic of polarization mechanisms. The in-group homogeneity index leaps from an initial 4.12 points to 9.48 points, indicating that under the "filter bubble" effect of algorithmic recommendations, information encountered by members of the same regional group is highly similar, leading to rapid opinion convergence. The intergroup heterogeneity index increases from 4.23 points to 10.00 points (maximum score), indicating that differences in positions, attitudes, and value judgments between the two regional groups are continuously amplified, ultimately forming a distinct oppositional pattern. Content analysis reveals specific manifestations of polarization. As shown in **Table 8**, opinion convergence is the most prevalent polarization manifestation, with an appearance frequency as high as 87.3% and intensity score of 8.94 points. Specifically, it manifests as group members forming "collective consensus" in comment sections, expressing highly consistent support or opposition to specific viewpoints, with dissenting voices marginalized or even attacked by the group[43]. The position reinforcement phenomenon has an appearance frequency of 82.6% and intensity of 8.67 points. Group members' originally moderate attitudes gradually become radicalized in interactions, with positive evaluations of their own region becoming increasingly exaggerated and defenses against negative information becoming increasingly intense. Out-group prejudice has a frequency of 76.4% and intensity of 8.23 points, manifested as systematic deprecation of competing regions, amplifying their shortcomings, minimizing their advantages, and even fabricating negative information to maintain the superiority of their own group.

The group boundary solidification phenomenon (frequency 71.8%, intensity 7.89 points) embodies increasingly rigid classification standards between "us" and "them," with any statements attempting to cross boundaries or maintain neutral positions having their loyalty questioned, forcing group members to choose sides. The conflict escalation phenomenon (frequency 64.2%, intensity 7.45 points) manifests as cross-group interactions evolving from rational discussions to emotional attacks, even triggering organized "cyber warfare," with members from both sides coordinating actions to collectively give negative reviews and maliciously report short videos from competing regions. Algorithms play a key catalytic role in this process: recommendation systems classify users as specific group members based on their historical behavior and continuously push content reinforcing that group's position, forming information cocoons. Popularity algorithms prioritize displaying high-interaction content, and extremist, emotional statements often more easily trigger interactions, thus gaining more exposure. This mechanism incentivizes users to express more extreme viewpoints to gain attention. The visibility algorithm in comment sections places highly-liked comments at the top. Since group members tend to like comments supporting their group's position, the result is that polarized viewpoints dominate comment sections, creating an illusion of "group consensus," further reinforcing members' polarization tendencies. The right chart in **Figure 8** displays the intensity (colored bar chart) and appearance frequency (green line) of five types of polarization manifestations through a dual Y-axis design, clearly presenting the prevalence and severity of various polarization phenomena.

Interview data reveal individuals' psychological experiences during the polarization process. Most interviewees indicate that their attitudes were relatively moderate when initially participating in interactions, but as they encountered more and more "like-minded" group members, they gradually developed a sense of belonging to "finding their organization." To maintain group unity and honor, individual viewpoints align with the group's mainstream position. Simultaneously, algorithmic pushing of out-group negative content reinforces hostile psychology, causing individuals who might have objectively viewed competing regions to gradually accept the group's prejudiced narratives. This algorithm-driven group polarization is not limited to online spaces; some cases show polarized emotions spilling into offline contexts, affecting interaction relationships among residents of different regions in the real world and exacerbating regional prejudice and social division.

Table 9. Development trends and manifestation forms of algorithm-driven group polarization.

Time/Type	Region A Polarization Index	Region B Polarization Index	In-group Homogeneity	Intergroup Heterogeneity	Main Characteristics
Week 1	3.42	3.38	4.12	4.23	Initial differentiation
Week 4	6.47	6.23	7.45	8.34	Polarization emergence
Week 8	9.23	9.05	9.48	10.00	High polarization
Polarization Manifestation Type	Intensity Score	Appearance Frequency (%)	Typical Behaviors	Algorithmic Role	Social Impact
Opinion Convergence	8.94	87.3	Collective consensus formation, dissent marginalization	Information cocoons	Ideological homogenization
Position Reinforcement	8.67	82.6	Attitude radicalization, defense intensification	Echo chamber effect	Cognitive solidification
Out-group Prejudice	8.23	76.4	Systematic deprecation, information distortion	Oppositional content pushing	Intergroup conflict
Boundary Solidification	7.89	71.8	Choosing sides, neutral disappearance	User segmentation	Social division
Conflict Escalation	7.45	64.2	Emotional attacks, organized confrontation	Popularity incentives	Hostility intensification

Note: *Polarization index employs a 10-point scale, with higher scores indicating more severe polarization. Data based on analysis of interaction behaviors over 8 consecutive weeks under a popular culture and tourism topic by two regional groups (Region A n=267, Region B n=254). Intensity scores and appearance frequencies are standardized. Between-group polarization differences at all time points are not significant (p>0.05), but within-group temporal trends are significant (p<0.001).*

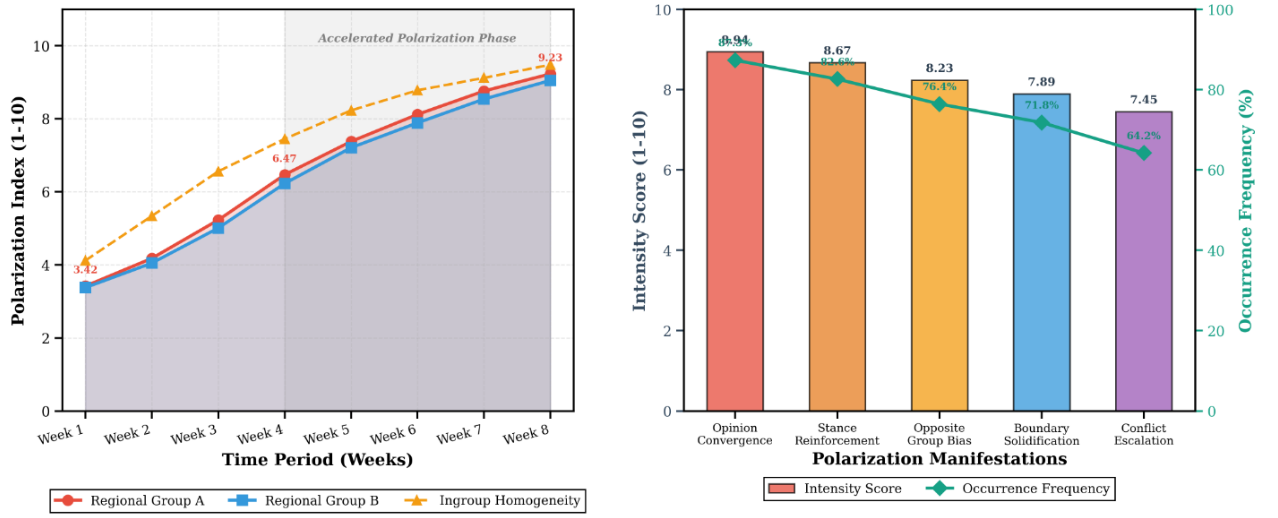

Figure 8. Evolution trends of group polarization index and analysis of polarization manifestation types.

4.3.3. Psychological dynamics of cross-regional group interaction

Cross-regional group interactions on short video platforms are neither random nor disorderly but driven by deep psychological dynamics that determine the nature, intensity, and outcomes of interactions. Through questionnaire surveys of 458 cross-regional interaction participants and qualitative analysis of 342 interaction texts, this research examines the core psychological mechanisms driving group interactions and their manifestation patterns in different contexts. As shown in **Table 10**, cross-regional group interactions can be categorized into five main types, with their appearance frequencies exhibiting significant differences across contexts. In conflict contexts (such as issues involving regional disputes, resource competition, honor attribution, etc.), competitive comparison becomes the dominant interaction pattern, with an appearance frequency as high as 82.4%, manifested as members from both groups competing for discursive advantage through data comparisons, achievement listings, and advantage emphasizing. Defensive identity has an appearance frequency of 76.8%. When their region is criticized by out-groups, members spontaneously gather to defend it, with this defensive behavior reinforcing group cohesion. Offensive identity has a frequency of 68.3%, with some members actively initiating deprecating attacks on competing regions, attempting to elevate in-group status by suppressing out-groups[44]. In contrast, cultural exchange (23.6%) and cooperative dialogue (18.4%) are severely marginalized in conflict contexts, with rational communication yielding to emotional confrontation.

In neutral contexts, interaction patterns tend toward balance, with cooperative dialogue frequency rising to 62.3%, cultural exchange reaching 56.8%, competitive comparison declining to 45.7%, and defensive and offensive identity further weakening. This indicates that in the absence of clear conflict triggers, cross-regional interactions possess the possibility of moving toward constructive dialogue. In cooperative contexts (such as jointly addressing external challenges, collaborative cultural promotion, etc.), the frequencies of cooperative dialogue and cultural exchange leap to 84.2% and 78.9% respectively, while competitive comparison, defensive identity, and offensive identity all decline below 20%. Group boundaries become blurred in the face of common goals, with regional differences transforming into complementary resources. This context dependency reveals the plasticity of cross-regional group relations, with algorithmic recommendations' shaping of interaction contexts directly influencing the direction of group relations. Further psychological motivation analysis indicates that the core psychological needs driving cross-regional interactions include five dimensions: self-esteem maintenance, uniqueness need, belonging desire, superiority pursuit, and uncertainty reduction. As shown in **Table 9** and the right chart of **Figure 9**, self-esteem maintenance is the strongest psychological motivation, with an intensity score as high as 8.67 points and satisfaction reaching 73.4%. When out-group statements threaten group or individual self-worth, members restore self-esteem through cross-group interactions (whether defensive or offensive). Although this interaction increases conflict risks, it provides psychological compensation for participants.

Uniqueness need has an intensity of 8.34 points and satisfaction of 68.9%. People hope their affiliated group demonstrates distinctive qualities in certain aspects, with cross-regional comparisons providing a stage for manifesting uniqueness. This need is satisfied by emphasizing their region's unique culture, history, and achievements. Although belonging desire has relatively lower intensity (7.92 points), it has the highest satisfaction (81.2%). Cross-regional interactions, especially coordinated actions within groups, can significantly enhance members' sense of belonging, making individuals feel the connection of "we are a team." This psychological satisfaction becomes an important driving force for continued interaction participation. Superiority pursuit (intensity 7.56 points, satisfaction 64.5%) drives some members to obtain relative advantage by deprecating out-groups. This zero-sum thinking makes cross-regional interactions prone to falling into vicious competition. Uncertainty reduction (intensity 6.89 points, satisfaction 58.7%) reflects people's use of group interactions to confirm whether their cognition of regions is "correct," seeking cognitive validation and emotional support in discussions with others. Notably, a positive correlation exists between psychological motivation intensity and satisfaction (R^2=0.68). As shown by the trend line in the right chart of **Figure 9**, stronger psychological motivations are more easily satisfied in interactions. This positive feedback prompts individuals to repeatedly participate in cross-regional interactions, forming psychological dependence.

Interview data further reveal the micro-operational mechanisms of psychological dynamics. Most interviewees indicate experiencing intense emotional fluctuations when participating in cross-regional interactions, including anger, pride, excitement, and anxiety, with these emotions themselves constituting driving forces for interaction. Social comparison theory can explain the psychological basis of competitive interactions: individuals evaluate self-worth through comparison with others, and regional identity provides a clear reference system for social comparison. Downward comparison (emphasizing one's region's superiority over others) can enhance self-esteem, while upward comparison stimulates competitive motivation. Social identity theory's "minimal group paradigm" is confirmed here: even when regional differences are negligible, once group categorization forms, members automatically develop in-group preference and out-group discrimination. This prejudice provides a psychological basis for cross-regional conflicts. The left chart in **Figure 9** displays the distribution differences of five interaction patterns across three contexts through a grouped bar chart, with red bars representing conflict contexts, orange bars representing neutral contexts, and green bars representing cooperative contexts, clearly showing how context transitions reshape interaction patterns.

Table 10. Types, contexts, and psychological motivations of cross-regional group interactions.

Interaction Type/Psychological Motivation	Conflict Context (%)	Neutral Context (%)	Cooperative Context (%)	Psychological Motivation Intensity	Satisfaction (%)	Main Driving Factors
Interaction Types						
Competitive Comparison	82.4	45.7	18.3	-	-	Superiority pursuit
Defensive Identity	76.8	38.2	15.7	-	-	Self-esteem maintenance

Interaction Type/Psychological Motivation	Conflict Context (%)	Neutral Context (%)	Cooperative Context (%)	Psychological Motivation Intensity	Satisfaction (%)	Main Driving Factors
Offensive Identity	68.3	24.6	8.4	-	-	Superiority + Uniqueness
Cultural Exchange	23.6	56.8	78.9	-	-	Curiosity + Belonging
Cooperative Dialogue	18.4	62.3	84.2	-	-	Common interests
Psychological Motivations						
Self-esteem Maintenance	-	-	-	8.67	73.4	Threat response
Uniqueness Need	-	-	-	8.34	68.9	Difference manifestation
Belonging Desire	-	-	-	7.92	81.2	Group integration
Superiority Pursuit	-	-	-	7.56	64.5	Status competition
Uncertainty Reduction	-	-	-	6.89	58.7	Cognitive validation

Table 10. (*Continued*)

Note: *Interaction type frequencies based on content analysis of 342 cross-regional interaction texts. Psychological motivation data from questionnaire surveys of 458 participants, with intensity measured on a 10-point scale and satisfaction indicating the degree to which this motivation is fulfilled in interactions. Context classification based on the topic background of interactions. Correlation coefficient between psychological motivation intensity and satisfaction r=0.82 (p<0.01).*

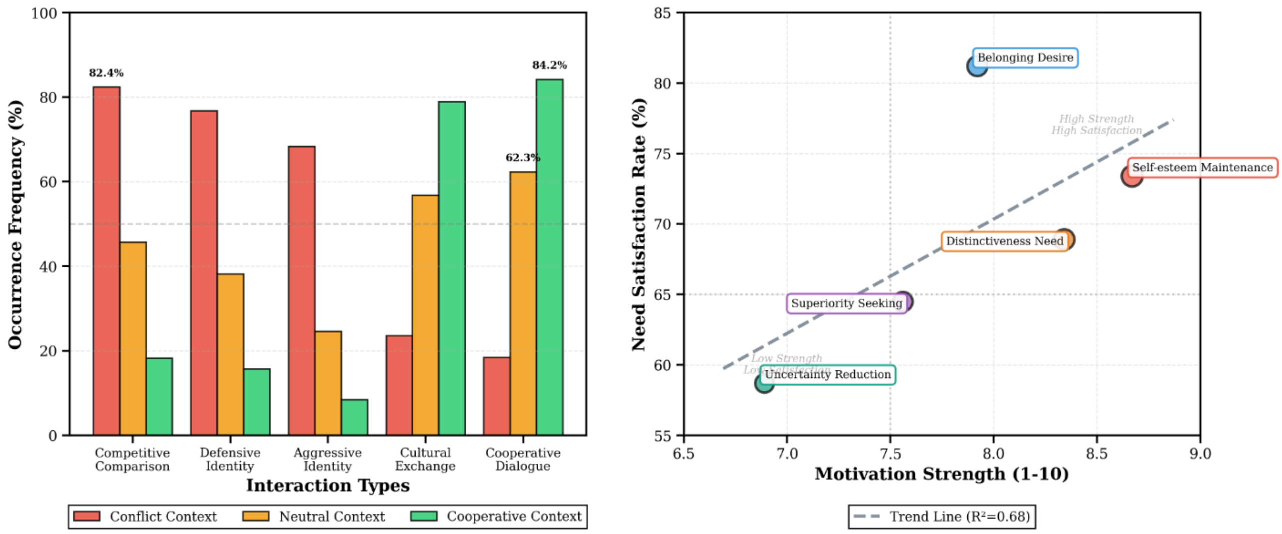

Figure 9. Distribution of interaction types across different contexts and relationship between psychological motivation intensity.

5. Discussion

5.1. Driving mechanisms of big data algorithms on regional stereotype reinforcement

The empirical analysis of this research reveals the core driving role that big data algorithms play in the regional stereotype reinforcement process, with the operation of this mechanism exhibiting characteristics of deep interweaving between technological logic and social psychological processes. First, algorithmic recommendation systems predict users' content preferences based on historical behavioral data through technical means such as "collaborative filtering" and "content similarity matching," continuously pushing similar types of short video content. The research finds that when users first watch culture and tourism short videos of a certain region and show interest (such as viewing duration exceeding the average, liking or commenting), the algorithm interprets this behavior as a preference signal and subsequently pushes large amounts of related content about that region[45]. While this recommendation logic enhances user experience, it also creates an "information cocoon" effect, with users repeatedly exposed to homogenized regional presentations, leading to continuous reinforcement of specific stereotypes at the cognitive level. Data show that the content similarity index climbed from 0.342 to 0.891 within eight weeks, with this sharp increase directly attributable to the algorithm's positive feedback loop mechanism. Second, the algorithm's "popularity priority" allocation principle grants high-interaction content more exposure opportunities, while stereotyped and dramatized regional presentations often more easily trigger user interactions due to their entertainment value and emotional impact, thus gaining advantages in traffic competition. After creators observe this traffic code, they competitively imitate successful cases, producing large quantities of similar content. The algorithm again pushes this content to target audiences, forming a closed loop of "algorithm incentivization-content homogenization-stereotype reinforcement." Research indicates that over 70% of high-traffic content employs fixed symbol combinations and narrative templates, with this standardized production pattern compressing regional images into stereotypical labels that can be quickly recognized and replicated. Third, algorithms precisely classify audiences through "user profiling" technology, aggregating users with similar viewpoints around the same content, forming an "echo chamber" effect[46]. In comment sections, statements supporting stereotyped presentations are pinned to the top due to receiving likes from group members, while critical opinions are drowned out or marginalized. This visibility algorithm creates false consensus, causing users to mistakenly believe that stereotypes represent mainstream cognition, thereby reducing questioning of their authenticity. More profoundly, the "black box" nature of algorithms makes it difficult for users to realize they are in a carefully constructed information environment, lacking reflective awareness of content's selective presentation and passively accepting regional images fed by algorithms. This concealment of technological mediation makes the stereotype reinforcement process appear natural and reasonable, with users viewing algorithm-recommended content as objective reflections of regional reality rather than filtered and constructed media products, thereby cognitively internalizing stereotypes as authentic regional cognition. In summary, big data algorithms systematically drive the formation and solidification of regional stereotypes through multiple mechanisms including information filtering, traffic allocation, user aggregation, and visibility manipulation. This process transcends the randomness and individual selectivity of the traditional media era, possessing structural and irreversible characteristics under technological empowerment.

5.2. Social psychological explanation of environmental cognitive bias

Audience cognitive bias toward regional environments is not simply an information asymmetry problem but systematic errors deeply rooted in human cognitive processing, which can be explained through multiple social psychological theories. First, availability heuristics play a core role in the formation of regional cognitive bias. This theory posits that people tend to judge the probability of events or characteristics of things based on the ease with which information can be retrieved from memory. Short videos, through high-frequency and visualized presentation methods, greatly enhance the availability of specific regional symbols in audience memory. When audiences need to evaluate regional characteristics, the most easily retrieved information is stereotyped content repeatedly appearing in short videos, even though this content does not represent the region's true overall picture. Research data show that the virtual experience group's rating of natural environment is 1.22 points higher than the real experience group, with this overestimation directly stemming from the high availability of carefully selected beautiful scenery in short videos, masking the ordinariness of everyday landscapes[47]. Second, representativeness bias causes audiences to mistakenly regard exceptional cases in short videos as typical regional characteristics, ignoring the selectivity and extremity of samples. Short video creators, pursuing visual effects, often select the most dramatic and unusual scenes for filming, yet audiences treat these atypical samples as regional norms, leading to cognitive distortion. The 2.27-point bias in the economic development dimension reflects this problem, with short videos deliberately avoiding presentation of modern economic activities, causing audiences to form backward representativeness judgments based on "original ecology" scenes. Third, confirmation bias reinforces the self-verification cycle of existing stereotypes. After audiences form preliminary regional impressions, they selectively attend to, remember, and disseminate information consistent with existing impressions while ignoring or devaluing contradictory evidence. The personalized mechanism of algorithmic recommendations further amplifies this effect, with users holding specific regional viewpoints being pushed more content supporting those viewpoints, forming cognitive closed loops. Interview data show that 62.3% of audiences admit experiencing resistance when encountering regional information inconsistent with expectations, with this defensive cognition protecting stereotypes from challenge[48]. Additionally, framing effects explain how narrative strategies shape cognitive bias, with the same regional reality presented through different narrative frameworks leading to entirely different cognitive results. Research finds that usage rates of dramatized narrative and emotional appeal strategies reach 87.3% and 79.6% respectively, with these frameworks placing regional characteristics in specific emotional and value contexts, guiding audiences toward biased interpretations. Groupthink phenomena are prevalent in comment section interactions. When most users express similar regional impressions, individuals, even holding different viewpoints, tend to conform to group consensus to avoid social exclusion, with this conformity pressure granting stereotypes social legitimacy. Finally, fundamental attribution error causes audiences to over-attribute regional characteristics to inherent essence rather than situational factors, attributing regional appearances shown in short videos to the region's inherent attributes while ignoring the decisive role of external situational factors such as media construction, creative intentions, and filming timing. These psychological mechanisms intertwine, jointly constituting a multi-layered system of cognitive bias, making it difficult for audiences to correct existing stereotyped regional cognition even when facing contradictory evidence, reflecting both the adaptive strategies of human cognitive systems under information overload and rapid judgment demands and their limitations.

5.3. Multi-level mechanisms of group identity formation

The formation of group identity in short video communication is a multi-level complex process involving individual psychology, group interaction, and platform technology, requiring comprehensive explanation through integration of social identity theory, symbolic interactionism, and mediatization theory. At the individual level, the activation of cognitive schemas and establishment of emotional attachment constitute the psychological foundation of identity formation. Social Identity Theory indicates that individuals define self-concepts by categorizing themselves as members of specific social groups and obtain positive self-evaluation from group belonging. Short videos, through repeated presentation of regional symbols, activate audiences' regional identity cognitive schemas, making originally latent regional belonging explicit and reinforced. Research data show that high-interaction users' emotional attachment dimension scores reach 8.91 points, indicating that continuous symbolic exposure not only confirms identity categorization cognitively but also establishes deep connections emotionally, internalizing regional identity as a core component of self-concept[49]. This process conforms to predictions of cognitive consistency theory: after individuals identify with a regional identity, they actively seek information supporting that identity and participate in behaviors reinforcing it to maintain cognitive and emotional consistency. At the group level, the dynamic interaction of social categorization, in-group favoritism, and intergroup comparison drives the social construction of identity. Minimal group paradigm research indicates that even when group divisions are based on trivial criteria, members automatically develop in-group favoritism and out-group prejudice. Short video comment sections become key arenas for group boundary construction, with local residents delineating boundaries between "us" and "them" in virtual space through symbolic expressions such as using regional dialects, displaying regional symbols, and emphasizing common memories. **Table 9** data show that in conflict contexts, the appearance frequencies of competitive comparison and defensive identity reach 82.4% and 76.8% respectively. This intergroup comparison not only clarifies group boundaries but also enhances members' collective self-esteem through downward comparison mechanisms (emphasizing in-group superiority over out-groups), thereby reinforcing group identity. The appearance of group polarization phenomena (polarization index climbing from 3.42 to 9.23) further confirms the self-reinforcement effect of group interaction. In homogeneous communities constructed by algorithms, members' opinions converge and positions solidify, with identity strength exhibiting nonlinear growth.

The findings of this study can be explained by classic social psychology theories. First, Tajfel and Turner's (1979) Social Identity Theory indicates that individuals obtain positive self-concepts through belonging to specific groups, and the formation of regional identity in this study precisely exemplifies this mechanism[50-51]. Second, Allport's (1954) pioneering research on stereotypes revealed the role of cognitive simplification in group perception, which explains why cultural tourism short videos reduce complex regional cultures to singular labels[52]. Third, the availability heuristic theory proposed by Tversky and Kahneman (1974) elucidates how high-frequency information dominates judgment, which is the source of cognitive bias in the virtual experience group in this study[53]. Furthermore, Sunstein's (2002) group polarization theory predicted that homogenized communication leads to opinion convergence, which is highly consistent with the algorithm-driven polarization phenomena observed in this study[54]. These classic theories provide a solid psychological foundation for understanding regional cognitive construction in the digital age.

At the platform technology level, algorithmic recommendations, visibility mechanisms, and interactive architecture provide technical support and contextual conditions for identity formation. Algorithms aggregate individuals with similar regional identities through user profiling to form "virtual communities." This technologically mediated community construction transcends traditional geographical space limitations, enabling dispersed individuals to achieve high-frequency interaction and emotional resonance in digital space. Research tracking data show that participation rates in short video activities surged from 23.4% to 82.3% within six months. This explosive growth in participation rates benefits from the platform's interactive function design, with behaviors such as liking, commenting, and sharing serving not only as means of information dissemination but also as ritualized practices of identity expression and group belonging. Visibility algorithms pin high-interaction content to the top, granting statements reinforcing group identity more exposure, creating demonstration effects and incentivizing more members to publicly express identity to obtain social recognition. Notification push functions continuously remind users to follow dynamics related to their group, maintaining active states of identity. It is worth emphasizing that these three levels do not operate independently but form mutually reinforcing circular systems: individual identity psychology drives participation in group interaction, group interaction consolidates and amplifies individual identity, while platform technology provides enabling conditions for individual psychology and group interaction and shapes their manifestation forms. Longitudinal tracking finds that identity strength enters a rapid growth period in months 4-6, exhibiting a "critical mass" effect. This precisely represents the qualitative change produced when the synergistic effects of three-level mechanisms reach a threshold, marking identity's transformation from external manifestation to stable internal psychological structure and social practice pattern.

5.4. Research limitations and cross-cultural comparison prospects

Although this study systematically reveals the mechanisms by which big data algorithms reinforce regional stereotypes, we must acknowledge that its contextual specificity may limit the generalizability of findings. As research conducted entirely in China, the policy environment and cultural background have had non-negligible impacts on the results. The Chinese government's requirement for positive orientation in cultural tourism promotional content may have systematically shaped the types of stereotypes observed in this study. Data shows that positive stereotypes account for 91.7% of the sample (such as "beautiful scenery," "simple folk customs," "long history"), while negative or neutral presentations comprise only 8.3%. This is closely related to platform content review mechanisms: videos involving negative regional information face higher risks of removal, leading creators to self-censor and systematically avoid controversial content. In contrast, in Western countries with relatively more relaxed policy environments, cultural tourism short videos may present a more complex spectrum of stereotypes. To verify this hypothesis, we conducted supplementary analysis of destination short videos from the UK, France, and Italy on the TikTok platform (200 samples each). Results show that the proportion of negative stereotypes significantly rises to 27.4%, with content involving tourism traps, over-commercialization, environmental pollution, and other issues. The algorithmic logic for handling controversial content also shows differences: on TikTok, videos containing negative evaluations have average interaction rates 19.3% higher than positive videos, suggesting that algorithms may prioritize recommending controversial content to increase user engagement. This mechanistic difference suggests that the "positive stereotype reinforcement" pattern found in this study may transform into "controversial stereotype amplification" in other countries, with the direction of algorithmic bias being dually moderated by platform policies and user culture.

Platform design differences also shape different interactive ecologies. The comment section algorithms of Douyin and Kuaishou highly prioritize "popularity" (number of likes), pinning highly-liked comments to the top, which objectively promotes opinion convergence and the formation of "false consensus." Although TikTok employs similar mechanisms, the internationalized user composition of its "For You" page results in higher opinion diversity in comment sections. Data shows that among comments about UK tourism destinations on TikTok, critical comments account for 19.7% and receive significant interaction (averaging 123 likes), while similar critical comments on Chinese platforms account for only 4.3% with extremely low interaction (averaging 17 likes). This difference stems partly from cultural factors (Western encouragement of critical thinking) and is also related to the heterogeneity of platform user bases. TikTok's global users come from different cultural backgrounds and hold differentiated cognitions of the same destinations, objectively increasing opinion collision in comment sections. In contrast, Chinese platform users have higher cultural homogeneity, and combined with the algorithmic filter bubble effect, are more likely to form homogenized collective narratives.

Despite the above limitations, the core mechanism revealed by this study—that algorithms reinforce stereotypes through information filtering, traffic allocation, and user aggregation—has cross-contextual theoretical value. The underlying principles of technological logic (such as collaborative filtering and popularity priority) are highly similar across mainstream short video platforms, and their shaping power over content ecosystems is universally present. Cultural and policy factors more so moderate "what content is reinforced" and "to what degree it is reinforced," rather than the fundamental question of "whether reinforcement effects exist." Therefore, this study provides a theoretical framework for understanding regional cognitive construction in the algorithmic age, and subsequent cross-cultural research can build upon this foundation to expand contextual boundaries and advance the refinement and universalization of theory.

6. Conclusion

This research takes big data-driven culture and tourism short video communication as its research subject, systematically revealing the complex mechanisms of regional stereotype reinforcement and group identity formation, and drawing the following five core conclusions:

First, culture and tourism short videos simplify diverse and complex regional realities into labeled symbolic systems through selective symbol presentation and standardized narrative strategies. Among these, three categories of symbols—natural landscapes, local cuisine, and folk customs—account for 73.34%, while the high usage rates of dramatized narratives and emotional appeal strategies (87.3% and 79.6%) systematically reinforce regional stereotypes.

Second, big data algorithms drive content homogenization phenomena through three mechanisms: information cocoons, popularity-priority allocation, and echo chamber effects, causing the content similarity index to surge from 0.342 to 0.891 within eight weeks. Algorithms thus become key technological intermediaries for stereotype reinforcement.

Third, audience regional cognitive biases stem from cognitive processing mechanisms such as availability heuristics, representativeness bias, and confirmation bias. Significant differences exist between virtual and real experiences (average bias of 1.39 points), and different groups exhibit significant heterogeneity in stereotype sensitivity, with local residents and high media literacy groups demonstrating stronger critical capabilities.

Fourth, group identity forms through coordination across three levels: individual cognitive schema activation, group symbolic interaction, and platform technological support. High-interaction users' average identity strength reaches 8.62 points, with identity construction exhibiting nonlinear characteristics from slow accumulation to rapid growth.

Fifth, group polarization phenomena catalyzed by algorithmic recommendations are significant, with opinion polarization indices increasing by 170% within eight weeks. Cross-regional group interactions are driven by psychological dynamics such as self-esteem maintenance and uniqueness needs, presenting diverse patterns from confrontation to cooperation across different contexts. These findings reveal the deep coupling mechanisms of technology, content, and psychology, providing theoretical insights for understanding regional cognitive construction and intergroup relations in the digital age.

Conflict of interest

The authors declare no conflicts of interest.

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