Travel and Tourism Research Association: Advancing Tourism Research Globally

Who Dominate TDI? A Big Data Evidence from DMO and UGC Short Videos

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1 Introduction

The development of various online communication tools such as YouTube, TikTok, and Instagram, has significantly changed the process of information creation and transmitting (Hays, Page, & Buhalis, 2013). Tourists increasingly share their travel experiences on social media by posting comments, photos and videos about tourism destination or product. Different from traditional brochures or advertisements, such data termed user-generated content (UGC), further affect consumer behavior, marketing strategies, and brand image(Hays et al., 2013) for its richness, diversity (J. Yu & Egger, 2021) and authenticity (C.-E. Yu & Sun, 2019). UGC has thus gradually become the mainstream medium to influence TDI and tourists' decision-making (Deng, Zhong, & Li, 2018; Dey & Sarma, 2010). Previous research has revealed that the content of DMO pictures and user-generated photography were not always consistent on destination images. More specifically, if UGC instead of DMO are more accepted by potential tourists, brand hijack will occur (Lv, Xv, & Lin, 2014). However, "brand hijacking" is a special phenomenon in TDI dynamic evolution process. There might be other interactive relationship patterns and calls for empirical research. Meanwhile, "brand hijacking" was just demonstrated conceptually the ideal result in the development of tourism destination's life cycle without empirical support (Lv et al., 2014). This make it difficult to get a full and deep understanding of actual evolution mechanism of DMO projected TDI compared with UGC projected TDI.

Different from texts and photos, videos' creators, especially short videos, often amateurs or ordinary people, appear in front of the camera, sharing the travel stories and showing the place around, which bring tourists a higher level of immersion (Dinhopl & Gretzel, 2016). Although more scholars have begun to investigate this powerful destination marketing tool, studies have yet to explore this influential image creator within big sample scale (Huertas, Míguez-González, & Lozano-Monterrubio, 2017), like some popular video-sharing sites (e.g., YouTube and DouYin). The UGC found in videos published on YouTube and other social media by individual tourists are even beyond the control of the DMOs (S. C. H. Li, Robinson, & Oriade, 2017), which offer an ideal data source for the study of the comparison of DMO and UGC projected images.

It is interesting and significant to examine the dynamically-varying influence of UGC and DMO in TDI formation process. Therefore, drawn from tourism destination's life cycle theory (Butler, 1980), the present study chose three destinations on behalf of varied destination destination's life cycle stages via logistic regression. Taken short videos collected from Douyin (a video-sharing social media), we then compared DMO and UGC projected images and identified the dynamic interaction between the two from several dimensions. This study will not only mend research gaps in TDI, but also offer valuables references for DMO managers in terms of marketing strategy adjustments.

2 Literature Review

2.1 The interaction of DMO and UGC projected image

Based on marketing and consumer behavior perspectives, a tourism destination image(TDI) (Hunt, 1975) has been conceptualized as being composed of two dimensions: projected image and perceived image (Grosspietsch, 2006). While projected image is related to a destination and its ideal attributes projected by key agents with specific purpose through marketing communications, perceived image refers to tourists' holistic impressions regard to the tourism products and services in a destination (Mak, 2017; Tasci & Gartner, 2007). Among various agents, destination marketing organizations (DMOs) are at the forefront of projecting a positive TDI through all kinds of representations, including video promotion, brochures, and advertisements, which are also known as organization-generated content (OGC). Projected image will affect the perceived image (Gunn, 1972). In the circle proposed by Urry (1990), these DMO projected images will transmit desirable information to attract potential tourists' attention, and then help shape or reinforce tourists' existing perceptions of destinations. Scholars named these new perceptions as overall image (Baloglu & McCleary, 1999) or re-evaluated images (Selby & Morgan, 1996). The development of web 2.0 platform has fundamentally blurred the boundaries of supply and demand side in TDI formation (He, Deng, Li, & Gu, 2021; Stepchenkova & Zhan, 2013). Tourists increasingly share their travel experiences on social media by posting comments, photos and videos about tourism destination or product. Lv, Xv, and Yang (2011) coined the tourist information power in order to describe the influence caused by exchanging user-generated content (UGC) among tourists. The influence of the tourist information power has gradually become the mainstream medium to influence potential tourists' decision-making (Deng et al., 2018; Dey & Sarma, 2010). Tourists have become new projectors in TDI formation (Deng & Li, 2018; Egger, Gumus, Kaiumova, Mükisch, & Surkic, 2022; G. Zhang, Yang, Ke, & Zhang, 2020). In order to expand the destination image literature, Lv et al. (2014)future put forward the concept of tourist projected image (TPI), comparing to the traditional DMO projected image(DPI).

The discrepancy of the DMO and UGC projected images have been empirically researched since the beginning of the century. Stepchenkova and Zhan (2013) compared the projected images from DMO and UGC photos posted on Flickr, which laid a foundation for Mak (2017)'s research with mixed sample; Lv et al. (2014) pointed out if TPI instead of DPI are more accepted by potential tourists, alienated evolution will occur in the process of TDI, Wipperfürth (2005) coined it "brand hijacking". It is originally a marketing term, refers to the actions taken by a group of consumers with common interests to forcibly occupy a brand from professional marketers and guide the evolution of the brand. Lv et al. (2014) further concluded that the occurrence of brand hijacking mainly needs to meet two requirements: (a) the influence of UGC should be more powerful than that of DMO; (b) there should be some huge deviations between UGC and DMO projected images. However, scholars just theoretically justified that brand hijacking was the extreme result of the gap of two projected images without enough empirical support, which make it difficult to get a full and deep understanding of actual evolution mechanism of DMO and UGC projected images.

DMOs used to be the leading role in transmitting information to visitors. Due to increasingly fierce competition in tourism industry, DMOs should adapt to the development of social media to co-create content with tourists (Lalicic, Huertas, Moreno, & Jabreel, 2020). More specifically, it is worthy for DMOs to make best use of the dynamic interactions of DMO and UGC projected images so as to maintain competitiveness and gain online visibility (Egger et al., 2022; S. C. H. Li et al., 2017). Therefore, this study aims to provide empirical supports for relevant theoretical hypotheses about this dynamic interaction, trying to figure out the reasons behind the phenomenon.

2.2 The tourism destination's life cycle

The evolution of tourism destinations is a lively self-organized phenomenon (Sun & Xue, 2007). Tourism Area Life Cycle (TALC) is a theory to describe such evolution process (Choy, 1992). Several models have been used to explore the evolution mechanism. One of the first model was presented by Christaller (1964). He believed that many destinations' evolution processes are relatively consistent consisting of discovery, growth and decline. Plog (1974) put forward psychological schema hypothesis by connecting the psychology and preferences of tourists with the rise and fall of destination. However, considerable research attentions have been devoted to the Butler (1980)'s destination's life cycle theory (Oreja Rodríguez, Parra-López, & Yanes-Estévez, 2008) according to which tourism destination development was divided into the six stages: exploration, involvement, development, consolidation, stagnation, decline or rejuvenation. Within the last two decades, many researches has applied these models to case studies (Oreja Rodríguez et al., 2008) or revisited them, even make some innovation both theoretically and methodologically. With the model proposed by Plog (2003), Lv et al. (2014) analyzed the alienated evolution process of destination image and divided the entire evolution process into several stages by comparing DMO and UGC projected images. Likewise, this study attempts to compare DMO and UGC projected images at the different tourism destination's life cycle stages based on Butler (1980)'s model.

In scrutinizing the TALC model, however, a methodological challenge is how to revisit the qualitative TALC model so as to meet the strong practical need in tourism forecasting or planning (Hovinen, 2002). A few studies have attempted to adopt the Logistic model (Pollard, 1973) to quantitatively devise the various stages of life cycle. By taking the derivative of this model, C. Zhang and Zhang (2017) figured out four mathematical properties within the Logistic model and three time nodes within the properties: $(\frac{a-1.317}{r},\frac{K}{4.732})$、 $(\frac{a}{r},\frac{K}{2})$、 $(\frac{a+1.317}{r},\frac{K}{1.268})$, to divide the curve into four stages:

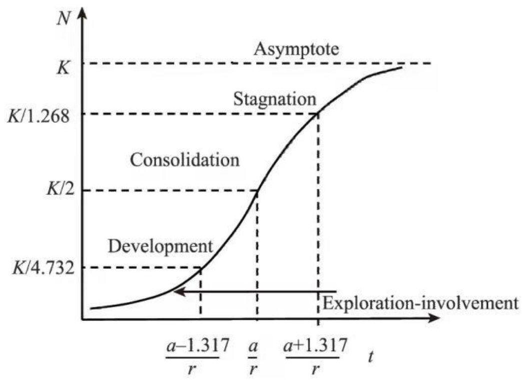

Figure 1 Quantitative Division of TALC Model by Logistic Model , adopted from C. Zhang and Zhang (2017)

Where parameters **a, r** and b are all greater than 0; **N** is the number of tourists; **K** is the theoretical limit value, namely, the maximum tourist reception of the destination in theory; **r** is the growth rate factor; **a**, **b** are constants. The mathematical properties and morphological features of Logistic model make the TALC model more practical (C. Zhang & Zhang, 2017). As a result, this research will adopt the Three-parameter Logistic model. Moreover, Lv et al. (2014)indicated that alienations might happen in the development period, functioned by tourist information right, which means the qualitative changes between DMO and UGC will take place in this period. Given the above discussions, it is necessary to further divide the development stages for the further discussion.

2.3 Video materials in tourism research

The relationship between mass tourism and photography has been reciprocal and inseparable. (G. Zhou, Song, & Liu, 2020). Tourists expect to look for non-everyday experiences or something perceived for the first time during their trips (Ekici & Çizel, 2017), Urry (1990) termed it"Tourist Gaze". Photograph can record this particular piece of organized visual experience (Goggin, 2006), thus be regarded as reflection of expectations, personality and values in describing tourists' experiences (Groves & Timothy, 2001). Different from photos, travel videos, especially short videos, are not limited by time during information transmission. Their contents are richer, issues are broader, and audience reach is wider (Aran, Biel, & Gatica-Perez, 2014). Videos also invite tourists to convey their respective projected image of a destination to a wider global audience (Peralta, 2019; Xu, Chen, Pearce, Mohammadi, & Pearce, 2021). Many scholars have carried out researches with this dynamic destination marketing tool. Alvarez and Campo (2011) found that tourism promotional video improves Turkey's destination image and its preference in terms of visitation in contrast to news. Gong and Tung (2017) discusses the influence of mini-movies in destinations' branding strategies. Although such research has enriched our understanding of video's impact on destination image, studies have yet to explore this influential image creator within big sample scale (Huertas et al., 2017).

Although video content is a good material for studying destination image，analyzing video content could be a cumbersome task (Schwenzow, Hartmann, Schikowsky, &

Heitmann, 2021). Quantitative description analysis and qualitative methods were still commonly employed in tourism articles. Although useful to some extent, it is labor intensive and prohibitively costly in big data setting and therefore, difficult to scale to the needs of many online video applications (M. Zhou, Chen, Ferreira, & Smith, 2021). Rose (2007)suggested that video mining can generally involves feature extraction, structure analysis and abstraction, parsing video into meaningful sequences, scenes, shot and frames. Indeed, the central component to any automated video analysis is the analysis of individual images (Schwenzow et al., 2021), and the biggest formidable methodological challenges to tourism scholars is how to translate low-level pictorial features (e.g., color, texture, shape, etc.) extracted by computer into high-level semantic elements (e.g., object, event, emotion, etc.) perceived by people, bridging the semantic gap as much as possible (He et al., 2021; Spyrou & Mylonas, 2016; Xie, Luan, & Wu, 2011). Significant progress has been made for massive online image analysis. Some of these developments from computer field have been adopted in marketing researches (e.g., (Hartmann, Heitmann, Schamp, & Netzer, 2021; M. Zhou et al., 2021)). Likewise, this research made in-depth mining of video content via mature methods from computer field, aiming to overcome the shortcomings of existing research methods to some extents.

In addition to contents analysis, video communication competency is also extensively researched topic in academic circles. Although lacking of a unified definition, more scholars have accepted that media communication competency is equal to its communicating effect in practical application (Jin & Wang, 2021; Shah, 2016). Kepplinger (2007)concluded that there might be three aspects in media effects: (a) media reports influence users; (b) users' media-affected behavior might have consequences on others; (c) the behavior of others might in turn influence the behavior of users (feedback). Those theoretical assumptions lay a foundation for video communication competency's quantitative evaluation. Video platforms, like DouYin, also offer some metrics (e.g., likes, dislikes, comments, and shares) to help analytics to afford quantitative insights into social video viewing and sharing (Bello-Bravo, Payumo, & Pittendrigh, 2021). Therefore, we measured the influence of DMO and UGC by defining the "short video communication competence". According to user participation, satisfaction and communication scalability dimensions (Wang & Xia, 2021), this research chose four metrics of short videos: the number of short videos, the number of likes, comments and shares, and used entropy weight method to determine the indicator weight, to quantitatively assess the reach of this type of media.

3 Methodology

3.1 Data collection

With more than 600 million daily active users and 400 million daily video searching record (Report, 2021), data was collected from public posts shared on DouYin application using Python , a strong programming software. Fig 2 outlines the data collection process.

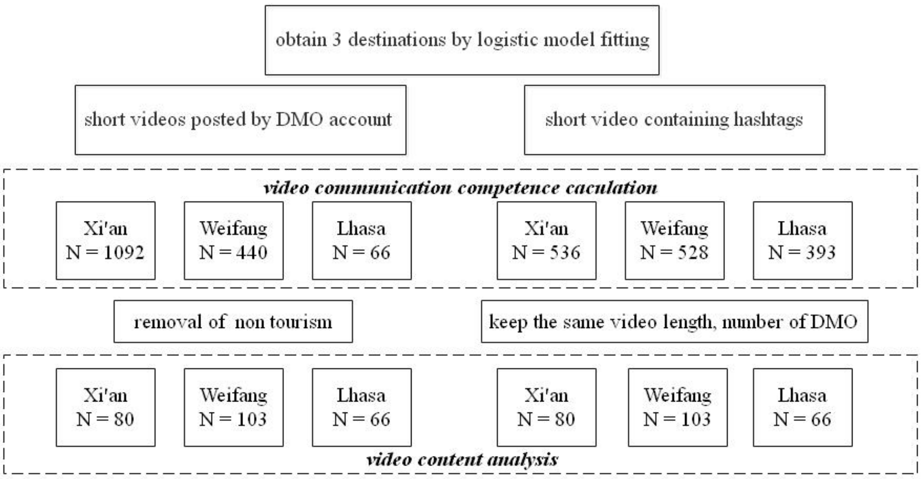

Figure 2 Data collection process for UGC (right side) and DMO (left side) videos

In order to figure out the suitable destinations, we firstly searched on DouYin with "Administration of Culture and Tourism", which is the municipal department governed tourism in China. 68 search results meeting the research needs are retained after data cleaning, namely 68 DMO cities accounts. We then collected the number of tourists in 20 years (2000-2019) of mentioned 68 destinations from Yearbook of Tourism Statistics to find data support for Logistic model fitting. Eight cities with complete data are finally identified.

Subsequently, this research mainly employed SPSS software to process the data. From the fitting results, it could point out that in the development stage, the growth rate of tourists in destination will reach the maximum point at the time of $\frac{a}{r}$.. Given what has been mentioned in the literature, the study chose half point of the development stage time span as watershed, further divided the development stage into the "initial development" stage and the "accelerated development" stage. Through the analysis of the fitting results, we finally focused three destinations on behalf of the initial development stage, accelerated development stage and consolidation stage respectively: Xian, Weifang and Lhasa. The more details are showed as bellow:

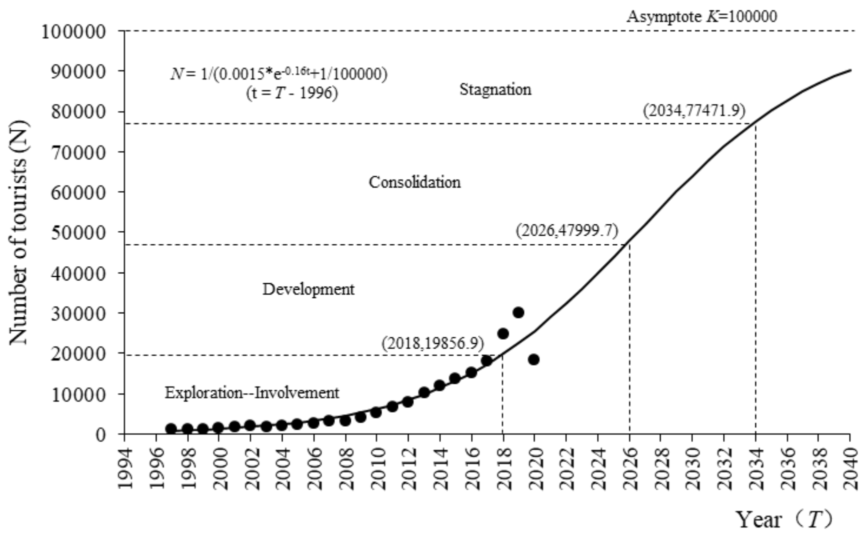

Figure 3 Stage Division of Xian City by Using Logistic Model

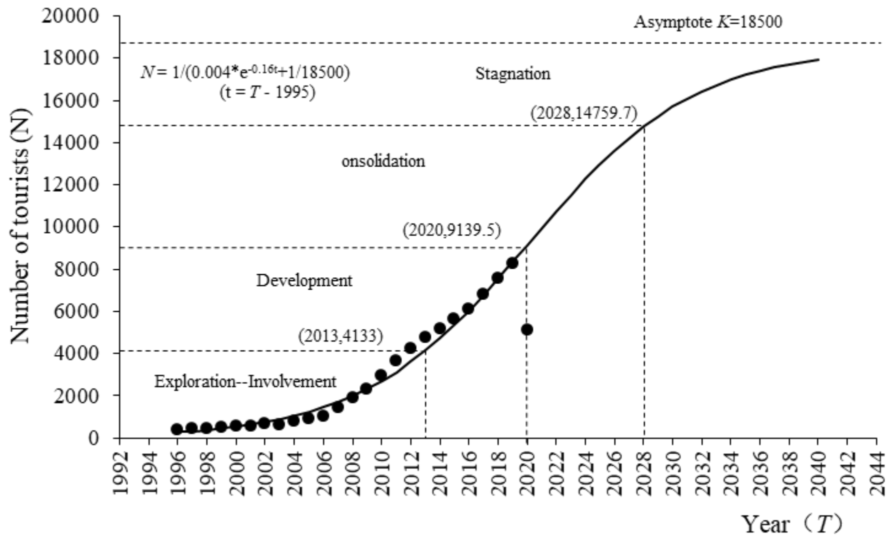

Figure 4 Stage Division of Weifang City by Using Logistic Model

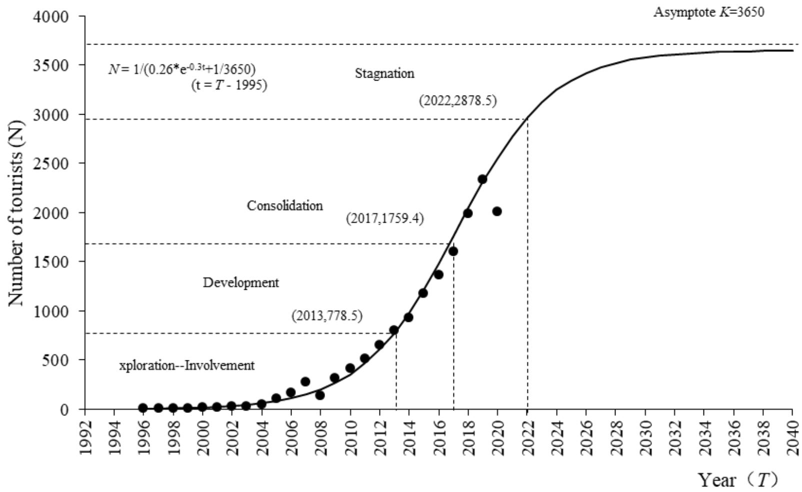

Figure 5 Stage Division of Lhasa City by Using Logistic Model

Subsequently, we collected all the videos, along with metadata (e.g., the amounts of likes, comments and shares), posted by three DMO accounts（“XIAN.TOURISM”, “weifangwenlv”, and “xingfudelasa”）for the analysis of DMO. There are 1092 videos for Xi’an DMO, 440 for Weifang, and 66 for Lhasa. As for UGC, in order to ensure the video content was highly related to the destination, only videos with hashtag “#Xi'an Tourism”, “#Weifang tourism” and “#Lhasa Tourism” were collected and screened. As a result, we remained 536 Xi’an UGC videos, 528 for Weifang, 393 for Lhasa.

3.2 Data analysis

3.2.1 Short video communication competence

This paper adopted the entropy weight method mentioned in the literature to calculate the weight of the four indicators affecting the communication power of short video: the number of short videos, the number of likes, comments and shares(Wang & Xia, 2021). Yet, there might be several great differences because of the biases resulted from the creator of short video, video style, video content, lead to high heteroscedasticity in direct calculation. This paper thus used the natural logarithm to standardize and compress the data scale before calculating the communication power. The standardization results are shown in Tab.1.

Table 1 Standardized Processing Results

Stage	Video Number （X_1）	Like (X_2)	Comment (X_3)	Share (X_4)
Initial development-DMO	6.996681	13.84221	10.12711	11.13228
Initial development -UGC	6.285998	16.56223	13.50525	14.35654
Accelerated development-DMO	6.084499	13.52303	11.2935	11.75151
Accelerated-development-UGC	6.269096	14.68164	12.37113	12.78753
Consolidation-DMO	4.204693	13.09302	10.11731	11.7426
Consolidation-UGC	5.963579	17.06979	14.4692	14.77705

Subsequently, we constructed the 4×6 decision matrix and computed p value to lay foundations to calculate the contributions of four indicators, which are 0.9939, 0.9971, 0.9948 and 0.9968， respectively. Finally, the weight of each indicator was reckoned by formula $w_j = \frac{d_j}{\sum_{j=1}^{4} d_j}$: 0.3517 was assigned for the number of videos (X_1), 0.298 for the number of comments (X_3), 0.1843 for the number of shares (X_4) and 0.1659 for the number of likes (X_2).

3.2.2 Video content analysis

In order to improve the accuracy of comparison between two projected destinations, non-tourism DMO videos were removed. In addition, as most of videos posted by DMO were within one minute, we removed collected UGC videos more than one minutes from the data set. And we also abandoned videos with contents been incompatible to correspondent hashtag. What’s more, we kept the same number of videos from UGC and DMO to guarantee comparison under the same conditions. Finally, we remained 160 videos of Xi’an, 206 videos of Weifang, and 132videos of Lhasa for video content analysis.

Just as depicted in Fig 6, this paper adopted the scene detection algorithm based on content aware, along with the algorithm based on inter frame difference to extract the main scene pictures of video. In other words, we extracted the key frames from the video and then got text information related to these images, all of which were quite helpful to compare the difference of destination image inflected by UGC and DMO videos.

Subsequently, we used the open source "image recognition" technology of Baidu to detect the picture. It was aimed to extract the scene information of key frames, namely, the category and keywords of the scene, which are the specific attributes of destination image represented by video. Fig 7 just shows an example.

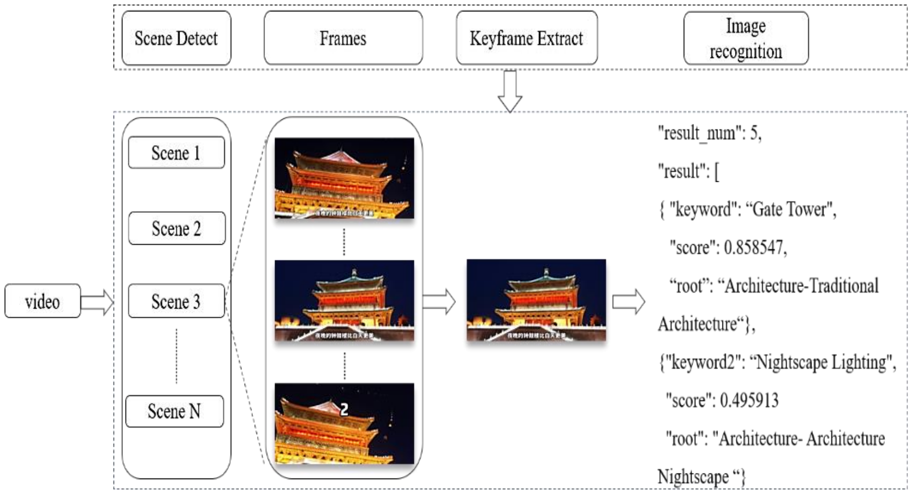

Figure 6 Technical Route of Video Content Analysis

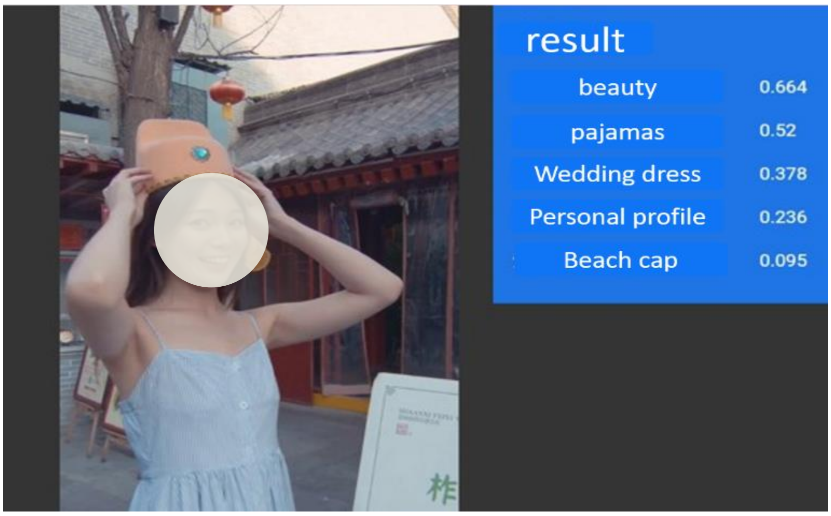

Figure 7 "Image Recognition" Technology

4 Result

The comparison of DMO and UGC projected image was conducted in two manners as described in literature (Lv et al., 2014): calculate short video communication competence to gauge the influence of DMO and UGC, analysis video content to differentiate the deviations between two projected images.

4.1 Comparable analysis DMO and UGC influence

Based on the weights calculated by entropy, we get the influence of DMO and UGC in three stages of destination's life cycle represented in Fig 9. When talking about the general changing trends, whether in initial development, accelerated development or consolidation, UGCs' influence is always higher than that of DMO, which means UGC will be more influential in the quicker rising development of destination. The reason is closely related to the tourists' information power. The prevalence of social media platforms and advanced mobile information technology make it more convenient and faster for people to exchange information. The stronger the ability of information dissemination, the greater the influence of tourists' information power(Lv et al., 2011).

Meanwhile, compare to UGC, DMOs has remained relatively stable with the minor fluctuations among the stages. This is because that tourists are susceptible to external environment(Lv et al., 2014), while DMO can't follow the changes of the market at all times like tourists as it is subject to the authoritative and grand traditional discourse system(Y. Li, Chen, Mao, & Huang, 2021).

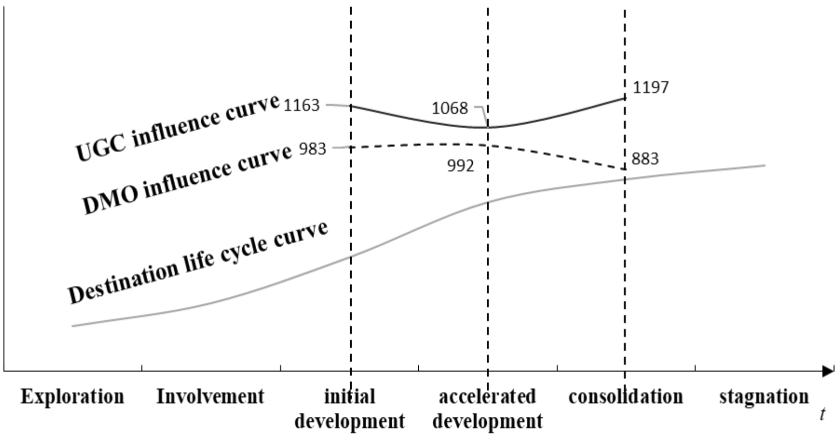

Figure9 Influence of DMO and UGC in Key Stages of Destination Life Cycle

4.2 Analysis on projection differences of DMO and UGC based on video representations

We extracted 6345 key frames from 498 short videos. By making the existing methods on dimensions of destination image as a reference, this paper further revised seven dimensions representing the destination image obtained by machine learning. The final dimensions are showed in the Fig. 8, almost cover the main attributes of the destination image.

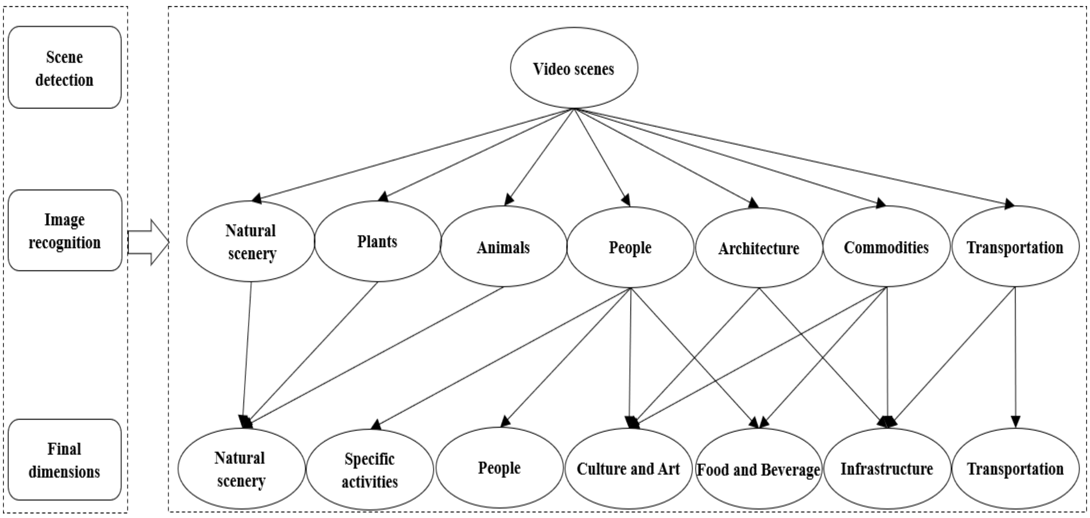

Figure 8 Main Dimensions of Destination Tourism Image

In the initial development, as we can see from the Tab. 2, the UGC and DMO share a lot of common in the core projected images, for example, both projections pay much attention to the *culture & art* aspect, significant differences still exist in the aspects of *infrastructure* and *people*. More specifically, UGC projected image is inclined to

Infrastructure (20.9% portion), which means tourists would pay much attention to the food, accommodation, travel, shopping and entertainment when recording their travel experience; as for DMOs, they prefer to focus on *people*、*Specific activities* aspects because they often use traditional festivals , local folk activities and celebrities to promote the destination. Likewise, in the accelerated development stage, DMO and UGC are highly consistent with each other, and there is almost no significant difference in the main projected image despite a little varied two of the seven dimensions. Interestingly, the findings show that the most prominent aspect has transformed to the *Nature Environment* in two projected images. This might be related to the consciousness of sustainable tourism. In general, DMO and UGC projected image seem to be relatively consistent in the development stage. Some special destination perception will be acceptable to increasing potential tourists due to the rapid development social media, then minor gaps between two projected images may escalate into major alienations during the TDI formation process(Lv et al., 2014).

In the consolidation stage, however, the two projected images begin to split. There are significant differences between UGC and DMO in many dimensions, such as *Culture & Art*, *Infrastructure*, *People* and so on. Although brand hijack is rarely easy to happen(Lv et al., 2014), if the DMO and UGC projected image continue to split, coupled with the expanding influence of UGC, it may become reality in the later period.

Table 2 Comparison of UGC and DMO Video Content

Stages	Class	UGC Freq.	Proportion	DMO Freq.	Proportion	χ^{2a}	p^b
Initial development	Nature Environment	133	11%	43	5%	23.289	.000
Initial development	Infrastructure	253	20.9%	127	14.7%	12.758	.000
Initial development	Culture & Art	415	34.3%	304	35.3%	0.221	.638
Initial development	People	227	18.7%	249	28.9%	29.278	.000
Initial development	Food & beverage	45	3.7%	13	1.5%	9.026	.003
Initial development	Specific activities	48	4%	110	12.8%	55.351	.000
Initial development	Transportation	90	7.4%	16	1.9%	32.266	.000
Accelerated development	Nature Environment	395	41.9%	315	45.3%	1.853	.173
Accelerated development	Infrastructure	145	15.4%	65	9.3%	13.066	.000
Accelerated development	Culture & Art	145	15.4%	112	16.1%	0.155	.694
Accelerated development	People	165	17.5%	125	18%	0.059	.808
Accelerated development	Food & beverage	15	1.6%	22	3.2%	4.475	.034
Accelerated development	Specific activities	32	3.4%	23	3.3%	0.010	.921
Accelerated development	Transportation	46	4.9%	34	4.9%	0.000	.995
Consolidation	Nature Environment	145	27%	180	24.6%	0.882	.348
Consolidation	Infrastructure	94	17.5%	82	11.2%	10.149	.001
Consolidation	Culture & Art	149	27.7%	114	15.6%	27.618	.694
Consolidation	People	82	15.2%	264	36.1%	68.087	.000
Consolidation	Food & beverage	25	4.6%	21	2.9%	2.792	.095
Consolidation	Specific activities	10	1.9%	55	7.5%	20.467	.000
Consolidation	Transportation	33	6.1%	15	2.1%	14.188	.000

Note: the degree of freedom in all χ2a tests is 1; test results were significant at the level of 0.05

5 Conclusion and discussion

We compared the DMO and UGC projected image in three stages of destination's life cycle to explore the TDI dynamic evolution mechanism. Based on the data result, we found although the influence of UGC projected image enjoyed a more influential status than that of DMO in the development stage (both initial and acceleration stage), the content of two projected had been consistent generally. UGC can help DMO to promote the publicity of destination image. However, when entering the consolidation stage, there is a large deviation in content between the projected image of UGC and DMO, plus the relatively huge gap in DMOs' and UGCs' video communication competency, destination image might evolve in an abnormal way.

5.1 Contributions

The theoretical contributions of the current study mainly involve two aspects. Firstly, the current study proposed a specific way to measure UGC and DMO projected destination images within real and large sample size video data. Compared prior studies, this study focused on short videos (vs. photos or text words in existing study). Secondly, previous research neither examined TDI at different destination life cycle stages nor provides empirical supports for theoretical hypotheses. The findings offer empirical evidence to further revise or perfect the prior qualitative researching conclusions about the TDI dynamic evolution based on life cycle theory.

For practical implications, the current research offer constructive references for DMO managers to judge development stage and work out corresponding marketing strategies. On the one hand, since UGCs' short video communication competence is always higher than that of DMO in every stage as studied before, DMO are suggested to tailor their official marketing strategies to satisfy tourists' needs according to significantly influential UGC projected image; on the other hand, DMO should actively bridge the gap between two projected images since consolidation stage ,or even accelerated development stage, guiding the tourists' behavior so as to promote the healthy development of destinations. Otherwise, alienated evolution might take place during formation of destination image, which means the publicity of DMO will be considered to platitude, hardly been a reference for potential tourists.

5.2 Limitations and future research

Limitations coupled with suggestions for future research, are discussed. First, Considering DouYin application hadn't been alive until 2016, we couldn't collect the full video data for the whole lifecycle in certain destination. That's why we turned to find typical destinations representing different stages of the destination's life cycle to study the dynamic comparison of UGC and DMO projected images. Besides, the analysis and discussion of short video content in this paper is still insufficient. Short video is a dynamic visual material with serious logic line, recording the entire story of the tourists. Therefore, exploring the narrative style of video and its influence on destination brand will be of great value in the future. In addition, it is still a "black box" that what kinds of destination attributes will stimulate tourists more and then influence their decision-making behaviors. There might be more researches in the future.

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