

FACTORS INFLUENCING THE LIKELIHOOD OF DOMESTIC TOURISM DEMAND IN GUANGZHOU, CHINA DURING THE COVID-19

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ABSTRACT

The demand for tourism, both domestic and international, has been widely explored in existing literature. However, the outbreak of the Coronavirus disease (COVID-19) in 2019 disrupted the development of Domestic Tourism (DT) in Guangzhou and may have altered tourists' behaviour. This study contributes to the literature by exploring the determinants of DT in Guangzhou, China. Unlike most existing tourism studies, we employ a binary logit model to systematically examine the factors influencing DT. Drawing on advanced information and communication technology, we utilise data from Baidu's user keyword searches, which provide a more accurate reflection of tourists' behaviour and preferences. The findings, therefore, provide evidence-based insights for policymakers and practitioners. Consistent with demand theory, our results reveal that income and price significantly affect domestic travel demand. More importantly, we observe that DT demand in Guangzhou is more strongly influenced by food, transportation, and weather than by hotels, tourist attractions, or tour guides. Overall, these findings suggest that tourism marketing strategies should be aligned with these preferences to enhance the resilience and competitiveness of the tourism sector in the post-pandemic era.

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Introduction

Guangzhou, with a history spanning more than 2,000 years, has long served as a commercial and cultural hub for multiple dynasties (Fong, 2014 ; Xu & Li, 2023). This enduring prominence has endowed the city with a rich cultural heritage and an abundance of tourist attractions. Notable examples include the 11-metre-tall iconic five-goat effigy at Yuexiu Park, the Gulong Canyon grand skywalk bridge, Baiyun Mountain, the Pearl River night cruise, Chimelong Safari Park, and the Canton Tower. Building on its historical role as a gateway for trade and culture, Guangzhou now holds a strategic position in the Guangdong–Hong Kong–Macao Greater Bay Area, linking mainland China with Hong Kong and Macao. It also plays a pivotal role in the

Maritime Silk Road and features prominently in the Greater Bay Area tourism route (Xu & Yeh, 2003).

Endowed with a wealth of “red culture” along with geographical, strategic, and economic advantages, the tourism sector in Guangzhou has experienced rapid expansion, particularly following China's economic reforms. According to the Guangzhou Municipal Bureau of Statistics, tourist arrivals increased from 160 million in 2014 to approximately 200 million in 2017 and 223 million in 2018. Following this, the China Inbound Tourism Development Report published by the World Tourism Alliance (2022) consistently ranked Guangzhou among

the top three most visited sub-provincial cities in China. Moreover, the World Travel and Tourism Council (WTTC, 2023) recognised Guangzhou as one of the world’s top 10 global cities for travel and tourism, with the sector contributing approximately US\$13.15 billion to the city’s Gross Domestic Product (GDP) in 2022.

The tourism sector and networking technologies have experienced remarkable growth over the past decades. Indeed, tourists rely on the internet to gather information before deciding on their holiday destinations. Data from the 48th and 49th Statistical Reports on the Development of the Internet in China, published by the China Internet Network Information

Centre (CNNIC, 2021, 2022), reveal that by June 2021, the number of internet users in China had reached approximately 1.011 billion. This is an increase of 21.75 million since December 2020 (Figure 1). Furthermore, the national internet penetration rate stood at 71.6%, representing a 1.2 percentage point rise over the same period. Accordingly, Figure 2 illustrates a steady upward trend in search engine usage, with the number of users increasing from nearly 765 million in June 2020 to approximately 795 million in June 2021, a yearly growth of 29.9 million. Additionally, in March 2021, Baidu recorded 558 million monthly active app users, a 2.6% increase compared to December 2020 (CNNIC, 2021).

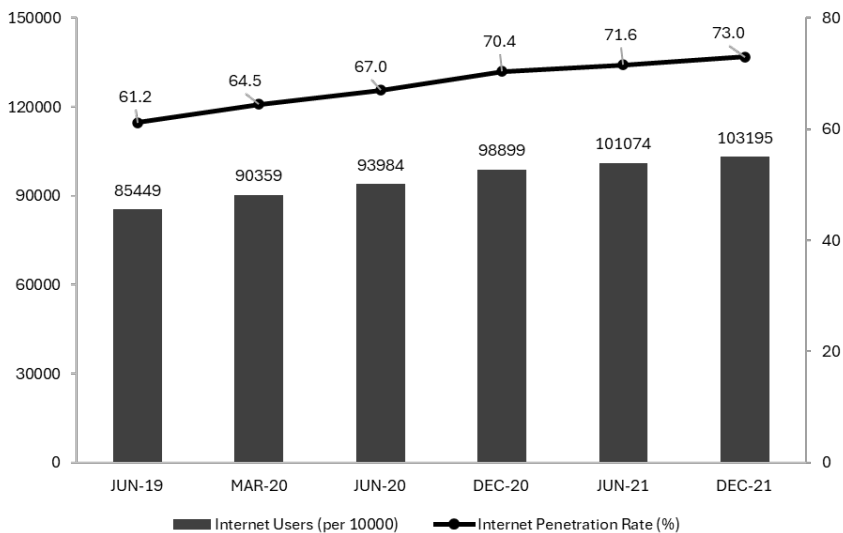


Figure 1: The Internet users and penetration rate in China from 2019 to 2021

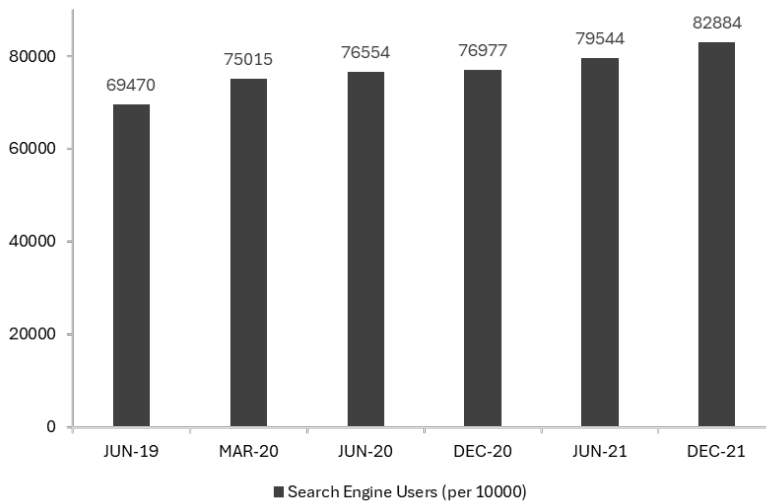


Figure 2: The search engine users in China from 2019 to 2021

Baidu, an internet company primarily engaged in search engine services, was founded by Robin Li and Xu Yong on 1st January 2000, in Zhongguancun, Beijing. The name “Baidu” originates from a poem by Xin Qiji, a poet of the Southern Song Dynasty, symbolising the persistent pursuit of an ideal. The company’s business scope includes search, Artificial Intelligence (AI), cloud computing, big data, and more.

Baidu Index is a data-sharing platform based on the massive behavioural data of internet users on Baidu. Correspondingly, it analyses and calculates the search volume of keywords in Baidu web searches. Subsequently, the search index is divided into a Personal Computer (PC) search index and a mobile search index. The Baidu Index provides a record of travellers’ queries and travel preferences, offering timely data. Given that the search engine data is publicly available, it complements data collection and is accessible to most researchers. Therefore, Baidu users’ query records and travel preferences can optimally indicate tourists’ tastes and inclinations (Song, Qiu & Park, 2019).

Motivated by the rapid transformation of the global technological landscape and the unprecedented disruption caused by the

COVID-19 pandemic, it is pivotal to explore the behaviour of domestic tourists in Guangzhou, China. Additionally, an empirical analysis of tourism demand in Guangzhou is crucial as it can provide valuable insights for policymakers and tourism stakeholders to inform strategic planning. This includes travel route optimisation, tourism resource distribution, the scientific design of tourism housing planning, and improvements in transport infrastructure. Moreover, the findings of this study may assist government authorities in regulating safe travel during health crises, enabling timely epidemic prevention and control measures. This essentially ensures smooth travel experiences and safeguards tourists’ well-being. Ultimately, effective epidemic management is vital to prevent large-scale outbreaks and to sustain the resilience of the tourism sector.

In addition, the findings of this study also contribute to strengthening tourism management. Tourist destinations that aspire to remain sustainable in the long run can foster local development while ensuring steady profit growth. Thus, accurate predictions of tourism demand are essential for supporting the robust development of enterprises and for guiding tourism product innovation and planning at scale. This, in turn, enables destinations to

meet or expand demand effectively. Beyond the economic dimension, this study also helps enhance tourist experiences. With most travellers now relying on the internet to gather travel information, digital evaluations of tourist destinations enable them to shape their initial impressions and influence their decisions. Still, the rapid growth of tourist arrivals and destinations has often resulted in management challenges, particularly due to inadequate manpower to serve tourists. Such constraints can lead to negative tourist experiences, unfavourable online reviews, and, ultimately, a decline in visitor numbers.

Empirically predicting tourist flows can facilitate tourist sites and enterprises to allocate manpower more efficiently, ensuring orderly operations and improved visitor experience. Accordingly, tourists who enjoy good holiday experiences are more likely to return and to attract new visitors through word of mouth. Well-managed and renowned destinations can, in turn, serve as a form of cost-free advertising, amplifying their reach. Alternatively, allocating resources towards accurate demand forecasting allows for better distribution of services, reduced resource wastage, and maximised economic benefits. Against this backdrop, the present study aims to investigate the determinants of Domestic Tourism (DT) demand behaviour in Guangzhou, China.

The balance of the study is organised as follows. The literature review will be discussed in the next section. Subsequently, the method and results will be discussed in Section 3. Finally, the conclusion will be presented in Section 4.

Literature Review

Understanding the behaviour of individuals engaging in tourism, particularly DT has gained increasing attention. This is especially true under the evolving circumstances brought on by the COVID-19 pandemic. Tourists' decision-making processes, preferences, and risk perceptions have been markedly influenced by pandemic-

related restrictions and uncertainties. As such, behavioural dimensions such as destination choice, travel timing, information-seeking behaviour, and the use of digital platforms for trip planning have become central themes in tourism demand research. Hence, this section reviews the existing literature, focusing on how tourist behaviour is captured and interpreted in empirical studies, with particular emphasis on the use of internet search data as a behavioural indicator.

Tourist behaviour is deeply shaped by both internal motivations (such as leisure, escape, and cultural experience) and external conditions (such as safety, convenience, and health risks). In recent years, the rise of digital technology has enabled researchers to infer behavioural patterns through online search activity, as tourists increasingly rely on search engines to plan and evaluate travel options. For instance, Gawlik *et al.* (2011) were among the first to link historical search volumes to tourism price trends, thereby treating internet search data as a real-time proxy for tourist interest and decision-making.

Nonetheless, the COVID-19 pandemic has brought significant changes to travel behaviour, including a growing preference for domestic over international destinations, reduced travel frequency, and heightened concern over health and safety. During such times of disruption, conventional data sources such as surveys and official statistics, often fail to reflect rapidly shifting behaviours in a timely manner. Internet search data, by contrast, offers a more immediate window into tourist intentions and concerns. Huang *et al.* (2021), in their study of Beijing's monthly tourist flow, demonstrated the timeliness and predictive validity of internet search data in capturing real-time behavioural responses. Similarly, Sun *et al.* (2019) argued that big data sources can compensate for the lag and sampling limitations of traditional statistics, especially when rapid behavioural shifts occur.

Furthermore, search engine data provides timely information while also reflecting the psychological and behavioural intentions of

prospective tourists. For instance, spikes in searches for terms such as “safe destinations”, “local travel restrictions”, or “uncrowded places” can signal widespread behavioural shifts in response to perceived risks. At the same time, the Baidu Index, which aggregates search behaviour across key terms related to tourism has been widely adopted in China as a behavioural data source. Studies have validated its use in modelling and forecasting domestic tourist demand (e.g., Höpken *et al.*, 2021; Yang *et al.*, 2015). Li *et al.* (2021) underscored the significance of robust keyword selection in accurately capturing tourist intent.

Building on this, poorly defined search terms can distort behavioural signals, whereas well-constructed indices can serve as a powerful behavioural proxy. Li *et al.* (2017) proposed a Generalised Dynamic Factor Model (GDFM) to structure search data into coherent behavioural indices, while Yao *et al.* (2021) advanced the rescale range (R/S) and Time Difference Relevance (TDR) analyses to refine internet search index construction. Collectively, these techniques help capture the evolving preferences, destinations of interest, and even seasonal timing of travel, all reflecting underlying behavioural shifts.

Even though modelling techniques vary, many studies align in treating internet search data as a valid reflection of behaviour and intent. For example, Otok *et al.* (2011) utilised neural networks combined with wavelet analysis to predict tourism flows, highlighting the dynamic nature of travel behaviour. On a similar note, Grey System Theory (GST) is frequently applied in the Chinese forecasting models and also incorporates behavioural changes over time (Xie, 2017). Conversely, Wang (2004) introduced a fuzzy grey Markov model that captures time-varying behavioural patterns through optimised modelling of historical data.

Furthermore, integrated and hybrid models have increasingly been used to forecast tourism demand by embedding behavioural insights within their predictive frameworks. Studies by

Sun *et al.* (2019) and Yang *et al.* (2015) established that models incorporating behavioural indices (such as those derived from Baidu searches) outperform traditional models such as the Autoregressive Integrated Moving Average (ARIMA) or basic regression, especially when accounting for pandemic-induced behavioural change. The inclusion of real-time behavioural data is thus methodologically advantageous and essential for understanding the contemporary dynamics of tourist activity.

Another vital aspect of behavioural analysis involves the choice of data platform. While Google Trends is commonly used globally, its application in China is limited due to platform accessibility. Li *et al.* (2017) and Yang *et al.* (2015) demonstrated that the Baidu Index is better suited to reflect the online behaviour of the Chinese domestic tourists. Although both platforms share similarities in terms of keyword strategy, Baidu’s localisation provides a more precise behavioural snapshot of China’s travel market. Sun *et al.* (2019) further illustrated that combining Google Trends and Baidu Index can improve prediction accuracy by offering complementary behavioural insights.

Despite the potential of social media to provide behavioural cues, Tian *et al.* (2021) observed that its contribution to tourism forecasting remains limited compared to search engine data, which more directly captures active travel-related intentions. Nevertheless, some researchers advocate integrating search data with other behavioural indicators such as weather concerns, health advisories, or mobility data (Li & Law, 2020; Li *et al.*, 2020), thereby enhancing the behavioural depth of forecasting models.

As tourism research moves further into the digital age, scholars such as Li *et al.* (2017) have called for more widespread use of behavioural big data, including Baidu and Google search queries, in tourism forecasting. Huang *et al.* (2017) likewise encouraged tourism operators to adopt real-time data analytics to better

understand and respond to evolving tourist needs. Building on this, there is also growing consensus that future studies should develop more holistic behavioural models that incorporate non-linear features and integrate multiple data sources such as social media, weather, or pandemic alerts (Huang & Hao, 2021 ; Yao *et al.*, 2021).

In summary, behavioural tourism research increasingly draws on digital footprints, particularly search engine queries, as proxies for planning, preferences, and travel decision-making. Concurrently, these data provide timely and flexible insights into how tourists behave under normal conditions and during crises such as COVID-19. Therefore, the behavioural dynamics of domestic tourists can no longer be studied solely through traditional statistical lenses. Rather, they require models and data sources that are dynamic, high-frequency, and behaviourally grounded. Generally, the present study contributes to this growing literature by examining the behavioural patterns of domestic tourists in Guangzhou using Baidu Index data in the context of the COVID-19 pandemic.

Methods, Results and Discussions

The present study aims to analyse factors that influence the likelihood of increasing DT in Guangzhou. The dependent variable is dichotomous in nature, where $DT=1$ if the demand for tourism in Guangzhou rises ($\Delta DT_t > 0$), and $DT=0$ otherwise. Given the binary nature of the dependent variable, applying a standard Ordinary Least Squares (OLS) estimator would likely violate the assumption of homoskedastic error variance and yield biased estimates (Greene, 2012). Therefore, a binary logit model is employed. In line with demand theory and previous empirical studies on tourism demand (Tang & Tan, 2016; Tang & Lau, 2021), the decision to engage in DT is generally affected by income and tourism prices. In addition, the present study incorporates two further determinants, namely the COVID-19 pandemic and the Baidu Index, to examine the impact of the COVID-19 shock and the role of social media (or digital technology) in explaining tourism demand. With these considerations, the logit regression model for this study is specified as:

$$\text{Logit}[p(DT_t) = 1] = \beta_0 + \beta_1 \text{income}_t + \beta_2 \text{price}_t + \beta_3 \text{COVID}_t + \beta_4 \text{BD}_t + \varepsilon_t, \quad (1)$$

where p denotes the probability of tourist demand for DT in Guangzhou; $DT_t=1$ if $\Delta DT_t > 0$ and zero otherwise. income_t is proxied by the logarithm of the Industrial Production Index (IPI), while price_t is measured by the logarithm of the Consumer Price Index (CPI). Moreover, COVID-19 is a dummy variable taking the value of 1 for $t \geq$ January 2020 and zero otherwise, and BD_t is a vector representing the Baidu Index for the tourism-related keywords: Foods, transportation, hotels, tourist attractions, tourist guide, and weather in Guangzhou. $\text{BD}_t=1$ if $\Delta \text{BD}_t > 0$ and zero otherwise. Based on theoretical considerations from demand theory, the expected signs of the coefficients are hypothesised as follows: $\beta_1 > 0$ (income positively influences demand), $\beta_2 < 0$ (higher tourism prices reduce demand), while $\beta_3 \neq 0$,

and $\beta_4 \neq 0$, as the impacts of the COVID-19 pandemic and Baidu keyword searches may vary in direction, though they are expected to be statistically significant.

This study employs monthly time series data spanning from January 2011 to July 2022 to investigate the behaviour of domestic tourist arrivals in Guangzhou. Data on domestic tourist arrivals are collected from the Statistical Information Management System of Guangzhou. By contrast, the IPI and CPI of China are sourced from multiple databases, including the CEIC database, the National Bureau of Statistics of China, and the International Financial Statistics (IFS) provided by the International Monetary Fund (IMF). In addition, data on the Baidu keywords index are extracted directly from the Baidu website (<https://www.baidu.com>).

Table 1 summarises the descriptive statistics of the variables used in this study. Of the total sample, merely 43.4% of the monthly arrivals of domestic tourists are growing (where $\Delta DT_t > 0$). Accordingly, the average income and price indices are 176.814 and 118.414, respectively. Considering the monthly pattern of the Baidu

keyword index, we observed that 52.9% of the keyword searches for foods in Guangzhou are growing. This is followed by tourist attractions (50.7%), weather (45.6%), hotels (44.9%), tourist guides (43.5%), and metro/subway (42.7%).

Table 1: Summary of descriptive statistics

Variables	Observation	Mean/ Percentage	SD	Min.	Max.
Domestic tourism	138	0.434	–	–	–
Income	138	176.814	43.681	85.065	258.526
Price	138	118.414	7.932	104.756	132.311
COVID-19	138	0.225	–	–	–
Dining:					
Food	138	0.529	–	–	–
Lodging:					
Hotel	138	0.449	–	–	–
Transportation:					
Metro/Subway	138	0.427	–	–	–
Tourism:					
Tourist attractions	138	0.507	–	–	–
Weather	138	0.456	–	–	–
Tourist guide	138	0.435	–	–	–

Turning to the estimated coefficients of logit regression in Table 2, we discovered that both income and prices are consistently significant at the conventional levels (i.e., 1%, 5%, and 10%) across all six models. This confirms that income and prices are two important determinants of DT in Guangzhou. In line with demand theory, our results revealed that demand for DT responds positively to income yet adversely to prices. In addition, these findings are consistent with previous empirical studies, including Liu *et al.* (2021), Tang and Lau (2021), and Jong *et al.* (2020), which similarly demonstrate that tourism demand rises with income.

Furthermore, the underlying reason is that higher income uplifts tourists' ability to purchase, whereas rising prices erode spending power and consequently reduce demand. Additionally, the coefficients of the COVID-19 variable reported in Table 2 are consistently positive and statistically significant across all models. In essence, this suggests that tourists in China were more likely to travel locally during the COVID-19 crisis, most likely due to the overseas travel restrictions imposed by the government in 2020.

Table 2: The logistic regression of domestic tourism demand in Guangzhou

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Constant	68.004** (0.018)	69.237** (0.041)	51.571* (0.096)	55.514* (0.091)	64.370* (0.054)	54.311 (0.158)
Income (log)	4.312*** (0.005)	4.651** (0.011)	3.366** (0.033)	3.896** (0.020)	4.449** (0.016)	3.727** (0.049)
Price (log)	-19.037*** (0.005)	-19.837** (0.014)	-14.657** (0.035)	-16.073** (0.030)	-18.691** (0.017)	-15.938* (0.057)
COVID	1.647** (0.012)	1.704** (0.012)	1.492** (0.025)	1.509** (0.024)	1.938*** (0.010)	2.042** (0.014)
Dining:						
Foods	-	1.484*** (0.000)	-	-	-	1.062** (0.036)
Lodging:						
Hotels	-	-	0.948** (0.012)	-	-	0.132 (0.800)
Transportation:						
Metro/ Subway	-	-	-	1.102*** (0.003)	-	1.244** (0.030)
Tourism:						
Tourist attractions	-	-	-	-	0.719* (0.074)	-0.276 (0.548)
Weather	-	-	-	-	2.071*** (0.000)	2.144*** (0.000)
Tourist guide	-	-	-	-	-0.378 (0.348)	0.647 (0.135)
Diagnostic Tests						
Likelihood ratio test	12.844*** (0.005)	28.734*** (0.000)	19.357*** (0.001)	21.646*** (0.000)	42.766*** (0.000)	58.594*** (0.000)
% correct prediction	58.7%	71.0%	64.5%	66.7%	76.1%	79.7%
McFadden	0.068	0.158	0.102	0.115	0.226	0.312

Note: ***, **, and * denote significance at the 1%, 5%, and 10%, respectively. (.) indicates the *p*-values after applying the robust standard errors.

In terms of the Baidu Index, our study segregates keywords into four categories (i.e., dining, lodging, transportation, and tourism) in order to assess the robustness of the estimation results. Generally, we noted that the significance of some estimated coefficients differs across models. For instance, the results that we discovered in models (2) and (3) demonstrate that hotels and tourist attractions are both significant and positively associated with DT demand. The results imply that the arrivals of domestic tourists are more likely to increase whenever there is a higher search for

information about hotels and tourist attractions in Guangzhou, compared to the arrivals in months with a lower search volume.

After accounting for the effects of other categories of Baidu keywords as presented in model (6), these two factors, however, become insignificant. Furthermore, no significant evidence of severe multicollinearity is observed among the Baidu keywords under investigation, as the Variance Inflation Factors (VIF) statistics range from 1.95 to 3.35. This is lower than the yardstick of 10 as stressed by Kennedy (2008).

Adhere to this, findings reported in model (6) are preferable. Thus, we may conclude that increases in online search volume for information on hotels and tourist attractions in Guangzhou city are not associated with the arrival of domestic tourists.

Building on this, our findings consistently reveal that a tourist guide does not affect the demand for DT in Guangzhou city. This is not a surprising finding since they are local tourists. At the same time, they are conversant with the accessible tourist spots and also fluent in the common language. Therefore, not many domestic tourists rely on tourist guides when travelling in their own country, province, or city.

Nevertheless, we discover that local food, transportation, and weather are three important factors consistently associated with the growth of DT demand in Guangzhou city. Given that the estimated coefficients are positive and significant at the 5% level, we may conclude that more people searching for information about local food, transportation systems, and weather in Guangzhou city are more likely to increase the arrival of tourists in the city compared to those with lower search volumes. Among the plausible justifications is that Guangzhou could be considered a gastronomy paradise.

For example, Qin *et al.* (2011) shared that Guangzhou is the ideal location for experiencing Cantonese cuisine, which is one of the eight distinct culinary styles. Meanwhile, Guangzhou food, including Guangzhou tea, congee, and sausage powder is considered to be one of the eight most well-known cuisines in China. This culinary tradition has a long and illustrious history. Moreover, Zeng *et al.* (2019) added that Guangzhou has a variety of trans-locality restaurants that cater to every type of gourmet, including Shanxi and Hunan cuisines. Overall, as attested by our findings, it should come as no surprise that Guangzhou's cuisine is a major draw for tourists.

In a similar vein, our study findings indicate that there is a general tendency towards a rise in the demand for tourism in the city of Guangzhou whenever there is an increase in

the number of individuals seeking information on the city's weather. This is attributable to the fact that tourism is environment contingent as it encompasses both indoor and outdoor activities (Peng *et al.*, 2020). In a psychological study, Ettema *et al.* (2017) noted that weather (climate) affects travellers' mood and satisfaction. Likewise, Tang and Lau (2021), Li *et al.* (2017), and Liu (2016) all reached a similar conclusion that weather is an important factor in explaining tourism demand. They also emphasised that tourists are concerned about the weather in their destination, as it affects their comfort and limits their activities. Generally, tourists are reported to be sensitive to environmental factors, and our findings of tourism demand in Guangzhou city tend to increase as more people search for weather information about the city, which is justifiable.

In addition to that, climate (weather) change affects tourists' comfort and well-being as noted by Li *et al.* (2016). However, the review of Böcker *et al.* (2013) documented that the effect also extends to car traffic and the choice of transportation mode. For example, Tang and Thakuriah (2012) and Guo *et al.* (2007) observed that bus and train ridership drops in rainy and snowy weather. Despite this, people are opting for public transportation rather than driving their cars, especially in heavy snowfall, since driving becomes difficult. Consistently, we also discovered that DT demand in Guangzhou city grows in tandem with the search volume for traffic and transportation information. Therefore, in addition to weather, our study affirmed that transportation and traffic conditions in the city are also among the factors that tourists would consider when they choose a visiting destination.

Conclusions

In the current body of research on tourism demand, it is frequently emphasised how crucial it is to account for both economic and non-economic factors when mapping the demand behaviour of tourists. Since the findings rely largely on standard factors, they might have neglected the significance of information

gleaned through online searches. Given the rapid expansion of the digital economy, information obtained through online searches is extremely important, as it is the primary source of data that reflects the true behaviour of internet users.

Correspondingly, we augmented the literature by employing the Baidu online searches dataset of Guangzhou city to holistically map the behaviour of domestic tourists through logistic regression analysis. Additionally, the empirical findings of this study could help the decision-makers and tourism stakeholders in Guangzhou city to develop relevant tourism-related strategies. For example, the findings of this study help prevent and control viral outbreaks and traffic congestion.

In tandem with the economic literature (e.g., Jong *et al.*, 2020; Liu *et al.*, 2021), Tang & Lau, 2021; we noted that both income prices are significantly associated with tourism demand. In response to these findings, a prudent macro policy such as a supply-side strategy is needed to improve economic performance sustainably while controlling inflation, which will ultimately strengthen the DT industry. Among the many Baidu online searches for tourism-related keywords, we find that demand for DT is more likely to react to food, transport, and weather rather than hotels, tourist attractions, and tourist guides. Hence, the stakeholders and policymakers may further promote gastronomy tourism through social media platforms to create attention and attract more tourists to Guangzhou.

To achieve better outcomes, policymakers should also consistently review and upgrade the transportation system to improve the speed of traffic and the supply chain of tourism in an effort to enhance the arrival of domestic tourists. Since tourism and climate change are both reliant on the quality of the environment, the government should work to preserve the environment and reduce environmental degradation by enhancing the existing quality of institutions and the educational system (Tang *et al.*, 2021). Accordingly, the environment is preserved and the likelihood of expanding the DT industry is effectively materialised.

Despite the fact that the present study offers several implications for policymaking and contributes to the existing body of knowledge, it is not without limitations. In particular, the analysis focuses exclusively on the demand for DT in Guangzhou, China. Consequently, the findings may not be readily generalised to other provinces within China or to different countries. At the same time, variations in socio-economic conditions, cultural preferences, and policy environments across regions could lead to differing outcomes, which this study does not account for.

In response, future research could extend the scope of analysis beyond a single city to encompass multiple provinces in China or adopt a cross-country comparative approach. This would allow for a broader understanding of the determinants of DT demand and improve the external validity of the findings. Moreover, incorporating longitudinal data could capture dynamic changes in tourism behaviour over time, while integrating other factors such as environmental quality, technological innovation, or cultural heritage could provide a more comprehensive perspective on DT demand.

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Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any personal, commercial, or financial relationships that could be construed as a potential conflict of interest. They further affirm that there are no conflicts of interest with the funding entities involved in this study.

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