

The Impact of Douyin, a New Generation Information Technology Platform, on Anhui's Tourism Industry: An Empirical Study Based on the Mediating Effect of Behavioral Intention

Chenghui Zheng ^{1,2}, Ali Khatibi ², Jacqueline Tham ²

¹ Hefei Technology College, Hefei, China, 230012

² Postgraduate Centre, Management & Science University, Shah Alam (40100), Malaysia
115777001@qq.com; alik@msu.edu.my; jacquiline@msu.edu.my

Abstract. This study examines how Douyin (Chinese Douyin), as a new-generation information technology platform, influences regional tourism development in Anhui Province through a behavioral transmission mechanism. To strengthen the paper's positioning within digital platform informatics and service-system research, the study conceptualizes Douyin's influence through three platform-related dimensions: Platform Features, Content Type, and User Interaction, and tests their effects on tourists' Actual Behavior with Behavioral Intention as a mediating variable. Drawing on the Theory of Planned Behavior, new-generation information technology theory, and flow economy theory, the study develops a mediation model that links short-video platform factors to observable tourism behavior. Data were collected from 486 valid respondents through a structured questionnaire distributed via Wenjuanxing, Douyin communities, and WeChat platforms. The data were analyzed using descriptive statistics, reliability and validity testing, correlation analysis, regression analysis, and Bootstrap-based mediation tests in SPSS. The results show that Platform Features, Content Type, and User Interaction all have significant positive effects on both Behavioral Intention and Actual Behavior. Behavioral Intention partially mediates all three relationships, with indirect effects accounting for more than half of the total effects in each pathway. Among the three predictors, Content Type exerts the strongest influence on Behavioral Intention, indicating that high-quality and culturally distinctive content is the most important driver of tourism conversion on Douyin. The findings suggest that Douyin functions not only as a communication channel but also as a digital platform infrastructure that shapes information dissemination, user engagement, and tourism service demand. The study contributes to the literature by clarifying the mediating mechanism through which short-video platform informatics is translated into regional tourism behavior, and offers practical implications for destination managers, tourism enterprises, and content creators seeking to improve the efficiency and sustainability of Anhui's digital tourism development.

Keywords: New Generation Information Technology; Short-Video Platform Informatics; Anhui Tourism Industry; Behavioral Intention; Mediating Effect; Actual Behavior

1. Introduction

The rapid advancement of new-generation information technologies has accelerated the convergence of the digital economy with traditional industries, fundamentally altering how destinations are discovered, represented, and consumed. Among the most consequential of these technologies is the short-video platform, which has emerged as a dominant force in tourism communication. Douyin, in particular, has surpassed 750 million daily active users by 2025, functioning not merely as an entertainment channel but as an algorithmic ecosystem that connects destinations with latent audiences at unprecedented scale and precision. Unlike conventional search-driven media, Douyin's recommendation infrastructure exposes destination content to users who have not actively sought travel information, a phenomenon of incidental exposure that has been shown to translate meaningfully into travel intentions (He et al., 2026). The platform's immersive visual-audio environment, frictionless interactivity, and viral dissemination dynamics have generated a series of "phenomenal" tourism cases in China, from the Zibo barbecue craze to the Harbin Ice and Snow World, empirically demonstrating Douyin's capacity to rapidly amplify destination visibility and convert audience engagement into actual visitation behavior.

Anhui Province offers a particularly salient context in which to examine this dynamic. The province commands an exceptional portfolio of cultural and tourism resources, encompassing natural landscapes such as Huangshan Mountain and Jiuhua Mountain, UNESCO-recognized heritage villages of Xidi and Hongcun, and distinctive folk-cultural assets including the She County fish lanterns and the "down-to-earth Three Kingdoms" festival in Fuyang. The Anhui cultural and tourism sector has grown substantially during the 14th Five-Year Plan period, with domestic tourism consumption reaching 943.3 billion yuan in 2024 and projected to surpass the trillion-yuan threshold in 2025. Douyin has played a visible catalytic role in this growth: during the Snake Year Spring Festival, short-video promotion campaigns in cities including Ma'anshan and Huangshan's She County generated measurable surges in catering, entertainment, and travel orders, with She County fish lantern-related video submissions rising by 168% year-on-year and driving local commercial orders more than fourfold. These outcomes confirm that Douyin functions as a substantive driver of Anhui's tourism economy, not merely a promotional accessory.

However, the chain from content communication to behavioral conversion remains poorly understood and unevenly optimized. Across Anhui's tourism ecosystem, practitioners confront persistent challenges: homogeneity in cultural tourism content, insufficient stimulation of users' behavioral intention, low efficiency in translating intention into actual travel behavior, and an over-reliance on traffic logic at the expense of authentic cultural representation. These operational challenges are compounded by theoretical gaps in the existing literature. While a growing body of research has examined the influence of short-video platforms on tourism marketing and consumer behavior, documenting effects of platform features, user-generated versus professionally generated content, and interaction behaviors on tourist attitudes and intentions (Polat et al., 2023; Kim et al., 2026), most studies treat behavioral intention as a terminal dependent variable rather than a mediating mechanism. The transmissive role of behavioral intention in converting Douyin-generated engagement into observable travel behavior has not been systematically tested, and no study has applied this mediation framework to a provincial tourism market in China.

The present study addresses these gaps by constructing an empirically grounded mediation model centered on three dimensions of Douyin's influence, namely Platform Features, Content Type, and User Interaction, and testing their effects on Anhui tourism Actual Behavior with Behavioral Intention as the core mediating variable. The theoretical foundation integrates the Theory of Planned Behavior, the new-generation information technology framework, and flow economy theory, providing a coherent basis for hypothesizing both direct and indirect pathways from platform antecedents to behavioral outcomes. Data were collected from 486 valid respondents via a structured questionnaire distributed through Wenjuanxing, Douyin communities, and WeChat platforms, and analyzed using SPSS-based mediation

testing procedures. By simultaneously estimating direct effects and testing the proportion of total effects transmitted through behavioral intention, this study distinguishes the relative magnitudes of direct and indirect influence pathways, a methodological contribution that existing regional studies have not yet achieved.

The findings of this study carry both theoretical and practical significance. Theoretically, by integrating multiple behavioral frameworks and explicitly modeling the mediating role of behavioral intention within a provincial digital tourism context, this research extends the empirical literature on short-video platforms and regional tourism development, and addresses identified gaps regarding mediation mechanisms that prior work has not resolved (Chen, 2025a). Practically, the results offer actionable guidance for cultural and tourism authorities, tourism enterprises, and content creators in Anhui Province, clarifying which platform features, content strategies, and interaction designs most efficiently stimulate behavioral intention and facilitate its conversion into actual travel. The study thereby supports the strategic ambition of transforming Anhui's tourism industry from one driven by ephemeral "traffic flow" to one characterized by sustained "retained volume" and incremental value, contributing to the broader goal of building a competitive "Picturesque Anhui" cultural and tourism brand. The remainder of this paper proceeds as follows: Section 2 reviews the relevant literature; Section 3 presents the theoretical foundation and research model; Section 4 describes the research design; Section 5 reports the empirical results; and Section 6 discusses the findings and their implications.

2. Literature Review

2.1 Douyin and Short-Video Platforms in Tourism

The rapid proliferation of short-video platforms has fundamentally reshaped tourism marketing and consumer behavior. Platforms such as Douyin and its Chinese counterpart Douyin have evolved from entertainment tools into powerful destination marketing channels, attracting scholarly attention for their distinctive technical architecture and behavioral influence. A systematic review of user-generated video research in hospitality and tourism reveals that platform-driven content increasingly shapes tourists' cognitive and affective responses to destinations (Polat et al., 2023). Moreover, empirical evidence highlights that social media platforms significantly amplify the impact of reference groups and user-generated content, thereby directly shaping tourists' destination awareness and final travel choices (Zheng et al., 2025). Furthermore, digital transformation through social media marketing has been proven to enhance visitor experiences and directly stimulate tourists' destination revisitation intentions (Do Bui Xuan Cuong et al., 2025). Unlike traditional social media, short-video platforms combine algorithmic recommendation, immersive visual-audio environments, and frictionless interactivity, creating a unique ecosystem for tourism communication.

Central to the appeal of Douyin is its algorithmic infrastructure. Research has shown that Douyin's recommendation algorithm significantly increases the reach and precision of tourism content delivery, enabling destinations to connect with users who exhibit relevant interest patterns even without prior exposure (Kim et al., 2026; Chen, 2025a). The algorithm's capacity to surface destination content to passive users—those not actively searching for travel information—constitutes what scholars describe as "incidental exposure," which has been demonstrated to translate meaningfully into travel intentions (He et al., 2026). This capacity for serendipitous discovery distinguishes Douyin from search-engine-based platforms and substantially expands the potential audience for regional tourism marketing. Studies of Generation Z users on Douyin further confirm that platform-specific attributes such as perceived ease of use and technology acceptance are significant antecedents of destination visit intention, particularly for niche and lesser-known destinations (Hong & Liang, 2026). Furthermore, the overall quality of digital e-tourism platforms sequentially influences tourists' perceived value and

satisfaction, which ultimately determines their behavioral intentions, with this effect being particularly sensitive to the visitors' level of destination familiarity (Sinh & Kiet, 2025).

Beyond algorithmic reach, the immersive properties of short videos contribute substantially to their marketing effectiveness. Studies examining visual elements, including motion speed, zoom effects, and multimodal composition, demonstrate that technical production choices directly influence destination attractiveness and viewer engagement (Zhang et al., 2026a; Su et al., 2026; Guo et al., 2026). Audio features, including tempo, rhythmic complexity, and human narration, have similarly been shown to modulate user engagement with destination content across different thematic categories (Yu et al., 2026). These findings collectively suggest that platform affordances extend beyond mere content delivery, actively shaping the affective and cognitive processing of destination information. Research on short-form video in destination retail contexts further confirms that platform-driven foot traffic effects operate across both online and offline behavioral domains (Slaton & Lee, 2025).

The aggregate impact of short-video platform activity on tourism demand has also attracted empirical attention. Social media communication indices derived from short-video platforms demonstrate predictive validity for tourism demand, capturing latent travel intentions that conventional forecasting models overlook (Bi et al., 2025; Qin et al., 2025). Research in the Chinese context has specifically documented how Douyin-driven viral content, exemplified by the "wanghong city" phenomenon, can generate rapid, large-scale shifts in destination visitation patterns (Zhang et al., 2026b). The platform's influence on destination image reconstruction has been observed across diverse city types, reflecting Douyin's capacity to redefine public perceptions of previously overlooked destinations. Despite this growing body of evidence, most existing research treats platform features as an undifferentiated background condition rather than explicitly decomposing them into theoretically motivated dimensions within a unified empirical model—a gap this study addresses by operationalizing platform features as a multi-dimensional construct encompassing algorithmic accuracy, immersive experience, information efficiency, and functional usability.

2.2 Content Type and User Interaction as Drivers of Tourist Behavior

The content ecosystem of short-video platforms is shaped by a dual-track production structure comprising user-generated content (UGC) and professionally generated content (PGC), each carrying distinct advantages in terms of authenticity, reach, and persuasive power. Research comparing these content types consistently identifies perceived authenticity as the primary mechanism through which UGC influences tourist attitudes and behavioral intentions. User-generated short videos from Douyin and Douyin generate significantly higher perceived authenticity than official promotional videos, reducing psychological reactance and enhancing destination brand attitude (Zhou & Liu, 2026). In the food tourism context, Douyin vloggers' content builds taste awareness and source credibility through authentic peer narratives, which in turn mediates visit intention (Guo et al., 2024). Similarly, food-hunting short video content satisfies users' gratification needs and translates viewer engagement into destination visit intentions through narrative transportation and social comparison mechanisms (Hu et al., 2026).

PGC occupies a complementary role, offering professional depth and authoritative information that UGC typically lacks. Tour guide-led travel videos deliver narrative, professional, emotional, and cultural value dimensions that stimulate travel inspiration and, subsequently, visit intention (Chen et al., 2025b). Research on virtual endorsers, a form of PGC employing AI-generated influencers, demonstrates that narrative transportation mechanisms can enhance tourists' visit intentions even with non-human presenters, highlighting the primacy of storytelling quality over source authenticity in professional content (Huang et al., 2025). The complementarity between UGC and PGC is further evidenced by studies showing that matching content source to destination type moderates the strength of persuasive effects: user-generated content proves more effective for experiential destinations, while official PGC performs better for heritage and cultural sites (Li & Tu, 2024). In the agricultural heritage

tourism context, digital food narratives produced by rural influencers on Douyin illustrate how PGC can reframe local cultural assets as tourism resources, stimulating both interest and behavioral intention (Wang et al., 2026).

Content characteristics beyond the UGC/PGC distinction also exert significant effects on tourist behavior. Sentiment expression, language style, and structural composition have been identified as determinants of content efficacy. Tourism videos conveying positive and emotionally resonant sentiments generate higher engagement rates on social media platforms (Liu et al., 2025), while poetic and culturally evocative language enhances destination affect and willingness to visit (Ruan et al., 2025). Structural elements, including narrative sequencing, sensory cues, and temporal framing, synergistically influence travel intention through both cognitive and affective pathways (Wang et al., 2025b). Research on internet memes within short videos further demonstrates that quirky, humor-embedded content activates dual processing pathways, simultaneously engaging heuristic and elaborative cognition to shape travel intentions (Song et al., 2025). Title design research on Douyin confirms that even textual elements such as information style, emotional appeals, and personalization cues operate as attention-capturing signals that amplify content reach and engagement (Zhang et al., 2026c).

User interaction behaviors constitute a distinct but interconnected dimension of the short-video tourism ecosystem. The interaction ritual sense surrounding tourist check-in short videos, encompassing commenting, liking, and sharing, activates social bonding mechanisms that reinforce destination identification and strengthen visit intention among participants (Xu & Zhou, 2025). Douyin influencer content generates engagement through parasocial interaction, telepresence, and perceived attractiveness, which collectively shape destination appeal and travel intentions among followers, including underrepresented user groups (Pham & Phan, 2025). Viral dissemination through sharing behaviors amplifies reach beyond the initial audience, creating network effects that extend the marketing impact of individual videos across social networks (Wang et al., 2025a). Multimodal destination image research confirms that higher audience engagement correlates with richer multi-sensory content integrating visual, auditory, and narrative dimensions (Tan et al., 2025). Within culinary short-video contexts, social food reels foster interactive cultural curiosity that stimulates behavioral engagement and contributes to destination sustainability (Rashidin et al., 2026).

Despite these contributions, fewer studies systematically integrate content type (UGC vs. PGC) and user interaction behaviors as co-equal independent variables within a unified model of tourist behavioral outcomes. Research typically examines these dimensions in isolation, limiting understanding of how they interact to shape the overall Douyin-tourism pathway.

2.3 Behavioral Intention as a Mediating Mechanism

Behavioral intention occupies a central position in tourism behavior research, drawing its theoretical foundation primarily from the Theory of Planned Behavior, which posits behavioral intention as the most proximal motivational antecedent of actual behavior, reflecting individuals' subjective willingness to perform a specific action. In the tourism context, behavioral intention has been operationalized across studies as visit intention, travel intention, and purchase intention, all capturing varying stages of the decision-making process that bridges attitudinal inputs to behavioral outputs. The four-stage social media tourism decision-making framework positions behavioral intention as the critical transition stage between information processing and behavioral execution, emphasizing that social media platforms reshape this transition by compressing and accelerating the traditional decision cycle (Chen, 2025a).

Research within the short-video tourism literature broadly confirms that platform and content variables exert their primary influence on actual tourist behavior through the sequential formation of behavioral intention. Studies integrating the Technology Acceptance Model with affective response frameworks demonstrate that informativeness, entertainment value, and emotional responses to Douyin

travel videos generate positive attitudes and travel intentions through both cognitive and emotional pathways (Kim et al., 2026). Within the specific context of Douyin live streaming, platform-driven green innovation practices effectively foster customer loyalty by synergistically enhancing users' perceived value and social identity (Li et al., 2025). Research based on the Stimulus-Organism-Response (S-O-R) framework further indicates that exposure to digital influencers significantly drives consumers' purchase intentions through psychological mediators such as the desire to mimic, social comparison, fear of missing out (FOMO), and materialism (Mendrofa et al., 2025). The dual-pathway model for meme-embedded short videos illustrates how both systematic and heuristic processing routes converge on behavioral intention as the proximal driver of travel decisions, with cognitive load and emotional engagement operating as moderators (Song et al., 2025). Destination anthropomorphism embedded in promotional videos operates through social presence perceptions to mediate between video attributes and visit intention, with behavioral intention functioning as the gateway through which content effects are converted into travel plans (Gao et al., 2025). Chain mediation models involving celebrity worship, advertisement attitude, and destination attitude further illustrate how behavioral intention represents the terminal link in a multi-stage psychological process triggered by Douyin content exposure (Yang et al., 2025). Similarly, in related digital commerce environments, platform characteristics such as real-time interaction and product display significantly drive impulsive purchase intentions through the mediating role of consumer sentiments (Liu et al., 2025).

The conversion from behavioral intention to actual behavior—a pathway receiving comparatively less empirical scrutiny—is nonetheless evidenced in several streams of research. Studies on impulse hotel booking via short-video live marketing platforms suggest that even ephemeral, unplanned behavioral intentions can rapidly convert to booking actions when platform design eliminates friction and maximizes engagement (Alam, 2026). Research on neurophysiological responses to tourism short videos demonstrates that distinct content types differentially activate decision-making processes for self-directed versus other-directed choices, suggesting that the intention-behavior pathway is sensitive to both content framing and individual decision context (Lei & Chen, 2026). Social media value co-creation research documents that virtual interactions in tourism development contexts generate tangible behavioral commitments from stakeholders, reinforcing the theoretical claim that intention-behavior conversion is facilitated by interactive social media engagement (Jiang et al., 2025). Tourism demand forecasting models provide macro-level corroboration: social media communication metrics capture latent behavioral intentions at the population level that subsequently materialize as observable visitation data (Qin et al., 2025).

The mediating role of behavioral intention between platform/content antecedents and actual tourist behavior, however, remains underexplored. Most existing studies either examine direct effects of social media variables on intention, treating intention as a terminal dependent variable, or analyze actual behavior as an outcome of non-mediated platform effects. Studies quantifying the proportion of total effects transmitted through behavioral intention, and thereby distinguishing the relative magnitudes of direct and indirect pathways, are particularly scarce in the context of regional Chinese tourism. The application of mediation testing methodologies such as the Bootstrap-based PROCESS macro to this specific three-variable pathway (Douyin platform factors → behavioral intention → actual travel behavior) has not been systematically conducted for any provincial tourism market in China.

The present study addresses these gaps by constructing a theoretically grounded mediation model in which behavioral intention serves as the core bridge connecting Douyin's three-dimensional influence, Platform Features, Content Type, and User Interaction, to tourists' actual travel behavior in Anhui Province. By simultaneously estimating direct and indirect effects and testing partial versus full mediation for each pathway, this study extends both the empirical evidence base and the methodological toolkit for regional digital tourism research, providing actionable insights for cultural and tourism marketing stakeholders in Anhui.

3. Theoretical Foundation and Research Model Construction

3.1 Definition of Core Concepts

3.1.1 Definition of Independent Variables

The independent variables in this paper include three dimensions: Platform Features, Content Type, and User Interaction, all focusing on the core elements of Douyin related to Anhui's cultural and tourism industry:

(1) Platform Features: refer to the core attributes of Douyin as a new-generation information technology platform that influence user cognition and behavior. Combined with the scenario of cultural tourism communication, it mainly includes four dimensions: accuracy of algorithm recommendation, immersion of technical experience, efficiency of information dissemination, and ease of functional use. Through big data analysis of user interests and preferences, Douyin accurately pushes Anhui's cultural tourism content to target users. Meanwhile, it enhances user acceptance and engagement with cultural tourism content through immersive video experiences and a concise user interface.

(2) Content Type: refers to various forms of content related to Anhui's cultural tourism on the Douyin platform, mainly divided into two categories: UGC (User-Generated Content) and PGC (Professionally-Generated Content). UGC includes users' shared real travel experiences in Anhui, check-in videos, food reviews, etc. PGC includes promotional videos released by official accounts of cultural and tourism authorities in various regions of Anhui, travel guides and cultural interpretation videos about Anhui produced by professional creators. The two types of content jointly form the content ecosystem of Anhui's cultural tourism on Douyin.

(3) User Interaction: refers to various interactive behaviors conducted by Douyin users around Anhui's cultural tourism content, mainly including liking, commenting, sharing, duet shooting, collecting, and other behaviors. User Interaction is not only an important reflection of content communication effect, but also a direct manifestation of users' cognition and attitude toward Anhui's cultural tourism content, which can further expand the scope of content dissemination and strengthen users' perception of the destination.

3.1.2 Definition of Mediating Variable

The mediating variable is Behavioral Intention, which refers to the subjective willingness of Douyin users to travel to Anhui after being exposed to content related to Anhui's cultural tourism. It mainly includes dimensions such as the degree of stimulated travel desire, the tendency to formulate travel plans, and the preference for destination selection. Behavioral Intention acts as a core bridge connecting user cognition and Actual Behavior, reflecting users' attitude and behavioral tendency toward traveling in Anhui, and serves as an important indicator for judging the communication effect of Douyin cultural tourism.

3.1.3 Definition of Dependent Variable

The dependent variable is Actual Behavior, which refers to the actual tourism-related behaviors of Douyin users driven by Behavioral Intention. It mainly includes dimensions such as the implementation of travel decisions (e.g., booking scenic spot tickets and hotels), investment in tourism consumption, expansion of consumption scenarios (e.g., participating in folk custom experiences and purchasing cultural and creative products), and repurchase and recommendation behaviors (e.g., revisiting Anhui for tourism and recommending Anhui's cultural tourism destinations to others).

3.2 Formulation of Research Hypotheses

3.2.1 Hypotheses on the Influence of Independent Variables on Mediating Variable

(1) Influence of Platform Features on Behavioral Intention: The algorithm accuracy of the Douyin platform can accurately push Anhui's cultural tourism content to target users and reduce users' information acquisition costs; immersive experience can enhance users' sense of involvement in cultural tourism content and increase their favor for the destination; ease of use lowers the threshold for users to participate in interactions and obtain information. According to the theory of the new generation of information technology, these characteristics can effectively improve users' cognition and favor for Anhui's cultural tourism, thereby stimulating Behavioral Intention. Therefore, the following hypothesis is proposed:

H1: Douyin Platform Features positively affect users' Behavioral Intention to travel to Anhui.

(2) Influence of Content Type on Behavioral Intention: High-quality UGC is characterized by authenticity and resonance. Users' sharing of real experiences can enhance content credibility and stimulate other users' travel desire. PGC is professional and systematic, which can fully display the characteristics and value of Anhui's cultural tourism resources and deepen users' cognition of the destination. According to the flow economy theory, high-quality content can achieve the aggregation and precipitation of traffic, thereby stimulating Behavioral Intention. Therefore, the following hypothesis is proposed:

H2: Douyin Content Type positively affects users' Behavioral Intention to travel to Anhui.

(3) Influence of User Interaction on Behavioral Intention: Interactive behaviors such as liking, commenting, and sharing conducted by users around Anhui's cultural tourism content can strengthen users' memory and recognition of the content, expand content influence through social communication, and form a group effect. According to the theory of planned behavior, User Interaction can enhance the impact of subjective norms on individuals, thereby improving Behavioral Intention. For example, when users see Anhui cultural tourism videos shared by friends and participate in comments, they will be influenced by their social circles and strengthen their willingness to travel to Anhui. Therefore, the following hypothesis is proposed:

H3: Douyin User Interaction positively affects users' Behavioral Intention to travel to Anhui.

3.2.2 Hypothesis on the Influence of Mediating Variable on Dependent Variable

According to the theory of planned behavior, Behavioral Intention, as users' intention to travel to Anhui, is a core bridge connecting cognition and actual behavior. When users develop a strong Behavioral Intention to travel to Anhui, they will take the initiative to collect travel information, formulate travel plans, and then implement travel behaviors (such as booking tickets, hotels, and purchasing tourism products). The stronger the Behavioral Intention, the higher the probability that users will convert it into actual behavior. Therefore, the following hypothesis is proposed:

H4: Douyin users' Behavioral Intention to travel to Anhui positively affects their Actual Travel Behavior.

3.2.3 Hypotheses on the Direct Influence of Independent Variables on Dependent Variable

In addition to indirectly affecting Actual Behavior through the mediating role of Behavioral Intention, independent variables may also exert a direct influence on Actual Behavior. For instance, the precise recommendation function of the Douyin platform may directly push purchase links of Anhui tourism products, allowing users to complete consumption without strong stimulation of Behavioral Intention; high-quality cultural tourism content may directly include practical information such as scenic spot reservations and food purchases, promoting direct user consumption; in the process of User Interaction, direct recommendations from friends may directly prompt users to implement travel behaviors. Therefore, the following hypotheses are proposed:

H5: Douyin Platform Features positively affect users' Actual Behavior toward traveling in Anhui.

H6: Douyin Content Type positively affects users' Actual Behavior toward traveling in Anhui.

H7: Douyin User Interaction positively affects users' Actual Behavior toward traveling in Anhui.

3.2.4 Hypotheses on Mediating Effect

Combined with the above hypotheses, Behavioral Intention may play a mediating role between independent variables and dependent variable: Platform Features, Content Type, and User Interaction promote users to implement travel behaviors by stimulating their Behavioral Intention. That is, Platform Features, Content Type, and User Interaction not only directly affect Actual Behavior, but also indirectly influence Actual Behavior through the mediating transmission of Behavioral Intention. Therefore, the following hypotheses are proposed:

H8: Behavioral Intention plays a mediating role between Douyin Platform Features and Anhui tourism Actual Behavior.

H9: Behavioral Intention plays a mediating role between Douyin Content Type and Anhui tourism Actual Behavior.

H10: Behavioral Intention plays a mediating role between Douyin User Interaction and Anhui tourism Actual Behavior.

3.3 Construction of Research Model

Based on the above theoretical foundation and research hypotheses, this paper constructs the following research model: taking Platform Features, Content Type, and User Interaction as independent variables, Behavioral Intention as the mediating variable, and Actual Behavior as the dependent variable, this study explores the direct influence of independent variables on the dependent variable and the mediating role of Behavioral Intention. The conceptual framework can be seen clearly in Figure 1.

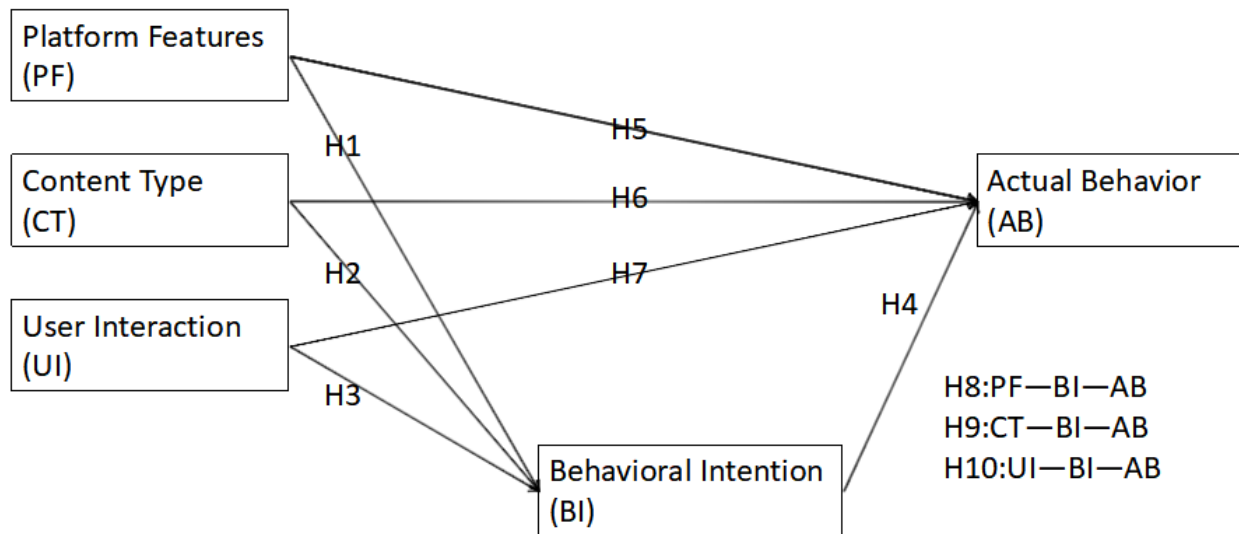


Fig.1: Conceptual Framework

4. Research Design

4.1 Questionnaire Design

The questionnaire in this study adopts a structured design and mainly consists of five parts:

The first part contains screening questions, with two criteria: “whether the respondent has used the Douyin platform” and “whether the respondent has watched Douyin videos related to Anhui’s

cultural tourism” . Only eligible users can continue to fill in the questionnaire, ensuring the relevance of the sample to the research topic.

The second part includes measurement items for the independent variables, covering three dimensions: Platform Features, Content Type, and User Interaction.

The third part consists of measurement items for the mediating variable, namely the Behavioral Intention dimension.

The fourth part includes measurement items for the dependent variable, namely the Actual Behavior dimension.

The fifth part collects basic demographic information of the sample, including gender, age, educational background, occupation, monthly income, etc.

4.2 Data Collection

The questionnaire survey was distributed online through channels such as Wenjuanxing, Douyin communities, and WeChat Moments, targeting Douyin users. The survey period was from August 1 to August 20, 2025.

During the survey, the principle of random sampling was strictly followed to ensure the representativeness of the sample. Meanwhile, a response time threshold (minimum completion time ≥ 60 seconds) was set to avoid invalid responses.

A total of 550 questionnaires were distributed, and 523 were collected. After screening, 37 invalid questionnaires (including those with excessively short response time, contradictory answers, no exposure to Anhui cultural tourism content, duplicate responses, etc.) were excluded. Finally, 486 valid questionnaires were obtained, with an effective recovery rate of 88.36%.

4.3 Data Preprocessing

Valid questionnaire data were preprocessed through the following steps:

(1) Missing value processing: The SPSS software was used to check for missing data. The proportion of missing values for all items was below 2%, indicating minor missingness. The mean substitution method was adopted to fill in missing values to ensure data integrity.

(2) Outlier processing: The boxplot method was used to identify outliers. A total of 6 outliers were detected, which were verified as random errors with no significant impact on the data distribution and thus retained.

(3) Data standardization: To eliminate dimensional differences among variables, scale data were standardized using the Z-score method, transforming each variable into standardized data with a mean of 0 and a standard deviation of 1, laying a foundation for subsequent empirical analysis.

(4) Common method bias test: As all questionnaire data were collected from the same respondents, common method bias might exist. The Harman one-factor test was conducted by performing exploratory factor analysis on all scale items. Without rotation, five common factors were extracted, and the variance explanation rate of the first common factor was 28.63%, lower than the 40% critical value, indicating no severe common method bias in the data.

5. Empirical Analysis Results

5.1 Descriptive Statistical Analysis

SPSS 26.0 was used to conduct descriptive statistical analysis on the basic sample information, Douyin usage status, and variable dimensions. The results are as follows:

5.1.1 Descriptive Statistics of Sample Basic Information

The statistical results of the sample's basic information are shown in Table 1.

In terms of gender distribution, there were 254 females (52.3%) and 232 males (47.7%), showing a relatively balanced gender structure.

For age distribution, 38.5% (187 respondents) were aged 18 – 25, 29.2% (142 respondents) aged 26 – 35, with young people accounting for 67.7% of the total sample. Middle-aged and elderly groups (46 years old and above) accounted for 13.6% (66 respondents). The sample was dominated by young users, consistent with the age distribution of Douyin users.

Regarding educational background, 67.3% (327 respondents) held a bachelor's degree or higher, 22.4% (109 respondents) had a junior college degree, and 10.3% (50 respondents) had a high school education or below, indicating a relatively high educational level of the sample.

In terms of occupation, enterprise employees accounted for 35.4% (172 respondents), students 27.6% (134 respondents), institution staff 18.1% (88 respondents), freelancers 12.3% (59 respondents), and other occupations 6.6% (33 respondents), presenting a wide occupational distribution.

For monthly income, 42.2% (205 respondents) earned 3,000 – 6,000 yuan, 28.6% (140 respondents) 6,000 – 10,000 yuan, 17.9% (87 respondents) below 3,000 yuan, and 11.3% (54 respondents) above 10,000 yuan. The sample was mainly composed of middle-income groups.

Table 1: Demographic information

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	232	47.7
	Female	254	52.3
Age	18 – 25 years	187	38.5
	26 – 35 years	142	29.2
	36 – 45 years	91	18.7
	46 years and above	66	13.6
	High school or below	50	10.3
Education	Junior college	109	22.4
	Bachelor's degree or above	327	67.3
Occupation	Student	134	27.6
	Enterprise employee	172	35.4
	Public institution staff	88	18.1
	Freelancer	59	12.3
	Others	33	6.6
Monthly income	Below 3,000	87	17.9
	3,000 – 6,000	205	42.2
	6,000 – 10,000	140	28.6
	Above 10,000	54	11.3

5.1.2 Descriptive Statistics of Variable Dimensions

The descriptive statistical results of each variable dimension are shown in Table 2. For the independent variables, the mean value of Platform Features is 3.86 with a standard deviation of 0.72; the mean value of Content Type is 3.92 with a standard deviation of 0.68; the mean value of User Interaction is 3.75

with a standard deviation of 0.75. The mean values of all three dimensions are higher than 3.5 (the midpoint of the 5-point Likert scale), indicating that users have a relatively positive perception of Douyin Platform Features, Content Type and User Interaction, which provides a sound foundation for the subsequent stimulation of Behavioral Intention and the transformation of Actual Behavior.

For the mediating variable, the mean value of Behavioral Intention is 3.96 with a standard deviation of 0.65, representing a relatively high mean, which suggests that Anhui cultural tourism content on Douyin can effectively stimulate users' Behavioral Intention.

For the dependent variable, the mean value of Actual Behavior is 3.62 with a standard deviation of 0.78, which is higher than 3.5, indicating that Douyin exerts a certain positive influence on users' Actual Behavior of traveling in Anhui. However, its mean value is lower than that of Behavioral Intention, revealing that the Behavioral Intention of some users has not been fully converted into actual behavior, implying room for improvement in conversion efficiency.

Table 2: Descriptive Statistics

Variable Dimension	Number of Items	Mean	Std. Deviation	Minimum	Maximum
Platform Features	4	3.86	0.72	1	5
Content Type	4	3.92	0.68	1	5
User Interaction	4	3.75	0.75	1	5
Behavioral Intention	3	3.96	0.65	1	5
Actual Behavior	3	3.62	0.78	1	5

5.2 Reliability and Validity Analysis

5.2.1 Reliability Analysis

Cronbach's α coefficient was used to test the internal consistency reliability of the scale, and the results are shown in Table 3. Overall, the total α coefficient of the scale is 0.902, which is greater than 0.9, indicating excellent overall reliability of the scale. The α coefficients of each variable dimension are as follows: Platform Features 0.865, Content Type 0.872, User Interaction 0.858, Behavioral Intention 0.843, and Actual Behavior 0.837, all of which are greater than 0.8 and far exceed the critical value of 0.7. This demonstrates that each dimension has sound internal consistency, and the questionnaire is scientifically designed and reliable to accurately measure the research variables.

Table 3: Reliability analysis

Variable Dimension	Number of Items	Cronbach's α	Reliability Evaluation
Platform Features	4	0.865	Excellent
Content Type	4	0.872	Excellent
User Interaction	4	0.858	Excellent
Behavioral Intention	3	0.843	Excellent
Actual Behavior	3	0.837	Excellent
Overall Scale	18	0.902	Excellent

5.2.2 Validity Analysis

This study adopted Exploratory Factor Analysis (EFA) to test the construct validity of the scale. The KMO test and Bartlett's test of sphericity were used to determine whether the data were suitable for

factor analysis, and factor loadings were employed to evaluate the convergent validity of each item with its corresponding dimension, so as to ensure the scientificity and effectiveness of variable measurement.

(1) Suitability Test The KMO value is 0.874, which is higher than the critical standard of 0.7. The chi-square value of Bartlett's test of sphericity is 3268.542 with 153 degrees of freedom, and $p < 0.001$, significantly rejecting the null hypothesis. This indicates strong correlations among variables and that the data are suitable for exploratory factor analysis.

(2) Convergent Validity Test Common factors were extracted using the principal component analysis method. After rotation by the varimax method, five common factors were extracted, which were completely consistent with the variable dimensions designed in this study (Platform Features, Content Type, User Interaction, Behavioral Intention, Actual Behavior). The cumulative variance contribution rate is 76.32%, higher than the 60% criterion, indicating that the common factors can effectively explain most of the information of each variable.

The standardized factor loadings of each item on its corresponding common factor range from 0.712 to 0.886, all above the critical value of 0.6. The Average Variance Extracted (AVE) of each dimension ranges from 0.584 to 0.672, all greater than 0.5. The Composite Reliability (CR) of each dimension ranges from 0.846 to 0.883, all higher than 0.7. These results show that the scale has good convergent validity, and each item can effectively reflect the core connotation of its corresponding dimension.

Table 4: Validity Analysis

Variable Dimension	Items	Factor Loading	AVE	CR
Platform Features	PF1	0.785	0.623	0.871
	PF2	0.812		
	PF3	0.764		
	PF4	0.793		
Content Type	CT1	0.826	0.651	0.883
	CT2	0.857		
	CT3	0.795		
	CT4	0.811		
User Interaction	UI1	0.742	0.596	0.859
	UI2	0.779		
	UI3	0.726		
	UI4	0.768		
Behavioral Intention	BI1	0.835	0.642	0.876
	BI2	0.864		
	BI3	0.829		
Actual Behavior	AB1	0.712	0.584	0.846
	AB2	0.753		
	AB3	0.737		
Fitting Indicators:	KMO = 0.874; Bartlett $\chi^2 = 3268.542$, df = 153, p < 0.001; Cumulative Variance Contribution Rate = 76.32%			

5.3 Correlation Analysis

Pearson correlation analysis was used to examine the correlation degree among variable dimensions, and the results are shown in Table 5. As can be seen from the table, the three independent variables of Platform Features, Content Type and User Interaction are all significantly positively correlated with the mediating variable Behavioral Intention ($r = 0.623, 0.658, 0.587$, respectively, all $p < 0.001$). The three independent variables are also significantly positively correlated with the dependent variable Actual Behavior ($r = 0.542, 0.576, 0.513$, respectively, all $p < 0.001$). The mediating variable Behavioral

Intention is significantly positively correlated with the dependent variable Actual Behavior ($r = 0.712$, $p < 0.001$).

The correlation coefficients among variables are all within a reasonable range (not exceeding 0.8), indicating no serious multicollinearity problem, which lays a foundation for subsequent regression analysis and mediation effect test.

Table 5: correlation analysis

Variable Dimension	Platform Features	Content Type	User Interaction	Behavioral Intention	Actual Behavior
Platform Features	1				
Content Type	0.594***	1			
User Interaction	0.562***	0.613***	1		
Behavioral Intention	0.623***	0.658***	0.587***	1	
Actual Behavior	0.542***	0.576***	0.513***	0.712***	1

Note: *** indicates $p < 0.001$, representing an extremely significant correlation.

5.4 Regression Analysis

To test Hypotheses H1-H7, stepwise regression was adopted to conduct multiple linear regression analysis. Regression models were constructed with Platform Features, Content Type, and User Interaction as independent variables, and Behavioral Intention and Actual Behavior as dependent variables respectively. The regression results are shown in Table 6 and Table 7.

5.4.1 Regression Analysis of Independent Variables on Behavioral Intention

Model M1 was established with Behavioral Intention as the dependent variable and Platform Features, Content Type, and User Interaction as independent variables, with the results presented in Table 6. The model fitness test shows that $R^2 = 0.528$, adjusted $R^2 = 0.523$, and $F = 108.632$ ($p < 0.001$), indicating a good model fitting effect.

Specifically:

The regression coefficient of Platform Features on Behavioral Intention is 0.286 ($p < 0.001$), showing a significant positive effect; thus Hypothesis H1 is supported.

The regression coefficient of Content Type on Behavioral Intention is 0.324 ($p < 0.001$), showing a significant positive effect; thus Hypothesis H2 is supported.

The regression coefficient of User Interaction on Behavioral Intention is 0.215 ($p < 0.001$), showing a significant positive effect; thus Hypothesis H3 is supported.

Table 6: Regression analysis of independent variables on Behavioral Intention

Variable	Regression Coefficient	p-value
(Constant)	1.025	<0.001
Platform Features	0.286	<0.001
Content Type	0.324	<0.001
User Interaction	0.215	<0.001

Model fit indicators: $R^2 = 0.528$, adjusted $R^2 = 0.523$, $F = 108.632$, $p < 0.001$

5.4.2 Regression Analysis of Independent Variables on Actual Behavior

Regression Model M2 was constructed with Actual Behavior as the dependent variable and Platform Features, Content Type, and User Interaction as independent variables (excluding the mediating variable). The results are shown in Table 7. The model fitness test shows that $R^2=0.436$, adjusted $R^2=0.430$, and $F=76.358$ ($p<0.001$), indicating a satisfactory model fitting effect.

Specifically:

The regression coefficient of Platform Features on Actual Behavior is 0.235 ($p<0.001$), showing a significant positive effect; Hypothesis H5 is supported.

The regression coefficient of Content Type on Actual Behavior is 0.267 ($p<0.001$), showing a significant positive effect; Hypothesis H6 is supported.

The regression coefficient of User Interaction on Actual Behavior is 0.189 ($p<0.001$), showing a significant positive effect; Hypothesis H7 is supported.

5.4.3 Regression Analysis of Behavioral Intention on Actual Behavior

Regression Model M3 was constructed with Actual Behavior as the dependent variable and Behavioral Intention as the independent variable. The results show that the regression coefficient of Behavioral Intention on Actual Behavior is 0.683 ($p<0.001$), indicating a significant positive effect. The model yields $R^2=0.506$, adjusted $R^2=0.505$, and $F=498.215$ ($p<0.001$), with an excellent fitting effect; Hypothesis H4 is supported.

5.4.4 Regression Analysis Including the Mediating Variable

Regression Model M4 was constructed with Actual Behavior as the dependent variable, incorporating both independent variables (Platform Features, Content Type, User Interaction) and the mediating variable (Behavioral Intention). The results show that: The regression coefficient of Behavioral Intention on Actual Behavior remains significantly positive ($\beta=0.527$, $p<0.001$); the regression coefficient of Platform Features on Actual Behavior decreases to 0.123 ($p<0.01$) and remains significantly positive; the regression coefficient of Content Type on Actual Behavior decreases to 0.145 ($p<0.01$) and remains significantly positive; the regression coefficient of User Interaction on Actual Behavior decreases to 0.098 ($p<0.05$) and remains significantly positive.

The model achieves $R^2=0.612$, adjusted $R^2=0.607$, and $F=124.573$ ($p<0.001$), with a better fitting effect than Model M2. This suggests that Behavioral Intention may play a partial mediating role, which requires further verification through mediation effect tests.

Table 7: Regression Analysis

Variable	Regression Coefficient (M2)	p-value (M2)	Regression Coefficient (M4)	p-value (M4)
(Constant)	1.236	<0.001	0.562	<0.001
Platform Features	0.235	<0.001	0.123	0.005
Content Type	0.267	<0.001	0.145	0.002
User Interaction	0.189	<0.001	0.098	0.032
Behavioral Intention	-	-	0.527	<0.001
Model fit for M2: $R^2=0.436$, Adjusted $R^2=0.430$, $F=76.358$, $p<0.001$;				
Model fit for M4: $R^2=0.612$, Adjusted $R^2=0.607$, $F=124.573$, $p<0.001$				

5.5 Mediation Effect Test

The mediation effect of Behavioral Intention was examined using the Bootstrap method (5,000 repeated samples, 95% confidence interval) to verify Hypotheses H8 – H10. Three conditions must be satisfied for a mediation effect: first, the independent variables significantly affect the mediating variable; second, the mediating variable significantly affects the dependent variable; third, after including the mediating variable, the effect coefficient of the independent variable on the dependent variable decreases significantly (partial mediation) or becomes insignificant (full mediation).

Combined with the previous regression results, the first two conditions have been satisfied, and the third condition requires further verification through the Bootstrap test, as shown in Table 8.

As shown in Table 8: (1) The mediation effect value of the path Platform Features → Behavioral Intention → Actual Behavior is 0.151, with a Bootstrap 95% confidence interval of [0.102, 0.205], which does not contain 0, indicating a significant mediation effect. Meanwhile, the direct effect value of Platform Features on Actual Behavior is 0.123, with a confidence interval of [0.045, 0.201], which does not contain 0. This shows that Behavioral Intention plays a partial mediating role between Platform Features and Actual Behavior, and Hypothesis H8 is supported.

(2) The mediation effect value of the path Content Type → Behavioral Intention → Actual Behavior is 0.170, with a Bootstrap 95% confidence interval of [0.118, 0.226], which does not contain 0, indicating a significant mediation effect. The direct effect value of Content Type on Actual Behavior is 0.145, with a confidence interval of [0.063, 0.227], which does not contain 0. This shows that Behavioral Intention plays a partial mediating role between Content Type and Actual Behavior, and Hypothesis H9 is supported.

(3) The mediation effect value of the path User Interaction → Behavioral Intention → Actual Behavior is 0.113, with a Bootstrap 95% confidence interval of [0.068, 0.165], which does not contain 0, indicating a significant mediation effect. The direct effect value of User Interaction on Actual Behavior is 0.098, with a confidence interval of [0.015, 0.181], which does not contain 0. This shows that Behavioral Intention plays a partial mediating role between User Interaction and Actual Behavior, and Hypothesis H10 is supported.

Further analysis of the proportion of mediation effect in the total effect:

The proportion of mediation effect for Platform Features is $0.151 / (0.151 + 0.123) = 55.1\%$;

The proportion of mediation effect for Content Type is $0.170 / (0.170 + 0.145) = 54.0\%$;

The proportion of mediation effect for User Interaction is $0.113 / (0.113 + 0.098) = 53.5\%$.

All three mediation effect proportions exceed 50%, indicating that the mediating transmission role of Behavioral Intention is relatively significant, serving as a core bridge connecting Douyin platform factors and tourists' Actual Behavior toward Anhui tourism.

Table 8: Mediating Effect Test

Path	Effect Type	Effect Value	Std. Error	Bootstrap 95% CI Lower	Upper	Mediation Effect Significant
Platform Features → Actual Behavior	Total Effect	0.274	0.041	0.194	0.354	—
	Direct Effect	0.123	0.039	0.045	0.201	—
	Indirect Effect	0.151	0.027	0.102	0.205	Yes
Content Type → Actual Behavior	Total Effect	0.315	0.043	0.231	0.399	—
	Direct Effect	0.145	0.041	0.063	0.227	—
	Indirect Effect	0.170	0.028	0.118	0.226	Yes
	Total Effect	0.211	0.038	0.137	0.285	—

Path	Effect Type	Effect Value	Std. Error	Bootstrap 95% CI Lower	Upper	Mediation Effect Significant
User Interaction → Actual Behavior	Direct Effect	0.098	0.037	0.015	0.181	—
	Indirect Effect	0.113	0.024	0.068	0.165	Yes

6. Conclusions and Recommendations

6.1 Conclusions

Taking the Douyin platform as the research carrier and Anhui Province's tourism industry as the research context, this paper constructs a theoretical model of "Platform Features, Content Type, User Interaction, Behavioral Intention and Actual Behavior" and empirically examines Douyin's influence mechanism on Anhui's tourism development. The core conclusions are as follows:

(1) Douyin Platform Features, Content Type, and User Interaction all exert significant positive effects on users' Behavioral Intention and Actual Behavior toward traveling in Anhui. Content Type demonstrates the strongest impact on Behavioral Intention ($\beta = 0.324$), indicating that high-quality, culturally distinctive content is the primary driver of travel intention. Platform Features and User Interaction also play important roles: precise algorithmic recommendation and immersive experience enhance content reach, while active interaction behaviors reinforce user identification and collectively promote Behavioral Intention and Actual Behavior.

(2) Behavioral Intention plays a partial mediating role in the relationships between each independent variable and Actual Behavior, with mediation ratios exceeding 50% in all three pathways. This confirms that Douyin platform factors influence Actual Behavior primarily by stimulating Behavioral Intention, which functions as the core bridge between digital engagement and tourism consumption.

6.2 Recommendations for High-Quality Development of Anhui's Tourism Industry

Drawing on the empirical findings, the following recommendations are proposed across four strategic dimensions.

6.2.1 Content Innovation: Build a Differentiated Content Matrix

Deeply explore Anhui's cultural assets, including Huizhou culture, northern Anhui folk customs, and Dabie Mountain red culture, to create serialized, story-driven content that counters homogeneity. Diversify content formats by adopting short dramas, live streaming, and challenge campaigns alongside conventional aerial and food content. Establish a UGC-PGC collaborative ecosystem: encourage authentic user-generated sharing through topic challenges while strengthening official accounts' authoritative cultural interpretation.

6.2.2 Industrial Integration: Build Precise Intention-to-Behavior Conversion Paths

Embed purchase links for scenic tickets, hotel packages, and tour products directly within cultural tourism videos to enable one-click booking. Integrate Douyin e-commerce to convert online inspiration into offline consumption of Anhui's cultural and creative products. Strengthen tourism infrastructure in northern and western Anhui to support traffic conversion, and reinforce user trust through UGC quality review and authentic official content.

6.2.3 Platform Governance: Build a Collaborative Provincial Communication Matrix

Break algorithmic information cocoons by optimizing content tagging and pursuing cross-domain collaborations with influencers in food, fashion, and outdoor niches. Under the coordination of the

Anhui Provincial Department of Culture and Tourism, build a "provincial, municipal, and county" three-level communication network and launch joint campaigns such as a "Picturesque Anhui • Global Tour" live broadcast series. Establish a data analytics team to track content performance and user behavior, enabling dynamic optimization of content strategy.

6.2.4 Talent Cultivation: Build a Compound Professional Operation Team

Introduce specialized short-video operation talent and partner with universities to develop training programs covering cultural tourism knowledge, content creation, and data analytics. Conduct regular Douyin operation training for frontline cultural tourism staff and establish incentive mechanisms to reward content innovation and high-performing creators.

This study has several limitations that point to productive directions for future work. First, the sample is predominantly composed of young, highly educated urban users, which may limit generalizability; future research should extend coverage to middle-aged and elderly users and to underrepresented regions of northern and western Anhui, and expand comparisons across multiple provinces to extract generalizable patterns. Second, this study captures a static cross-sectional snapshot; longitudinal research designs tracking changes in platform factors, Behavioral Intention, and Actual Behavior over time would better illuminate Douyin's long-term influence on tourism development. Third, the variable system could be enriched by incorporating moderating variables such as policy environment and seasonal factors, and by introducing additional mediators, such as destination image and perceived value, into a multiple mediation framework that more fully maps the internal logic of Douyin's empowerment effect on regional tourism.

Author Contributions

Zheng contributed to the conception and design. Jacqueline and Alik performed research and analyzed the data. All of the authors drafted and revised the manuscript together and approved its final publication.

Funding

2025 Major Scientific Research Project of Hefei Technology College "Research on the Support of Hefei Vocational Education for the Development of New Industries"(Project Number: 2025CXYSKZD01).

References

- Alam S.S. (2026), Impulsive hotel booking intention in short video live marketing platforms: The role of engagement and media literacy. *Journal of Hospitality Marketing & Management*, Vol. 35, No. 3, 363–395.
- Bi J., Qin F. & Huang C. (2025), *Social media communication index in tourism forecasting*. Current Issues in Tourism.
- Chen H., Lai I.K.W. & Pai C.K. (2025b), The value of short tour guide-led travel videos in stimulating tourists' intention through travel inspiration: a mixed-methods study. *Asia Pacific Journal of Tourism Research*, Vol. 30, No. 9, 1245–1260.
- Chen Z. (2025a), Four-stage framework of tourism decision-making in the social media era. *Journal of Hospitality and Tourism Technology*.
- Do Bui Xuan Cuong, Tran Khanh, Bui Thanh Khoa & Le Dao Ngoc Thanh. (2025), Digital Transformation and Sustainable Tourism: An Integrated Model for Heritage Destination Revisitation in the Service Innovation Era. *Journal of Service, Innovation and Sustainable Development*, Vol. 6, No. 1, 14-27.

- Gao J., Liang S., Sun S. & Wang S. (2025), Bridging the distance: Understanding the role of destination anthropomorphism in videos on tourists' travel intention. *Journal of Travel Research*.
- Guo R., Gao H. & Yang Z. (2024), Douyin food vloggers' impact on visit intention: Taste awareness as a mediator. *Social Behavior and Personality*, Vol. 52, No. 12, e13792.
- Guo S., Wang D. & Deng N. (2026), Deciphering the myths of engagement with destination short video: The perspective of modality. *Tourism Management*, 113, 105286.
- He J., Tang L., Ji C. & Sthapit E. (2026), The digital wanderlust: Exploring how tourism short video cyberloafing translates into travel intentions. *International Journal of Tourism Research*, Vol. 28, No. 1, e70166.
- Hong Y. & Liang X. (2026), Determinants of Douyin Generation Z users' intentions to visit niche tourist destinations: A hybrid approach using PLS-SEM, MGA and fsQCA. *Asia Pacific Journal of Tourism Research*, Vol. 31, No. 2, 434–464.
- Hu X., Hu C. & Cheng P. (2026), Converting viewers to tourists: Gratifications from food-hunting short videos and their impacts on destination visit intentions. *Journal of Destination Marketing & Management*, 40, 101086.
- Huang J., Huang D. & Huang K. (2025), Enhancing tourist visit intentions through virtual endorsers' short videos: A narrative transportation theory. *Tourism Management Perspectives*, 58, 101389.
- Jiang M., Wang L. & Zhang H. (2025), Virtual interactions for actual value: Unpacking the role of social media in value cocreation large-scale tourism development projects. *Project Management Journal*.
- Kim J.S., Goh B.K., Zhao T. & Lee T. (2026), Understanding travel intention formation through TikTok short-form videos: An integrated TAM and ARM approach. *Journal of Hospitality and Tourism Technology*.
- Lei M. & Chen W. (2026), Differentially impacted self- and other-decisions by tourism short videos: A neurophysiological perspective. *Journal of Hospitality and Tourism Technology*, Vol. 17, No. 2, 519–535..
- Li H. & Tu X. (2024), Who generates your video ads? The matching effect of short-form video sources and destination types on visit intention. *Asia Pacific Journal of Marketing and Logistics*, Vol. 36, No. 3, 660–677.
- Li J., Hatakitpanitchakul W. & Khunthong U. (2025), The Impact of Green Innovation in Social Media Live on Customer Loyalty Based on Tiktok Platform in Sichuan of China. *Journal of Logistics, Informatics and Service Science*, Vol. 12, No. 5, 214-235.
- Li R. & Yu J. (2026), Meme magic: The role of memes on tourism short videos. *Asia Pacific Journal of Tourism Research*, Vol. 31, No. 3, 564–581..
- Liu B., Supasettaysa G. & Ratchatakulpat T. (2025), The Influence of Characteristics of E-commerce Live Streaming on Impulsive Purchase Intention: The Mediating Role of Consumer Sentiments. *Journal of Logistics, Informatics and Service Science*, Vol. 12, No. 9, 1-21.
- Liu J., Zhao J., Wei W. & Yang T. (2025), Captivating the crowd: Unraveling sentiments in tourism short videos for effective destination marketing on social media. *Current Issues in Tourism*.
- Mendrofā Y., Rini E.S., Muda I. & Fadli. (2025), A Moderated Mediation Analysis on The Influence of E-Tourism Quality in Predicting Revisit Intentions in Nias Island Tourism. *Journal of Logistics, Informatics and Service Science*, Vol. 12, No. 6, 138-156.

- Pham N.A. & Phan T.A. (2025), LGBTQ+ TikTok influencers: Shaping travel engagement and destination appeal. *Journal of Vacation Marketing*.
- Polat E., Celik F., Ibrahim B. & Koseoglu M.A. (2023), Unpacking the power of user-generated videos in hospitality and tourism: A systematic literature review and future direction. *Journal of Travel & Tourism Marketing*, Vol. 40, No. 9, 894–914.
- Qin F., Bi J., Li H. & Xu H. (2025), Tourism demand forecasting using social media data: A deep learning-based ensemble model with social media communication conversion rates. *Annals of Tourism Research*, 115, 104058.
- Rashidin M.S., Taheri B., Del Chiappa G. & Javed S. (2026), From cultural curiosity to culinary sustainability: How social food reels foster food culture preservation. *International Journal of Contemporary Hospitality Management*, Vol. 38, No. 13, 28–48.
- Ruan W., Tang Y., Zhang S. & Wang M. (2025), "Poetic" marketing: How language makes destinations beloved. *Journal of Hospitality and Tourism Management*, 65, 101340.
- Sinh N.H. & Kiet N.T. (2025), How Social Media Influencers Drive Purchase Intentions: A Stimulus-Organism-Response Analysis of Vietnamese Consumers' Psychological Responses. *Journal of Logistics, Informatics and Service Science*, Vol. 12, No. 4, 58-74.
- Slaton K. & Lee H. (2025), From scroll to store: How short-form video drives foot traffic in destination retail. *Journal of Theoretical and Applied Electronic Commerce Research*, Vol. 20, No. 4, 335.
- Song X., Ge J. & Zhu S. (2025), Memes in motion: Do quirky tourism shorts spark travel intention? A dual-pathway study based on ELM-CLT theory. *Journal of Hospitality and Tourism Technology*.
- Su L., Yang Y., Huang S. & He X. (2026), Dynamism by design: The zoom effects in short video tourism marketing. *Tourism Management*, 114, 105358.
- Tan J., Cheng M., Chen J., Zhu J., Yu Q. & Chen S. (2025), Multimodal destination image and user engagement: A sequential research design. *Tourism Management*, 111, 105209.
- Wang J., Fang Q., Wu Y., Du S. & Yin X. (2025a), From watching to sharing and visiting: Impact of short video marketing on tourist behavioral intentions from a seasonal iconness perspective. *Asia Pacific Journal of Tourism Research*.
- Wang J., Su M., Wang M. & Zhang M. (2026), Digital food narratives and rural influencer: Rethinking the local food in agricultural heritage tourism. *Journal of Vacation Marketing*.
- Wang M., Xie X., Zhang H., Du Y. & Chu Z. (2025b), Synergistic effects of content structure and sensory elements: Exploring the impact mechanism of tourism short videos on travel intention. *Transformations in Business & Economics*, Vol. 24, No. 2.
- Xu S. & Zhou L. (2025), The interaction ritual sense of tourist check-in short videos: A new lens on visit intention. *Journal of Vacation Marketing*.
- Yang X., Wu H. & Bao Y. (2025), The effect of 'Juzhang endorsement' on visit intention: The chain mediating effect of celebrity worship, attitude toward an advertisement, and attitude toward a destination. *Current Issues in Tourism*.
- Yu J., Hong W.C.H. & Egger R. (2026), The sound of reels: Effects of audio features of destination short videos on user engagement. *Journal of Hospitality & Tourism Research*.
- Zhang C., Zhao B., Yu C., Wang S. & Zhang X. (2026c), "We got you!": Determinants of attention-grabbing short tourism video titles—Evidence from Douyin in China. *Tourism Management Perspectives*, 61, 101458.

Zhang M., Li X., Xia Q., Li J. & Huang H. (2026a), How do short videos leverage motion speed and visual content to bolster destination attractiveness? A construal level perspective. *Journal of Hospitality and Tourism Management*, 66, 101417.

Zhang S., Zeng A., Ruan W. & Li Y. (2025a), The 'time effect' of tourism short videos: How to match the advertising format and background music. *Current Issues in Tourism*.

Zhang S., Zeng A., Ruan W., Li Y. & Zhou Y. (2025b), How different destination brand personalities choose the right tourism short video ads? *Journal of Vacation Marketing*.

Zhang W., Chen J., Ni Z. & Si X. (2026b), Short videos and destination image reconstruction: A multidimensional comparative analysis on three Chinese wanghong tourism cities. *Asia Pacific Journal of Tourism Research*.

Zheng C., Khatibi A. & Tham J. (2025), Social Influences in Tourist Destination Choice: An Empirical Informatics-Based Analysis Using SPSS. *Journal of Logistics, Informatics and Service Science*, Vol. 12, No. 6, 262-276.

Zhou X. & Liu G. (2026), From TikTok to travel: The impact of sport related user-generated short videos on destination brand attitude and purchase intention. *Journal of Retailing and Consumer Services*, 90, 104709.