Travel Vloggers on *TikTok*: Their Distribution and Impacts on Regional Tourism Development

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Abstract: Anecdotal evidence from multiple cities suggests that short videos boost destination awareness and subsequently, tourism visitation. *TikTok* has now become one of the most popular short video platforms and accordingly, has attracted intensive attention from the tourism industry and scholars querying the implications. While previous tourism studies have primarily concentrated on the platform's viewers and user-generated content, studies focused on travel vloggers are scarce, and their roles in tourism development remain understudied. This study utilizes big data from *TikTok* in China and employs spatial analysis to investigate the distribution characteristics and impacts of travel vloggers in regional tourism development. The spatial analysis methods utilized include Moran's *I* index and Geodetector. The Moran's *I* analysis results indicate that cities with a similar number of travel vloggers tend to be clustered; however, this tendency is higher with regard to non-travel-themed vloggers. The Geodetector results reveal that travel vloggers significantly influence provincial tourist arrivals, demonstrating larger impacts than conventional variables such as scenic areas, travel agencies, and transport infrastructure. The most crucial factor contributing to the impact of travel vloggers is their number. This is followed by their productivity in terms of the number of videos they upload, which wields a larger impact than the shares or likes they receive. Within the productivity metric, the cumulative productivity of travel vloggers from previous years exerts a higher influence than their recent productivity from the past year. Interestingly, the number of their followers does not necessarily impact regional tourist arrivals. These insights can assist policymakers and practitioners in leveraging vloggers for regional tourism development.

Keywords: travel vloggers; *TikTok*; regional tourism development; big data; spatial analysis methods, Geodetector; Moran's *I* index.

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1. Introduction

The advent of social media has brought radical transformations to the tourism industry as well as research (Asongu & Odhiambo, 2019). Short videos are representative of video-centric social media due to their high media richness, with *TikTok* emerging as the most prominent platform (Cheng, 2024). There have been cases of cities experiencing a tourism boom triggered by short videos from time to time. A notable example is the city of Zibo in the eastern region of China’s Shandong Province, whose tourism industry recovered particularly rapidly from the COVID-19 pandemic downturn.

Although Zibo is now better known as an industrial city, it is where Ancient Linzi, the capital of the powerful ancient State of Qi, was located. It is a tourist city famous for its historical sites and museums. With a population of 4.7 million, the city experienced serious setbacks in tourism due to measures such as lockdowns and social distancing during the COVID-19 pandemic.

However, following the easing of COVID-19 restrictions, Zibo quickly emerged as one of the hottest tourism destinations in early 2023. The upsurge in tourist arrivals began in March and peaked during the May Day Golden Week, a five-day national vacation from April 29th to May 3rd. During Golden Week, Zibo welcomed approximately 240,000 tourists, marking a 55% increase (85,000 persons) compared to 2019 (Cui, 2023). This rate of increase significantly exceeded the national average of 19% (MCTC, 2023).

Interestingly, tourists are not flocking to the city for its famous scenic spots or historical sites but for its barbecue skewer meals. A series of short videos tagged “Zibo-Barbecue” have spread exponentially nationwide since early March 2023, drawing people to the city. This has made Zibo a notable example of a tourism boom triggered by short videos. The successful contribution of short videos to tourism promotion has also been noted in other cities. Despite this anecdotal evidence, research that empirically tests the relationship between the short video boom and regional tourism development remains limited.

Existing research on short videos and tourism predominantly focuses on aspects such as viewers' tourism intention (Han et al., 2021; Jiang et al., 2022; Liu et al., 2023; Wu & Ding, 2023), tourism destination choices (Zhou et al., 2023), and tourism destinations' images (Li et al., 2019). Although *TikTok* has grown to be the largest and most prominent online short video platform globally, previous tourism studies have primarily concentrated on its viewers (Han et al., 2021; Zhou et al., 2023) and user-generated content (Li et al., 2019; Tham et al., 2024). Video creators on *TikTok* have been largely overlooked.

Individuals who create and share video content on online platforms are generally referred to as video bloggers, i.e. vloggers. In this article, vloggers who specialize in travel content are termed "travel vloggers." Vloggers of all topics are collectively referred to as "vloggers in general." Despite several existing studies investigating their online sharing intentions (Zhao et al., 2022) and the impact of their motivations on media content production (Tham et al., 2024), studies focused on travel vloggers are scarce, and their roles in tourism development remain understudied.

To address this gap, this study aims to empirically examine travel vloggers on *TikTok*, by unveiling their distribution characteristics and their roles in regional tourism development. China is selected as the case study area because *TikTok*, known as *Douyin* in China, was established there and boasts the largest user base in the world. In addition, since China implemented strict zero-coronavirus restrictions and did not fully lift them until December 2022, China in 2023 serves as a well-suited case to observe the recovery of the tourism industry since COVID-19. China's May Day Golden Week in 2023 serves as a significant milestone for evaluating this resurgence.

The research questions of interest are as follows:

① What are the spatial distribution characteristics of travel vloggers in China?

② Does the distribution of travel vloggers have any impact on regional tourism development? If so, does the impact come from the travel vloggers' productivity (i.e., the number of videos a vlogger has uploaded) or viewer engagement (i.e., the number of likes, shares, and followers a vlogger has received)?

This study utilizes big data from *TikTok* to document the number of travel vloggers in Chinese cities and employs the spatial analysis methods of Moran's *I* index and Geodetector to conduct the analysis. Since there are relatively few data samples with information on tourist arrivals, the investigation of research question ② is an exploratory study conducted with a limited sample size. Nevertheless, this study contributes to tourism literature by expanding the academic understanding of the distribution characteristics of travel vloggers in China and how they influence regional tourism development.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature on factors influencing the regional tourism destination market in China and the role of *TikTok* in tourism. Section 3 details data and variables. Section 4 presents the spatial distribution characteristics of travel vloggers. Section 5 reports the results of the analysis on the impact of travel vloggers on tourism. Section 6 concludes with academic contributions, policy implications, and limitations.

2. Literature Review

2.1 Factors Influencing the Regional Tourism Destination Market

A rich body of literature has explored a wide range of factors influencing the tourism market, including internal factors (tourists' intention, motivation, destination choice behavior, experience, culture, etc.), source market push factors (disposable income, population, vacation policy, etc.), destination pull factors (tourism resources, tourism products, environment, infrastructures, service facilities, etc.), and resistance factors (distance, means of transport, budget, etc.) (Yang et al., 2011; Feng & Huang, 2015).

Several previous studies have explored the factors affecting provincial-level tourism development in China. Wang and Chen (2011) employed a Pearson correlation analysis in their empirical study and determined that both foreign exchange earnings and domestic tourism revenues in Chinese provinces are positively affected by resource endowments, transport infrastructure, and economic development levels. They argue that these factors are essential to understanding regional differences in the tourism economy. Ao and Wei (2006) find that the main factors contributing to provincial differences in tourism revenue are regional tourism resources, regional fundamental infrastructures represented by transport infrastructure, service facilities represented by hotels, and economic development levels. These results apply to foreign, domestic, and overall tourism revenue. Ma and Yang (2003) argue that the scale of regional tourism industries—as measured by the number of travel agencies, employees in the tourism industry, and tourism foreign exchange earnings—is positively associated with the number of AAAA-rated (4A) tourist attractions in each province. A rating of 4A represents the second-highest level in the tourist attraction rating system implemented by the China National Tourism Administration to assess the quality of tourist attractions. According to this system, scenic areas are classified into five categories, with A being the lowest level and AAAAA (5A) the highest. Additional evidence reveals a correlation between provincial tourism resources and foreign tourism in China, suggesting that tourism resources serve as the objective foundation for developing tourism (Zhao, 2008). It is also argued that the impact of service facilities is complex. While service facilities are a significant factor affecting foreign tourism in central and western China, they do not affect foreign tourism in eastern China or at the national level (Zhao, 2008). However, existing studies on provincial-level tourism development mainly focus on traditional tourism-boosting factors, while studies exploring the impact of social media on regional tourism development are scarce.

2.2 The Role of TikTok in Tourism

Social media is a group of Internet-based applications that builds on the ideological and technological foundations of Web 2.0 and allows for the creation and exchange of user-generated content (Kaplan & Haenlein, 2010). The popularity of social media has facilitated the creation of an extensive repository of user-generated content, personalized and readily accessible to its users. In the tourism landscape, people can use social media to glimpse at other tourists' experiences in a destination, view online content posted by fellow users, participate in conversations and reviews, share information with friends, and so on. People engage in these activities for various reasons—to inform others of their personal preferences, for purely hedonic purposes to connect with others, or sometimes to enhance their knowledge (Aleti et al., 2018).

The production of online short videos has become much easier and more popular due to the widespread use of smartphones and advancements in applications. These videos have started to exert a growing impact on the tourism landscape. For instance, an online survey conducted in China revealed that, out of 2000 samples, 57% utilize short video platforms as a channel for travel information. Remarkably, 90% of travelers are willing to share their travel experience online, with 59% opting for short video platforms (Oceanengine, 2022). Since its launch in 2016, *TikTok* has rapidly become one of the largest social networks globally. As of January 2024, it boasts a monthly active user base of 1,562 million in countries other than China (Statista, 2024). In China, *TikTok* has amassed a monthly active user base of over 761 million as of December 2023, firmly establishing its dominance in the Chinese online short video market (QuestMobile, 2024).

Short videos uploaded on *TikTok* typically can range from 15 seconds to 60 seconds. Compared to longer videos, short videos are more flexible and better at reaching a large audience. These short videos are particularly popular among young people, with the majority of *TikTok* users in China falling in the 18–35 age range (Randeng Search Academy, 2020). *TikTok* recommends videos to viewers based on algorithms. It constantly analyzes a viewer's watching behaviors and improves its model over time, showing more content tailored to the viewer's preferences and interests (Herrman, 2019). This personalized approach keeps viewers engaged and encourages them to return for more.

Previous studies on *TikTok* have mainly focused on its viewers and explored its impacts on the tourism intentions and destination choices of potential tourists (Han et al., 2021; Zhou et al., 2023). Wengel et al. (2022) warn that a sudden surge of tourists triggered by *TikTok* videos can burden the environment and facilities in a destination. Further issues include users' perceived trust (Zhou et al., 2023) and unverified tourism claims (Ying et al., 2021) resulting from *TikTok* videos. However, this strand of studies primarily relies on surveys targeting *TikTok* end-users or the general public (Tham et al., 2024).

A few studies have used data on user-generated content from *TikTok*. For example, Tham et al. (2024) manually decoded 30 videos related to a *TikTok* campaign for Penang, Malaysia, and categorized their content based on a designated framework. Their findings suggest that media content production is influenced by the roles and motives of different stakeholders, including tourism destination management organizations (DMOs), *TikTok* influencers, and other *TikTok* end-users who participated in the campaign contest. The results underscore the importance of information resources and raise concerns about how influencers' videos may result in the fragmentation and dilution of a destination's image. Li et al. (2019) also employed user-generated content and analyzed the online comments under *TikTok* food short videos to investigate the impact of short videos on the tourism destination image of Chengdu in China. *TikTok* allows its users to add geolocation information by using geotags in their videos. Zhang et al. (2022) used this geo-tagged information to analyze people's virtual and physical visiting preferences in Beijing, China. Despite these efforts, research incorporating user-generated content from online video platforms, *TikTok* included, is still in its infancy.

In addition to the viewer and content, the content creator, i.e. vlogger, is crucial to *TikTok*, serving as the lifeblood of the online short video platform. *TikTok* offers various tools to simplify video creation, including filters, effects, auto-caption, and the ability to search for sounds to score one's video, making the initial step of becoming a video creator easy. The algorithm-driven content recommendation system enables a *TikTok* video to potentially experience a snowball effect in viewership, once it starts gaining traction. These two factors attract a wide range of individuals and organizations to join the vlogger group, boosting content creation across various niches, including tourism. Several studies focusing on travel vloggers include Tham et al. (2024), who determined that vloggers' different roles affect their content creation on *TikTok*. Although not specified to *TikTok*, Zhao et al.'s (2022) study revealed that travel vloggers' online sharing intention is affected by factors such as the consistency of values, entertainment motivation, emotional engagement, and the parasocial relationships between tourists and travel vloggers. Nevertheless, travel vloggers have been largely overlooked and their roles in regional tourism development remain understudied.

3. Data

The data on travel vloggers and vloggers in general were obtained from *Chanmama*, a data provider for *TikTok* in the mainland of China as of October 2023. For ethical considerations, it needs to be declared that the data has undergone anonymization processing. The number of travel vloggers is calculated based on the residence self-reported on *TikTok*. The data sample includes 185,655 travel vloggers distributed among 364 cities of 31 provinces. These cities include four direct-administered municipalities under the control of the Central Government, 30 county-level administrative units, and one forest region directly administrated by the corresponding provinces, with the majority being prefecture-level administrative units. Travel vloggers account for only 1.47% of all 12.61 million vloggers.

Variables for travel vloggers' performance encompass productivity metrics represented by the number of videos, as well as viewer engagement metrics represented by the number of shares, likes, and followers. These metrics are considered for both the overall term and specifically for the past year.

The data on tourist arrival numbers for each province during the 2023 May Day Golden Week was released through news announcements by the Administration of Culture and Tourism in each province. However, four provinces, namely Hebei, Shanxi, Jiangxi, and Anhui, have not released this data, leaving 27 provinces with data available for analysis in Section 5.

This study employs several control variables. The number of scenic areas, travel agencies, and hotels, are obtained from the *China Statistical Yearbook of Culture, Cultural Relics, and Tourism 2022*. The index of transport infrastructure is constructed using the method proposed by Ao and Wei (2006): Index of transport infrastructure = (Density of railway network in km/km^2) * 30% + (Density of roads and highways in km/km^2) * 30% + (The percentage of secondary roads and above among all roads and highways) * 20% + (Density of inland waterways in km/km^2) * 20%. The relevant data are from the *China Statistical Yearbook 2022*. The descriptions and summary statistics of variables are listed in Table 1.

Table 1. Descriptions and summary statistics of the dependent variable and potential determinants.

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
Tourists	Number of tourist arrivals during May Day Golden Week	27	2196.83	1528.52	116.77	5518.04
Tvloggers	Number of travel vloggers	31	5988.87	4116.14	607	16653
Ntvloggers	Number of non-travel-themed vloggers	31	401035.90	320189.80	15962	1355643
Vloggers	Number of all vloggers	31	407024.80	324238.60	16790	1372296
Videos	Number of travel vloggers' videos in total (10 thousand)	31	92.57	62.89	7.33	250.47
Videos1year	Number of travel vloggers' videos within the previous year (10 thousand)	31	33.77	23.39	2.75	95.90
Followers	Number of followers in total (million)	31	21.70	17.01	1.33	63.13
Followers1year	Number of followers within the previous year (million)	31	118.04	89.60	7.26	358.01
Likes	Number of likes in total (million)	31	670.96	485.26	45.28	1973.57
Likes1year	Number of likes within the previous year (million)	31	225.62	173.09	12.64	688.33
Shares	Number of shares in total (million)	31	75.27	57.08	3.97	221.74
Shares1year	Number of shares within the previous year (million)	31	36.71	30.67	1.36	140.38
Ascenicareas	Number of A-level and above scenic areas	31	478.94	288.19	84	1322
A5scenicareas	Number of 5A-level scenic areas	31	10.84	6.62	2	34
Tagencies	Number of travel agencies	31	1000.03	617.02	155	2455
Hotels	Number of starred hotels	31	247.61	113.08	64	483
Hotelrooms	Number of rooms in starred hotels	31	36159.58	21858.43	2437	94818
Hotelbeds	Number of beds in starred hotels	31	61718.13	40090.37	4130	183014
Transport	Index of transport infrastructure	31	1.15	1.16	0.20	5.23

Note: The above variables are at the provincial level.

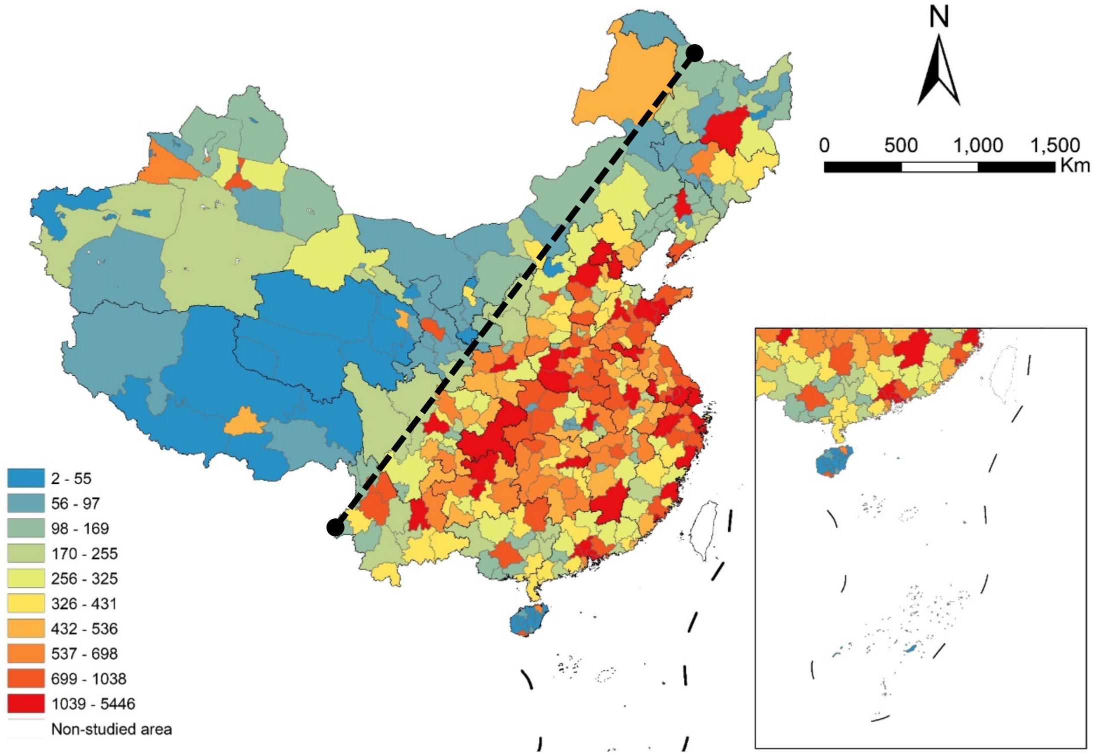
4. Spatial Distribution of Travel Vloggers

4.1 Visualization of Distribution

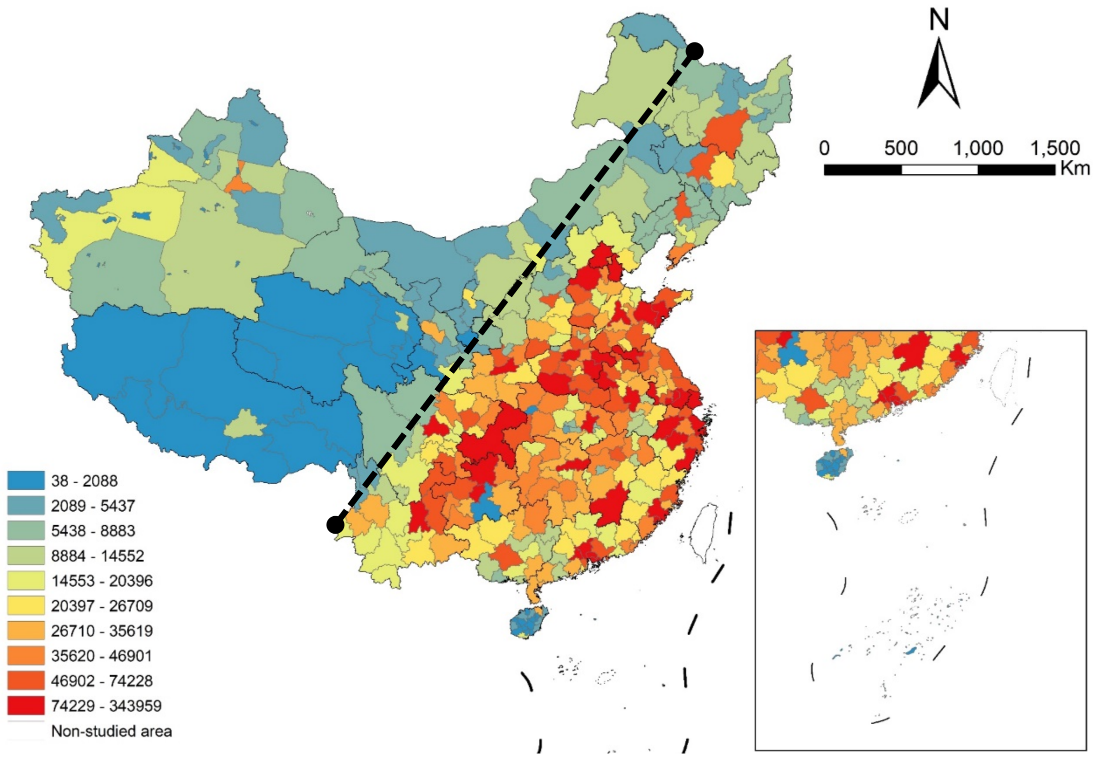
First, this study analyzes the spatial characteristics of travel vloggers by visualizing their distribution using data from sample cities. The number of travel vloggers in each city is categorized into ten quantiles. The map is color-coded to reflect these levels, with darker shades indicating a higher number. The results indicate that travel vloggers are predominantly concentrated in areas east of the Hu Huanyong Line, the conceptual geographic dividing line in China proposed by the renowned Chinese geographer Hu Huanyong (Hu, 1935) (Figure 1a). These areas are also where most of the population and economic activities in China are located.

Out of 364 cities, 77 cities (21.2%) have less than 100 travel vloggers, while 246 cities (67.6%) have less than 500 travel vloggers. Only 37 cities (10.1%) have more than 1000 travel vloggers. The top ten cities with the highest number of travel vloggers are Beijing (5,446), Chengdu in Sichuan (4,340), Chongqing (4,245), Shanghai (4,109), Shenzhen in Guangdong (3,536), Guangzhou in Guangdong (3,449), Xi'an in Shaanxi (3,247), Hangzhou in Zhejiang (2,825), Zhengzhou in Henan (2,705), and Wuhan in Hubei (2,111). These cities include three direct-administered municipalities and seven provincial capitals. They are distributed across the eastern, central, and western regions, but not in the northeastern region.

The maps in Figures 1a and 1b show that the distribution patterns of travel vloggers and vloggers in general are broadly similar, although vloggers in general are slightly more concentrated in the southern regions east of the Hu Huanyong Line.



(a)



(b)

Figure 1. Decile map of the number of travel vloggers (a) and vloggers in general (b) by cities.

4.2 Spatial Autocorrelation Analysis

Tobler (1970, p. 236) proposed the first theory of geography, stating, "Everything is related to everything else but near things are more related than distant things." This principle may also be applicable in the distribution of travel vloggers. Global and local indicators of spatial autocorrelation can be useful tools to identify such spatial heterogeneity and agglomerations (Romão & Saito, 2017).

4.2.1 Global Spatial Autocorrelation Analysis

Moran's *I* index is a commonly employed metric for assessing global spatial autocorrelation. It was initially suggested by Moran (1948) and popularized through the work of Cliff and Ord (1973). For an observation at location *i* with attribute *x*, we have the deviation calculated as $z_i = x_i - \bar{x}$, where $\bar{x}$ is the mean of variable *x*. Moran's *I* index is then expressed as

$$I = \frac{\sum_i \sum_j w_{ij}\, z_i \cdot z_j / S_0}{\sum_i z_i^2 \,/ n},$$

where w_{ij} is the element of the spatial weight matrix, $S_0 = \sum_i \sum_j w_{ij}$ is the sum of all the weights, and *n* is the number of observations.

Moran's *I* index examines whether there are any associations between the locations and the values of a variable. Its value is usually between −1 and 1. A positive value indicates that the distribution of similar values tends to be spatially clustered. A negative value indicates that locations with similar attribute values tend to be spatially dispersed. An approximate zero value indicates that the distribution of the values is truly randomly distributed. The *z*-score and *p*-value are measures of statistical significance.

The spatial weights for cities are defined as a matrix based on contiguity order 1 (Queen). In this approach, the neighboring cities of city *i* are assigned a weight of 1 if they share a common side or vertex with city i. If city j does not share any side or vertex with city i, its weight, w_{ij}, is set as 0.

GeoDa software is utilized to calculate Moran's *I* for travel vloggers (*Tvloggers*), non-travel-themed vloggers (*nTvloggers*), and vloggers in general (*Vloggers*). Table 2 reports the results of these calculations and shows that the global Moran's *I* for the three variables are all significantly positive.

These results indicate that cities with similar numbers of travel vloggers tend to be clustered. There are several possible explanations for these results. First, travel vloggers in nearby locations have access to comparable tourism resources. Geographic proximity enables travel vloggers in nearby cities to easily access and showcase these resources in short videos. Second, the spillover of travel vlogging know-how and its exemplary effects are more easily diffused to nearby cities. Third, nearby cities share a similar cultural background, making it similarly easy or difficult to encourage people into such new endeavors.

Similar clustering tendencies also exist in regard to non-travel-themed vloggers. However, the Moran's *I* indices reveal that travel vloggers (0.156) show a lower tendency toward clustering compared to non-travel-themed vloggers (0.257). It appears that travel vloggers originate from a broader geographic range, resulting in a relatively more scattered distribution. This indicates moderated regional differences compared to non-travel-themed vloggers.

Table 2. Global Moran's *I* index.

Variable	Moran's *I* index	*z*-score	*p*-value
Tvloggers	0.156**	4.4592	0.002
nTvloggers	0.257***	7.9757	0.001
Vloggers	0.256***	7.9388	0.001

Note: *** and ** denote significance levels of 0.001 and 0.01, respectively. A *z*-score above 1.96 indicates the existence of global spatial effects.

4.2.2 Local Spatial Autocorrelation Model

The local Moran's *I* index, introduced by Anselin (1995), is an extension of the global Moran's *I* index. It assesses the degree of spatial autocorrelation at a local level by evaluating the similarity or dissimilarity of a specific location with its neighboring locations, considering both the attribute values and spatial proximity. For an observation at city *i*, its spatially lagged variable representing the weighted average of the neighboring values is

$$L_i = \sum_{j=1}^{n} w_{ij} \frac{(x_i - \bar{x})}{\sqrt{\sum_{j=1}^{n}(x_j - \bar{x})^2 / n}} \cdot \frac{1}{n},$$

where $\bar{x}$ is the mean of variable x, w_{ij} is the element of the spatial weight matrix, and *n* is the number of observations. Clusters occur when the value of location *i* is more similar (in the case of positive autocorrelation) or dissimilar (in the case of negative autocorrelation) to the value of the spatially lagged variable than it would be in the case of spatial randomness. When positive and significant autocorrelation is identified, the location can be categorized as statistically significant clusters of high values (HH clusters) or low values (LL clusters). When negative and significant autocorrelation is identified, the location can be categorized as an outlier in which a high value is surrounded primarily by low values (HL outlier) or a low value is surrounded primarily by high values (LH outlier).

The results of the local Moran's *I* analysis of travel vloggers reveal 20 clusters with high values (HH clusters) (Figure 2a). They mainly include cities in the three most highly developed regions (Beijing–Tianjin–Hebei Region, Yangtze River Delta, and Pearl River Delta), the coastal province of Shandong, and several middle-region provinces (Guizhou, Hunan, Hubei, and Shaanxi). It appears that travel vloggers tend to cluster in regions that provide attractive destinations, tourism opportunities, or a supportive environment for travel vlogging.

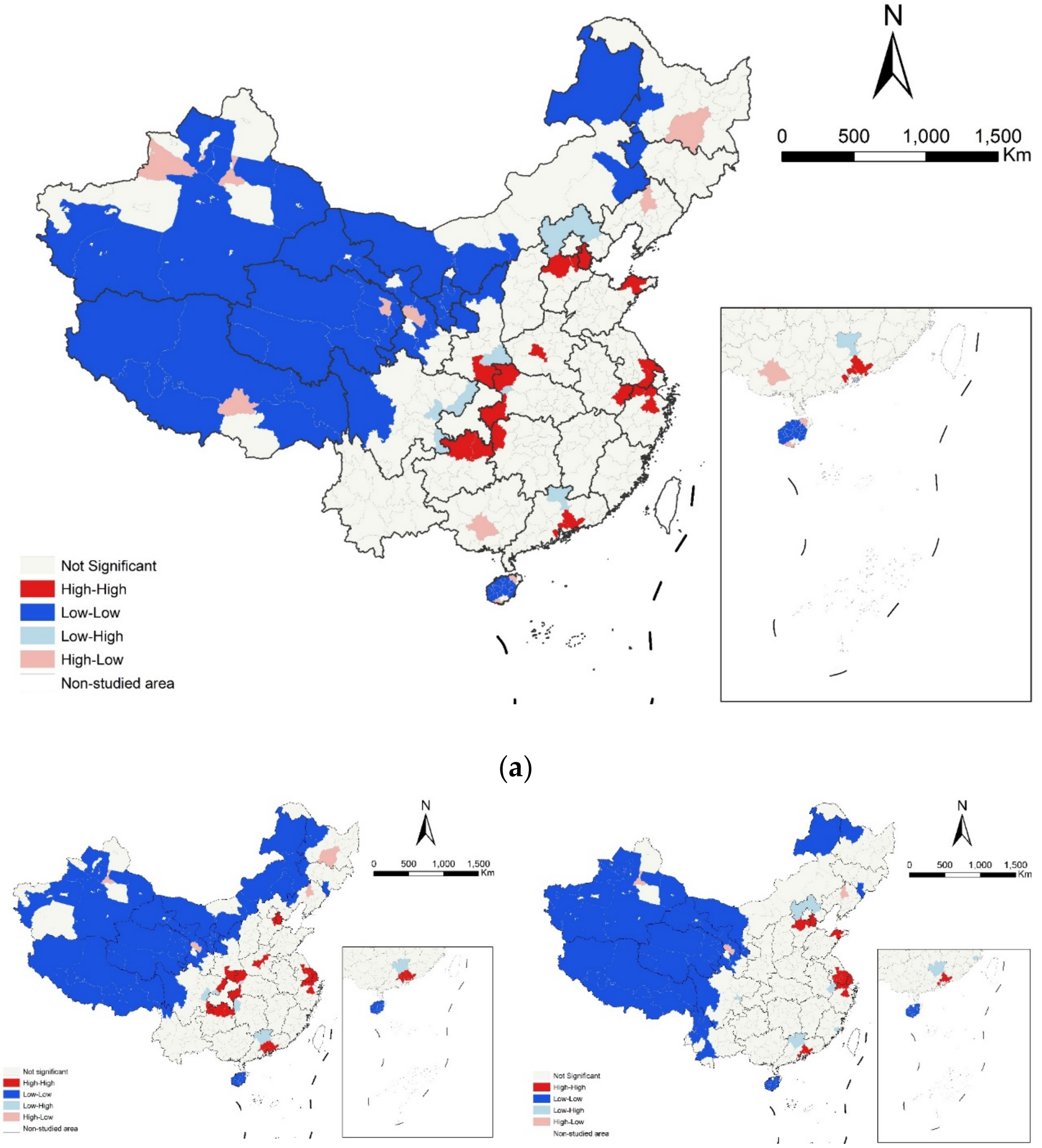
There are 52 clusters with low travel vlogger numbers (LL clusters). They include most cities in Xinjiang, Gansu, Ningxia, Qinghai, Xizang, and Inner Mongolia. A few cities in western Sichuan, northern Shaanxi, western Jilin, and western Heilongjiang are also included. These are generally less economically developed regions.

Twenty-one outliers are markedly dissimilar from their surroundings, with 11 cities being identified as low–high outliers (LH outliers). They are mainly located in Sichuan, including Dazhou, Guang'an, Luzhou, Suining, and Ziyang. Other LH outliers include Chengde and Zhangjiakou in Hebei, Shangluo in Shaanxi, Shaoguan in Guangdong, and Shennongjia in Hubei. These LH outliers are typically smaller cities located near much larger cities and appear to be the "sole losers" of nurturing travel vloggers within their regions while neighboring cities flourish.

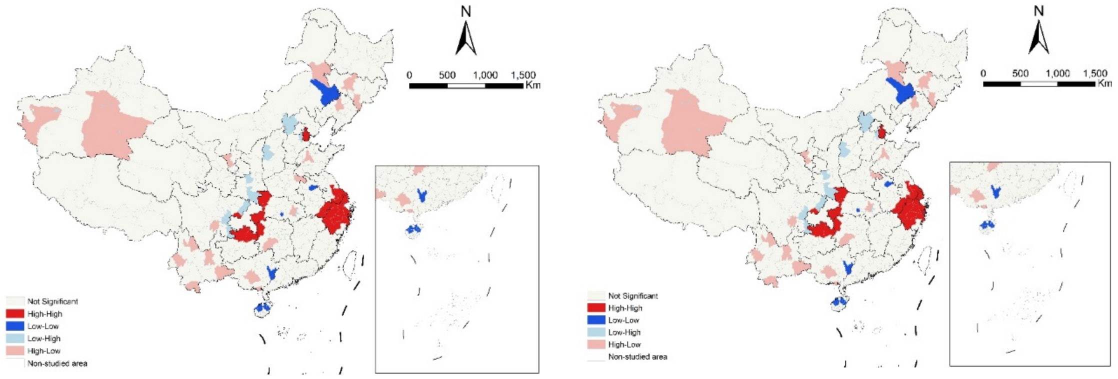
There are ten significant high–low outliers (HL outliers). They include Haerbin in Heilongjiang, Haikou and Sanya in Hainan, Lasa in Xizang, Lanzhou in Gansu, Nanning in Guangxi, Shenyang in Liaoning, Wulumuqi in Xinjiang, Xining and Yili in Xinjiang. These are typically capital cities or central cities in less developed provinces, marked by economic disparities with their surrounding regions.

Last, no significant results were found for 275 cities. Interestingly, Zibo belongs to this category. Its number of travel vloggers has no significant correlation with its neighboring cities.

A comparison of Figures 2a and 2b reveals that the spatially clustering pattern of vloggers in general is quite similar to that of travel vloggers. Both of their LL clusters resemble the LL clusters of GDP (Figure 2c), and their HH clusters are similar to the HH clusters of scenic areas (Figures 2d and 2e). It is speculated that regional economic size and tourism resources collectively shape the distribution of travel vloggers. This speculation could initiate further investigations into the factors influencing travel vlogger participation in these areas.



(**a**) (**b**) (**c**)



(**d**) (**e**)

Figure 2. Spatial distribution map of local Moran's *I*: (**a**) Travel vloggers; (**b**) Vloggers in general; (**c**) GDP; (**d**) A-level and above scenic areas; (**e**) 5A-level scenic areas.

Section 4 has elucidated the distribution pattern of travel vloggers across Chinese cities. Next, this study aims to determine whether this distribution influences regional tourism development. If such an impact exists, regional disparities in the number of travel vloggers may exacerbate discrepancies within the tourism industry, perpetuating a Matthew effect, where successful cities advance more rapidly while disadvantaged ones progress at a much slower pace.

Anselin (1988) emphasized that omitting the spatial correlations in an econometric analysis when variables are spatially correlated would lead to bias. The analysis in Section 4.2 has demonstrated the existence of spatial autocorrelation in the distribution of travel vloggers. Contemporary tourists' travel behavior also exhibits spatial correlation (Ma et al., 2015). Therefore, to reveal the impact of travel vloggers on tourism development, spatial analysis methods are more appropriate than regular econometrical models. Hence, the analysis in Section 5 employs the spatial analysis tool, Geodetector.

5. The Impact of Travel Vloggers on Tourism: A Geodetector Approach

Geodetector is a collection of statistical analysis tools that can explore the spatial differences and determinants of specific phenomena. It is designed to detect and quantify the spatial heterogeneity and relationships between a dependent variable and a set of independent variables by utilizing a geographically weighted regression (GWR) framework for estimation. The underlying assumption is spatial stratified heterogeneity, which assumes that the within-strata variance is less than the between-strata variance (Wang et al., 2016; Wang & Xu, 2017). One advantage of Geodetector is that it does not require a linear hypothesis and is sufficiently robust to handle multicollinearity among multiple independent variables. It handles discrete data as independent variables, assuming that the samples within each stratum are similar. As a result, Geodetector provides more reliable estimation results for the relationship between dependent and independent variables when the sample size is small (e.g., less than 30) (Wang & Xu, 2017). This is another notable advantage of Geodetector.

Since the original independent variables are continuous, this study uses the natural breakpoint method to discretize them to meet the requirements of Geodetector. This process involves dividing each variable into five strata.

5.1 Factor Detector

Geodetector's Factor Detector helps uncover the underlying factors that shape the observed spatial patterns of tourist arrivals. It reports a q-statistic for each independent variable, representing the magnitude of a factor's impact on spatial differences in tourist arrivals. It is calculated as follows:

$$q = 1 - \frac{1}{N\sigma^2} \sum_{h=1}^{L} N_h \sigma_h^2 .$$

N represents the number of the studied provinces (i.e., 27). σ^2 is the discrete variance of tourist arrivals in each province. L is the number of strata based on the stratification by dependent variable Y and independent variable X (in this case, L equals 5). N_h is the number of provinces in stratum h. σ_h is the variance of tourist arrivals in provinces within stratum *h*. $q \in [0,1]$, and a larger *q*-statistic value indicates a stronger impact of the corresponding factor on the observed spatial patterns. The corresponding *p*-value represents the significance level.

Table 3. Factor detection analysis results of the factors affecting tourist arrivals.

Variable	*q*-statistic	*p*-value	Variable	*q*-statistic	*p*-value
Tvloggers	**0.7624**	**0.0000**	***Likes***	**0.5028**	**0.0150**
NTvloggers	**0.7459**	**0.0000**	***Transport***	**0.4787**	**0.0444**
Vloggers	**0.7459**	**0.0000**	***Ascenicareas***	**0.4784**	**0.0468**
Videos	**0.7043**	**0.0000**	*A5scenicareas*	0.4747	0.0555
Videos1year	**0.6913**	**0.0000**	*Hotelbeds*	0.4652	0.1317
Travelagencies	**0.5667**	**0.0107**	*Followers*	0.4304	0.0646
Shares1year	**0.5534**	**0.0267**	*Hotels*	0.4165	0.1216
Likes1year	**0.5261**	**0.0173**	*Followers1year*	0.4128	0.0606
Shares	**0.5112**	**0.0209**	*Hotelrooms*	0.3942	0.0757

Based on the results reported in Table 3 show that ten variables are statistically significant factors affecting tourist arrivals. Their ranking in descending order based on their magnitudes of impact is as follows: Travel vloggers (*Tvloggers*) > Non-travel-themed vloggers (*NTvloggers*) > All Vloggers (*Vloggers*) > Videos in total (*Videos*)> Videos within the previous year (*Videos1year*) > Travel agencies (*Travelagencies*) > Shares within the previous year (*Shares1year*) > Likes within the previous year (*Likes1year*) > Total Shares (*Shares*) > Total Likes (*Likes*) > Transport infrastructure (*Transport*) > A-level and above scenic areas (*Ascenicareas*).

The results show that vlogger-related variables generally demonstrate greater impacts than conventional tourism-boosting variables. Here, the conventional variables encompass A-level and above scenic areas (representing tourism attractions), travel agencies (representing tourism-receiving capacity), and transport infrastructure.

Travel vloggers exhibit a stronger influence than non-travel-themed vloggers, despite their smaller number. This suggests that vloggers who specialize in travel-themed short videos are more likely to appeal to potential tourists. Regarding the performance of travel vloggers, the number of videos they uploaded shows a higher influence than the shares or likes they received. Notably, the total number of videos uploaded has a more pronounced influence than the number within the past year. This indicates that travel vloggers primarily influence regional tourist arrivals through their productivity and their content's enduring appeal. Not only are the newly uploaded videos attracting tourists, but the older videos from a year prior are also proving to be influential, with the latter being even more significant.

The viewer engagements received by travel vloggers, such as shares and likes, have a significant but slightly weaker influence. Specifically, the shares and likes received in the past year have a greater impact than the cumulative number from previous years. Surprisingly, the number of a travel vlogger's followers does not necessarily impact regional tourist arrivals. This suggests that the influence of travel vloggers may extend beyond their follower count, reaching a broader audience.

Of the conventional factors that contribute to regional tourism growth, A-level and above scenic areas have a significant correlation with the number of tourist arrivals; however, 5A-level scenic areas do not exhibit a significant association. This result deviates from previous studies that suggested tourists typically select higher-level tourism destinations during macro-spatial scale travel (Chen & Bao, 1988). While 5A-level scenic areas have traditionally been believed to be particularly effective in attracting visitors, our findings suggest a different narrative. Due to the current widespread use of social media and years of tourism development, scenic areas of all levels are attracting inbound tourists to provinces.

This study's findings show that transport infrastructure is significantly related to tourist arrivals, which is in line with those of Ao and Wei (2006). However, the high-speed railway and airports were not included in constructing the index due to data unavailability, despite their growing influence. This constitutes one of the limitations of this study and should be addressed in future research.

Last, the results reveal that the number of starred hotels, hotel rooms, and beds are not significantly related to regional tourist arrivals. This indicates that the accommodation capacity is no longer a constraint for attracting tourists, as it was from 1990 to 2003 (Ao & Wei, 2006).

5.2 Ecological Detector

Ecological Detector compares the impact of two factors on the tourist arrivals' spatial distribution. This detector measures the impact differences between two variables with the *F* statistic:

$$F = \frac{N_{x_1}(N_{x_2} - 1)\sum_{h=1}^{L_1} N_h \sigma_h^2}{N_{x_2}(N_{x_1} - 1)\sum_{h=1}^{L_2} N_h \sigma_h^2}.$$

N_{x_1} and N_{x_2} are the sample sizes of x_1 and x_2, respectively. L_1 and L_2 are the number of strata of variables x_1 and x_2, respectively. The detection sets the null hypothesis as H_0: $\sum_{h=1}^{L_1} N_h \sigma_h^2 = \sum_{h=1}^{L_2} N_h \sigma_h^2$. If H_0 is rejected at the significance level of 5%, x_1 and x_2 play significantly different roles. In that case, the associated value in the table of results is reported as *Y*. If the roles of x_1 and x_2 are not significantly different, the associated value is then reported as *N*. Here only the variables identified as significant in the Factor Detector (Table 3) are included in this ecological detection analysis.

The results reveal significant differences between travel vloggers and three traditional variables including transport infrastructure, A-level and above scenic areas, and travel agencies (Table 4). This suggests that travel vloggers exert a greater influence on tourists compared to conventional factors.

Significant differences also exist in the pairs of non-travel-themed vloggers and traditional variables. These results highlight vloggers' growing importance as a new influential force in the tourism industry. Nurturing vloggers can provide an additional stimulus to tourism in conjunction with conventional tourism-promoting efforts.

The number of videos travel vloggers produce plays a different role than transport infrastructure and A-level and above scenic areas but not travel agencies. This pattern holds true for both the cumulative productivity of travel vloggers represented by the total number of videos from previous years and their recent productivity represented by the number of videos from the past year. The viewer engagement metrics of followers, likes, and shares do not show significant differences with any traditional variable.

Table 4. Ecological detection analysis results of tourist arrivals at the provincial level.

Variable	*Transport*	*Ascenicareas*	*Travelagencies*
Tvloggers	Y	Y	Y
NTvloggers	Y	Y	Y
Vloggers	Y	Y	Y
Followers	N	N	N
Videos	Y	Y	N
Likes	N	N	N
Shares	N	N	N
Followers1year	N	N	N
Videos1year	Y	Y	N
Likes1year	N	N	N
Shares1year	N	N	N

Note: The significance level for the F-test is 0.05.

5.3 Interaction Detector

Interaction Detector tests the joint impact of two factors on the spatial disparities in tourist arrivals. With factor x_m, x_n being interacted, the q-statistic of their interaction $q(x_m \cap x_n)$ will be compared to $q(x_m)$ and $q(x_n)$. If $q(x_m \cap x_n) > \max(q(x_m), q(x_n))$, the impact of the interaction is larger than each factor independently.

The results reveal a significant increase in the interactions between any two factors compared to their individual components. For the interaction between conventional variables and vlogger-related factors, the effective combinations are as follows (Table 5):

- Scenic areas exhibit a greater influence when interacting with travel vloggers compared to non-travel-themed vloggers. Specifically, scenic areas have the strongest impact when interacting with travel vloggers' shares in the past year.
- Travel agencies similarly have a greater influence when interacting with travel vloggers than with their non-travel-themed counterparts. They have the greatest influence when interacting with travel vloggers' likes in the past year.
- Transport infrastructure exhibits a stronger influence when interacting with non-travel-themed vloggers.

These results provide valuable insights into effective collaborations. Governments and practitioners within the tourism industry should acknowledge the importance of such collaborations and take the necessary actions to capitalize on them.

Table 5. Interaction detection analysis results of the affecting factors.

Variable	*Ascenicareas*	*Travelagencies*	*Transport*
Tvloggers	**0.8122**	**0.8511**	0.9313
NTvloggers	0.8014	0.8041	**0.9445**
Vloggers	0.8014	0.8041	0.9445
Followers	0.7267	0.7499	0.7934
Videos	0.8789	0.7856	0.8514
Likes	0.8353	0.7594	0.7827
Shares	0.8743	0.7527	0.7692
Followers1year	0.7826	0.6866	0.7776
Videos1year	0.8792	0.7813	0.9070
Likes1year	0.8329	**0.8564**	0.7643
Shares1year	**0.8809**	0.7913	0.7564

6. Concluding Remarks

Using big data from *TikTok*, the largest short video platform in China, this study analyzes the spatial characteristics of travel vloggers and their impact on provincial tourist arrivals. A primary conclusion of this work is the spatial heterogeneity and agglomerations of travel vloggers across Chinese cities. The 185,655 travel vloggers are primarily concentrated in areas east of the Hu Huanyong Line, where most of China's population and economic activities are located. Cities with similar numbers of travel vloggers tend to be clustered, but this clustering tendency is slightly lower than that of cities with similar numbers of non-travel-themed vloggers. This indicates the potential to leverage the impacts of travel vloggers to promote regional development in less remote and less developed areas.

This exploratory work reveals the pivotal role of content creators from short video platforms in tourism development by confirming that travel vloggers have a significant impact on regional tourist arrivals and their influence is greater than conventional tourism-boosting factors. While studies on *TikTok* and tourism have primarily concentrated on its viewers (Han et al., 2021; Zhou et al., 2023) and user-generated content (Li et al., 2019; Tham et al., 2024), this study contributes to the social media stream of tourism research by highlighting the valuable roles of content creators in regional tourism development.

This study is also among the first to examine the sources of impact of travel vloggers, providing a fresh perspective on studying social media. The variables encompass various aspects of travel vloggers, including their numbers, their productivity measured by the number of videos they created and uploaded, and viewer engagement quantified by the number of followers, likes, and shares they received. Furthermore, this study accounts for the temporal effect by comparing travel vloggers' overall performances to those from the past year. The results suggest that, among various aspects, the number of travel vloggers is the most crucial, with their productivity ranking second. Within the productivity metric, the impact of the cumulative number of videos from previous years surpasses that of the number of videos from the previous year.

The results of this study have several policy implications. Governments and DMOs can capitalize on the impact of travel vloggers in tourism development and develop promotion strategies that incorporate short videos. These include actions such as integrating short video platforms into destination marketing plans, organizing tourism events to provide topics for travel vloggers, and initiating collaborations between scenic areas and travel vloggers. Among all Chinese cities, the 11 LH outliers (i.e., areas with low numbers of travel vloggers while neighboring areas have high numbers of travel vloggers) are particularly vulnerable to being left behind in the tourism industry. Thus, these areas require special attention from policymakers and practitioners in destination planning to ensure that they do not become the sole losers in the efforts to nurture travel vloggers.

Policymakers and practitioners must also be cautious about potential pressures and damages to the environment and facilities at destinations arising from the *TikTok* tourism boom (Wengel et al., 2022). Dispersing tourism over time and space is one of the most frequently adopted strategies to pursue sustainable tourism. Although people are aware that certain short videos can become popular and boost local tourism, predicting which videos will gain popularity is challenging. Consequently, constantly creating popular videos related to a destination is very difficult. However, this exploratory study finds that among the various aspects of travel vloggers' performances, the number of videos wields a greater influence than the shares or likes they receive. Specifically, the total number of videos uploaded has an even larger impact than the number from the previous year. These results suggest that setting aside the potential tourism boom brought about by popular short videos, the productivity of travel vloggers, and their long-lasting and accumulative efforts may be a more promising power to sustain tourism development. Nurturing the relationships with more local travel vloggers and encouraging them to consistently showcase a city could be utile in counterbalancing and alleviating the adverse effects of the *TikTok* boom. Other effective strategies may include leveraging sponsored content partnerships with travel vloggers to showcase lesser-known destinations and those in the off-season and diversifying tourism products.

The discussion on sustainable tourism still predominantly revolves around a growth-oriented perspective (Nieuwland, 2024). Scholars argue that instead of merely minimizing the negative impacts of tourism, the focus should shift away from capitalist thinking (Nieuwland, 2024). Society must prioritize social and ecological values over economic gains. New forms of tourism are being introduced, such as degrowing tourism and regenerative tourism (Nieuwland, 2024), and virtual tourism can be embraced as a substitute for physical travel (Frenzel et al., 2022). Since social media platforms are where marginalized groups can be empowered and their voices can be heard (Cheng, 2024), *TikTok* can be an extremely powerful instrument to advocate and showcase the ideas, knowledge, and experiences of these new forms of tourism. Future research is necessary to investigate the roles of travel vloggers in promoting these new types of tourism.

One limitation of this study is that the residence of a travel vlogger does not necessarily align with the locations featured in their video content. Nevertheless, despite their inherent mobility, our findings confirm that travel vloggers are significantly associated with tourist arrivals in their respective provinces. Future research can delve deeper into the locations featured in video content and conduct comparisons.

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References

1. Aleti T., Ilicic J., & Harrigan P. (2018). Consumer Socialization Agency in Tourism Decisions. *Journal of Vacation Marketing, 24*(3), 234–46. https://doi.org/10.1177/13567667177001
2. Anselin, L. (1988). *Spatial econometrics: Methods and models*. Dordrecht: Springer.
3. Anselin, L. (1995). Local Indicators of Spatial Association—LISA. *Geographical Analysis, 27*(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x
4. Ao, R. J., & Wei, Y. S. (2006). A Study on the Regional Tourism Resources and the Unbalanced Development of the Tourism Industry in China. *Journal of Finance and Economics*, *32*(3), 32–43. https://doi.org/10.16538/j.cnki.jfe.2006.03.003
5. Asongu S., & Odhiambo, N. M. (2019). Tourism and Social Media in the World: An Empirical Investigation. *Journal of Economic Studies, 46*(7), 1319–31. https://doi.org/10.1108/JES-07-2018-0239
6. Chen, J. C., & Bao, J. G. (1988). A study of tourist behavior and its practical significance. *Geographical Research*, *7*(3), 44–51. https://10.11821/yj1988030006
7. Cheng, M. M. (2024). Social media and tourism geographies: mapping future research agenda. *Tourism Geographies*, 1–10. https://doi.org/10.1080/14616688.2024.2304782
8. Cliff, A., & Ord, J. K. (1973). *Spatial Autocorrelation*; Pion: London, UK. https://doi.org/10.1177/030913259501900205
9. Cui, G. T. (2023, May 4). *During the May Day holiday, the total number of passengers arriving and departing at Zibo Station reached 480,000, setting three historical records*. Luzhong News. http://news.lznews.cn/luzhong/zibo/202305/t20230504_11849676.html
10. Feng, X. G., & Huang, H. P. (2015). Influential Factors and Developing Strategies of Inter-provincial Tourist Destination Market: An Experience Analysis with a Spatial Panel Model. *Journal of East China Normal University (Humanities and Social Sciences),* (05),137–149+223. https://doi.org/10.16382/j.cnki.1000-5579.2015.05.015
11. Frenzel, F., Giddy, J. & Frisch, T. (2022). Digital technology, tourism and geographies of inequality. *Tourism Geographies, 24*, 6–7, 923-933. https://doi.org/10.1080/14616688.2022.2142843
12. Han, J. L., Ming, Q. Z., Shi, P. F., & Luo, D. S. (2021). Analysis of the Influence Factors of Tourist Behavioral Intention of Video Social Media Users: Based on Mediation Effects

of Trust. *Tourism Research*, *13*(4), 1–14. https://doi.org/10.3969/j.issn.1674-5841.2021.04.001

13. Herrman, J. (2019). *How TikTok Is Rewriting the World*. New York Times. https://www.nytimes.com/2019/03/10/style/what-is-tik-tok.html
14. Hu, H. Y. (1935). The Distribution of Population in China, With Statistics and Maps. *Acta Geographica Sinica*, *2*(2), 33–74. https://doi.org/10.11821/xb193502002
15. Jiang, J., Hong, Y. X., Li, W. W., & Li, D. (2022). A study on the impact of official promotion short videos on tourists' destination decision-making in the post-epidemic era. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.1015869
16. Kaplan, A.M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons*, *53* (1), 59–68. https://doi.org/10.1016/j.bushor.2009.09.003
17. Li, Y., Xu, X., Song, B., & He, H. (2019). Impact of Short Food Videos on the Tourist Destination Image—Take Chengdu as an Example. *Sustainability*, *12*(17), 6739. https://doi.org/10.3390/su12176739
18. Liu, J., Wang, Y. J. & Chang L. Y. (2023). How do short videos influence users' tourism intention? A study of key factors. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.1036570
19. Ma, T., Hong, T., & Zhang, H. Z. (2015). Tourism spatial spillover effects and urban economic growth. *Journal of Business Research*, *68*(1), 74–80. https://doi.org/10.1016/j.jbusres.2014.05.005
20. Ma, X. L., & Yang, X. J. (2003). A study on the 4A tourism area (spots) in China: spatial characters and industrial distribution. *Economic Geography*, 23(5), 713–716+720. https://doi.org/ CNKI:SUN:JJDL.0.2003-05-028
21. Ministry of Culture and Tourism of China (MCTC). (2023, May 3). *Cultural and Tourism Market Situation in May Day Holiday 2023*. https://www.mct.gov.cn/whzx/whyw/202305/t20230503_943504.htm
22. Moran, P. A. P. (1948). The Interpretation of Statistical Maps. *Journal of the Royal Statistical Society B*, *10*, 243–251. https://doi.org/10.1111/j.2517-6161.1948.tb00012.x
23. Nieuwland, S. (2024). Urban tourism transitions: doughnut economics applied to sustainable tourism development. *Tourism Geographies*, *26*(2), 255–273. DOI: 10.1080/14616688.2023.2290009
24. Oceanengine. (2022). *2022 China Digital Map Tourism Research Report*. https://trendinsight.oceanengine.com/arithmetic-report/detail/781?source=nav_portal

25. QuestMobile. (2024). *QuestMobile 2023 China Mobile Internet Annual Report*. https://www.questmobile.com.cn/research/report/1752183696050458625
26. Randeng Search Academy. (2020). *Douyin user portrait and crowd analysis*. https://www.randengseo.com/seo-15623.html&wd=&eqid=cdad102c000c8ea800000004645a3391
27. Romão, J., & Saito, H. (2017). A spatial analysis on the determinants of tourism performance in Japanese Prefecture. *Asia-Pacific Journal of Regional Science, 1*(1), 243-264. https://doi.org/10.1007/s41685-017-0038-0
28. Statista. (2024). *Most popular social networks worldwide as of January 2024, ranked by number of monthly active users (in millions)*. https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/
29. Tham, A., Chen, S.-H., & Durbidge, L. (2024). A pentadic analysis of TikTok marketing in tourism: The case of Penang, Malaysia. *Tourist Studies, 24*(1), 75–103. https://doi.org/10.1177/14687976231218483
30. Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography*, *46*, 234–240. https://doi.org/10.2307/143141
31. Wang, D. G., & Chen, T. (2011). Spatial Analysis for Regional Difference of Tourism Economy in China. *Scientia Geographica Sinica, 31*(5), 528–536. https://doi.org/10.13249/j.cnki.sgs.2011.05.528
32. Wang, J. F., Zhang, T. L., & Fu, B. J. (2016). A measure of spatial stratified heterogeneity. *Ecological Indicators*, *67*, 250–256. http://dx.doi.org/10.1016/j.ecolind.2016.02.052
33. Wang, J. F., & Xu, C. D. (2017). Geodetector: Principle and prospective. *Acta Geographica Sinica*, *72*(1), 116–134. https://doi.org/10.11821/dlxb201701010
34. Wengel Y., Ma L., Ma Y., Apollo M., Maciuk K., & Ashton A.S. (2022). The TikTok effect on destination development: Famous overnight, now what?. *Journal of Outdoor Recreation and Tourism*, *37*, Article 100458. https://doi.org/10.1016/j.jort.2021.100458
35. Wu, G. H., & Ding X. Y. (2023). Which type of tourism short video content inspires potential tourists to travel. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1086516
36. Yang, X. Z., Gu, C. L., & Wang, Q. (2011). Study on the driving force of tourist flows. *Geographical Research*, *30*(1), 23-36. https://doi.org/10.11821/yj2011010003
37. Ying, T. Y., Wang, K. Y., Liu X. Y., Wen, J., & Goh, E. (2021). Rethinking Game Consumption in Tourism: A Case of the 2019 Novel Coronavirus pneumonia Outbreak in

China. *Tourism Recreation Research, 46*(2), 304–9. https://doi.org/10.1080/02508281.2020.1743048

38. Zhang, Y. Y., Zhang, E. J., & Long, Y. (2022). Revealing virtual visiting preference: Differentiating virtual and physical space with massive TikTok records in Beijing. *Cities, 30*, 103983. https://doi.org/10.1016/j.cities.2022.103983
39. Zhao, C., Shen, H. W., & Zhang, Y. T. (2022). The study on the impact of short video tourism Vloggers at social media platform on online sharing intention. *Frontiers in Psychology, 13*. https://doi.org/10.3389/fpsyg.2022.905002
40. Zhao, D. X. (2008). Study on the Influencing Factors of the Development of China's Provincial Inbound Tourism—Analysis Based on the Provincial Panel Data. *Tourism Tribune*, *23*(1), 41–45. https://doi.org/10.3969/j.issn.1002-5006.2008.01.012
41. Zhou, Q., Sotiriadis, M., & Shen, S.W. (2023). Using TikTok in tourism destination choice: A young Chinese tourists' perspective Author links open overlay panel. *Tourism Management Perspectives, 46*, 101101. https://doi.org/10.1016/j.tmp.2023.101101