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The Cultivation Effect of Architectural Heritage YouTube Videos on Perceived Destination Image

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Abstract: A positive and robust destination image endows a competitive advantage. As architecture appeals to tourists, it may be helpful to improve people's perceptions of a place's image. Social media cultivates the destination image. This study focused on the interrelationship of architectural heritage and destination image and aimed to investigate the potential of architectural heritage YouTube videos in communicating and cultivating the destination image of Beijing. It collected and analysed 2237 YouTube videos in French and 25,234 comments related to Beijing's architectural heritage in tourism. The social networks analysis found that viewers lacked interaction. The sentiment analysis via artificial intelligence findings demonstrate that most video descriptions (94%) and viewers' comments (91%) had a neutral or complimentary attitude on the buildings' heritage in Beijing. The keyword in context (KWIC) results found that when people viewed Beijing's architectural heritage tourism relevant videos and were fascinated by the content, they associated it with China rather than the city where the architectural heritage was located. This indicates a cultivation effect on the destination country image of China. The significance of this study is to provide suggestions to improve a country's destination image with YouTube via architectural heritage. It also raises the importance and social awareness of architectural heritage conservation and provides insights for policymakers on destination country image building.

Keywords: architectural heritage; destination image; YouTube; social network analysis; sentiment analysis; artificial intelligence; KWIC

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1. Introduction

Architectural and historical assets portray cultural heritage [1]. Architecture can serve as a medium for country promotion and a symbol of territorial identity [2]. Among the various aspects of cultural heritage studied in several countries, historical architecture, castles, and museums have been identified as fascinating places that attract tourists worldwide. Scholars have found that architectural heritage appeals to tourists and improves perceptions of place image [3,4]. The essence of understanding, defining, and interpreting living heritage for future generations is thus associated with illustrating the relationship between the architectural heritage and the tourists' perception [3,5].

Destination image is essential in destination choice decision making, brand differentiation, and marketing [6]. Being competitive and differentiating themselves in the market is necessary for destinations [6], given that tourists desire more genuine and unique experiences [7]. Previous research showed that the destination image perceived by people is constantly evolving. At the same time, a nation's history and culture have become a significant part of reality that subsequent generations cannot change [8]. Marketing materials are used as representative symbols in tourism discourse to shape tourists' interpretation of a destination image [9]. The role of information in portraying the destination image is

widely acknowledged in academia [10]. In the social media era, user interaction has far more subtle effects on destination image representation than what has been theorised and empirically investigated [11]. In the tourism industry, social media significantly impacts how people seek information and share it, their perception of destination image [12], and travelling choices [13].

Keeping a presence on social media is inescapable for destinations worldwide [14], and recent research on media's effect on forming destination image focused on diversified social media platforms [15]. Cultivation theory is widely used to analyze how social media cultivates a destination image. Therefore, the controversy lies in selecting the online platforms and the content to promote the destination. It has been demonstrated that videos are more engaging because they can influence the potential demand from tourists [14]. YouTube is one of the largest video platforms worldwide [16] and the most popular media sharing website globally [17]. Therefore, the impacts of YouTube on destination image have attracted scholars' attention.

Beijing, the capital of China and a historical city with more than 3000 years of history, possesses plenty of historical relics and cultural architectures. Its ancient charm of history is the main factor that attracts tourists [18]. Figure 1 presents a glimpse of the Forbidden City, and Figure 2 presents the location of eight architectural heritage sites investigated in this study.



Figure 1. A glimpse of the Forbidden City in Beijing (photo: first author).



Figure 2. Map of the 8 architectural heritage locations in this study in Beijing (source: generated by authors).

According to the Academy of Contemporary China and World Studies [19], Beijing has been the most popular Chinese city among worldwide visitors. It is also the most crucial destination in China and a starting point for travelling to China [20]. French is one of the most widely used languages on the Internet and, at the same time, the only language with English on five continents among the top five widely spoken languages in the world [21]. The French content on YouTube is a considerable data source. The research rarely studies the formation of Beijing's destination image via architectural heritage on YouTube. Therefore, fulfilling this research gap in understanding French-speaking users' perception of Beijing's architectural heritage will provide insight into strategies to enhance Beijing's destination image in francophone territory. Thus, this study proposed the following three research questions:

(1) How does Beijing's architectural heritage in French YouTube videos cultivate Beijing's destination image?
(2) How do YouTube viewers perceive Beijing's architectural heritage tourism destination image cultivated by these videos?
(3) What are the characteristics of YouTube video networks?

Based on this context and the three questions, this paper reviewed the literature on architectural heritage in tourism and online destination image cultivation via YouTube. Then, using big data mining, social network analysis, and natural language processing, this paper analysed Beijing's architectural heritage from the projection and perception perspectives. Finally, this study discusses the data analysis results and provides implications and future research orientations.

2. Literature Review

2.1. Architectural Heritage in Tourism

Architectural heritage is a kind of immovable cultural heritage, including historical buildings, monuments, and archaeological sites [22]. According to Taher Tolou Del et al. [23], it is comprised of three components: monuments refer to all structures and buildings, including their fixtures and fittings, that have a prominent archaeological, aesthetic, historical, social, scientific, or technological interest; groups of buildings with historical, social, archaeological, aesthetic, scientific, or technical significance and which are sufficiently coherent to define topographic units; and sites that are partially built upon, distinctive enough to be topographically defined, and homogenous enough to be of significant archaeological, social, historical, artistic, scientific, or technical interest.

Architectural heritage motivates visitors to visit specific destinations [24]. It shapes people's, especially tourists', perception of a goal [3]. The creativity and aesthetics of various ethnicities in various places can be witnessed in historic architecture, which encompass many different types of monuments/sites and old buildings [25]. As a remarkable component of cultural heritage and tourism resources [26], architectural heritage includes the most significant commemorative and secondary buildings and their natural and artificial environments in historic towns and distinctive villages [27]. Therefore, numerous destinations have supported and subsidised their repurposing [3].

The research on architectural heritage and tourism has thus been developed from different perspectives. The majority of recent studies focused on its relationship with sustainable tourism, such as Wang et al. [28], Hmood et al. [29], Esmail [30], and Bogan [31]; protection and conservation of architectural heritage in tourism, such as Giannakopoulou and Kaliampakos [32], Zhang et al. [33], and Zhang et al. [34]; and territorial tourism development, such as Kostopoulou [35], Buchrieser [36], and Cocola-Gant [37].

However, research rarely explores its value in forming destination images, despite the critical role of architecture in the destination image. Previous studies usually considered cultural heritage as a measurement attribute of the destination image [38–42]. Others confirmed that the architectural heritages affected the representation or perception of the online destination image. For example, Kaur and Kaur [43] stated that architectural heritage is one of the image dimensions affecting tourists' intention to recommend a heritage

destination. Lojo et al. [44] found that Chinese travel blogs of Barcelona highly resembled the traditional city representations. Su et al. [45] evaluated Nanluoguxiang heritage street. They stated that multistakeholders shared the cognitive image as a classical, traditional street with Beijing style. Yang et al. [46] investigated the Grand Canal's destination image in the WeChat official account. They summarised the tourist attraction's features and offered suggestions for constructing destination brand image from the supply side.

Generally speaking, the existing literature considered architectural heritage only as a cognitive image attribute instead of investigating how it shapes and interprets the destination image on social media in depth.

2.2. YouTube and Online Destination Image Cultivation

The destination image is commonly defined as the beliefs, ideas, and impressions people have of a destination of place [47], in other words, the destination representation of an individual [48]. It has been considered the soul of the tourism industry's development, which is crucial to destination competition and significantly impacts tourists' purchase decisions [49].

Current studies confirmed that media could impact people's perception of destination image [50–52], mainly social media in our era [53], such as Twitter [54], Sina Weibo [13], TripAdvisor [55], and YouTube [56]. Therefore, an increasing number of studies are currently introducing the idea of an "online destination image" due to the Internet's recent emergence as the primary medium for communication and information sharing [46]. The online destination image refers to an online portrayal of knowledge, collective beliefs, ideas, feelings, and overall impression people hold about a destination [57]. There are three basic dimensions of a destination image: cognitive, emotional (named also affective image), and the overall images composed of cognitive and emotional images [46,47]. The emotional part of online content can be expressed through adjectives or information concerning subjective feelings, while the cognitive part can be expressed through nouns or information concerning the object [58]. The online destination image can be explained by the perceived image of the tourists and the projected image of the destination [8,59]. For a long time, the projected image could be studied by reviewing how destination marketing organisations, marketers, and tourism-relevant websites benefit from the Internet for promoting a destination, which can be seen as a brand image or reputation [46]. While most research throws light on the perceived destination image and is centred around the perception of visitors or potential visitors [45], there is a lack of study on both the projected and perceived destination images of the general public.

Moreover, there is controversy that the perceived destination image is continuously changing. It needs the accumulation of collected information and time [60], and the destination image often relies on content and information generated by visitors, residents, and suppliers [61]. However, the history and culture of the country are objective and cannot be changed by later generations [8], especially the architectural heritage. Therefore, the importance of media information in constructing and communicating the destination image has become more critical.

Currently, information sources and communication methods have radically evolved. Social media offers multifunctional online platforms which meet people's need for image cultivation, real-time communication, and creative self-realisation [62]. Tourists increasingly rely on social-media-generated online destination images [63]. They also construct the timely online destination image [46]. Therefore, selecting the appropriate platform and content to promote the destination is vital. Among all types of content, such as text, audio, and figure, videos are more engaging, and they might have a stronger impact on the potential demand of tourists [14].

YouTube is one of the largest video platforms and most popular media-sharing social networks worldwide [16,17]. YouTube allows destination management organisations, tourists, tourism companies, and other businesses to showcase their brands and identities [14]. Its impact on a place image and how it impacts the place image have attracted

scholar's attention, such as Tiago, Moreira, and Borges-Tiago [14], Huertas et al. [64], and Chang [56]. Therefore, it would be meaningful to study YouTube content.

Most scholars believe that various types of social media remarkably impact destination image perception [65–67]. They attempt to explain the impact of media on destination image. Introduced by Gerbner, cultivation theory focuses on how comprehensive messages gradually influence the public as they expose to media messages daily. This theory emphasises how the institutional practices of the media can shape meanings in the process of mass dissemination of information, thereby influencing public knowledge and beliefs over time [68]. This system approach divides the interaction effect into three components: firstly, media institutions refer to new symbolic environments being created due to the mass production and rapid dissemination of messages. Secondly, mass-produced messages mean that specific meanings are produced and shared throughout the media environment. Thirdly, the cultivation effect refers to widespread messages that cultivate public beliefs in media [68].

Accordingly, three analysis types are outlined. First, institutional analysis investigates how the mass media interact with other institutions, make decisions, create message systems, and carry out their societal roles. Second, message system analysis explores how collections of messages can be viewed as dynamic systems with symbolic functions having social consequences. Finally, cultivation analysis investigates what common ideas, images, thoughts, and associations these messages try to cultivate in large and heterogeneous communities and the implications for public policy [68,69].

The empirical evidence on the formation of Beijing's destination image via architectural heritage on YouTube needs to be more presented. This article aimed to fill these gaps. First, it needed a deeper understanding of the impact of architectural heritage on destination images via big data mining, social network analysis, and natural language processing methods. Second, a comparison between projected and perceived images was needed. Third, French was selected, as it is one of the most widely used languages on the Internet and the second most used diplomacy language [21]. It is also the only language spoken on five continents alongside English [70].

3. Data Collection and Analysis

Following the system approach of cultivation theory [69] and the online destination types [46], this section analyses Beijing's online architectural heritage destination image from both the projection and perception sides.

First, data on Beijing's architectural heritage tourism relevant French videos on YouTube were collected via YouTube API v3. Open application programming interfaces (APIs) promote interoperability via the provision of data-sharing tools to create widely used web apps, enable seamless social media service integration, give rise to developer ecosystems that are mutually beneficial, and build on top of social media platforms [71].

Then, the comments of these videos were retrieved via NodeXL version 1.0.1.510, an open-source graph visualisation tool from Microsoft. It was utilised for a social network analysis of the YouTube data. It is installed as an add-in to Microsoft Excel. NodeXL supports social network structure analysis. It can directly import social network data from Twitter, YouTube, Flickr, and email or use a multifunctional plug-in to capture real-time social network data from social networks. It can perform centrality analysis by multiple clustering methods. NodeXL also supports manual and various automatic layouts in real-time and filters and displays data according to specified conditions [72]. Through the official YouTube API (v3), NodeXL allows researchers to collect videos and comments with titles, keywords, descriptions, or users' IDs. The collected metadata can then be visualised through several algorithms and methods, such as Clauset–Newman–Moore algorithm, Harel–Koren fast multiscale algorithm, force-directed, and Treemap [72]. NodeXL has been proven as a useful tool for collecting and analysing YouTube data [73,74].

Next, as per Deng and Li [58], to understand the online cognitive and emotional images, sentiment and KWIC analyses were applied. The sentiment analysis was conducted

via MeaningCloud version 1.0.0 to understand the emotion of the architectural heritage in the YouTube videos and their comments. The accuracy of MeaningCloud has been ensured, since it uses hybrid machine interpretation, which combines lexicon with a rule-based machine translation (RBMT) approach and corpus-based interpretation and machine learning. Various studies have accepted and proved its accuracy for sentiment analysis [75]. KWIC analysis was applied for understanding the cognitive–emotional image. KWIC refers to extracting cooccurrence words from the text [76]. Given a specific keyword, this technique extracted words' strings and presented the keyword's dominant meaning and contexts [77]. To be specific, the projected emotional images were investigated through sentiment analyses of YouTube video descriptions. The perceived emotional images were investigated through sentiment analyses of videos' comments. A KWIC analysis was applied for investigating the perceived cognitive–emotional image.

In addition, to understand the video viewers' and commentors' behaviour on sharing information concerning Beijing's destination image regarding architectural heritage, video viewers' preference of video type was investigated via MANOVA by SPSS 19. Video commentors' interactive behaviour was investigated through social networks analysis.

3.1. Data Collection

To determine the keywords for mining data on YouTube, which is the most appreciated tourist architectural heritage in Beijing in the eyes of French speakers, this research referenced Beijing's tourism site rank on TripAdvisor. TripAdvisor is now the largest travel platform [78], where the reviews are deemed to be reliable [79,80]. Referencing the rank of the most appreciated monuments in Beijing on TripAdvisor [81], we eliminated 2 modern architectures and merged all 8 sections of the Great Wall as one keyword, i.e., the Great Wall. Finally, 8 French keywords of the traditional architectural heritage of Beijing for mining data on YouTube are shown in Table 1.

Table 1. Top architectural heritages of Beijing.

Rank	Name (in French)	Name (in English)
1	La Grande Muraille	The Great Wall
2	Cité Interdite	The Forbidden City
3	Palais d'Eté	Summer Palace
4	Temple du Ciel	Temple of Heaven
5	Parc Jingshan	Jingshan Gongyuan
6	Parc Beihai	Beihai Park
7	La Ville d'Eau de Gubei	Gubei Water Town
8	Place de Tiananmen	Tiananmen

Source: adapted from TripAdvisor [81].

YouTube open application programming interfaces (open APIs) were utilised for gathering the relevant data on YouTube. As per Yao, Li, and Song [73], this study gathered 2646 YouTube videos in French. After eliminating the videos without descriptions, finally, 2237 videos were reserved, and their 25,234 comments were collected. The data collected via open APIs included channel ID, channel title, video ID, publication date, video title, video description, tags, video category, duration, dimension, definition quality, view count, like count, dislike count, favourite count, comments of videos, and some technical parameters.

3.2. Data Analysis

3.2.1. Video Type Preference

The first analysis step involved an investigation of YouTube users' preference for video type. When uploading videos, YouTube users can assign standard categories (label tags) for them [73]. This study found that there were 7 video types. MANOVA was applied to

understand the type of video concerning previous architectural heritage in Beijing that fascinated the most French-speaking YouTube users. A multivariate analysis of variance was used when there were two or more dependent variables. It is helpful for inferring interaction effects in metric multivariate multifactor data [82].

The result was presented in Tables 2 and 3. The data are usually analysed based on Wilk's lambda [82]. Wilks' lambda was used to test the dissimilarity between the means of identified groups [83]. The multivariate tests showed that the *p*-value of Wilk's lambda was 0.000, which means $p < 0.0005$. There was a statistically significant difference in YouTube users' behaviour (number of views, likes, and comments) between video types, $F(18, 7456) = 3.59$, $p < 0.0005$; Wilk's $\lambda = 0.976$, and partial $\eta 2 = 0.008$. Tukey, a pairwise comparison technique, was applied as a post hoc test in this study. Its function is to use the predetermined statistical distribution to calculate the honest significant difference (i.e., the HSD) between two means [84]. According to the Tukey post hoc comparisons, YouTube users tended to view, like, and comment on entertainment videos.

Table 2. MANOVA results.

Multivariate Tests [c]							
Effect		**Value**	**F**	**Hypothesis df**	**Error df**	**Sig.**	**Partial Eta Squared**
Intercept	Pillai's Trace	0.002	1.708 [a]	3.000	2636.000	0.163	0.002
	Wilks' Lambda	0.998	1.708 [a]	3.000	2636.000	0.163	0.002
	Hotelling's Trace	0.002	1.708 [a]	3.000	2636.000	0.163	0.002
	Roy's Largest Root	0.002	1.708 [a]	3.000	2636.000	0.163	0.002
VideoType	Pillai's Trace	0.024	3.580	18.000	7914.000	0.000	0.008
	Wilks' Lambda	0.976	3.590	18.000	7456.219	0.000	0.008
	Hotelling's Trace	0.025	3.598	18.000	7904.000	0.000	0.008
	Roy's Largest Root	0.018	7.717 [b]	6.000	2638.000	0.000	0.017

[a] Exact statistic. [b] Statistic is an upper bound on F that yields a lower bound on the significance level. [c] Design: Intercept + VideoType.

Table 3. Tukey post hoc comparisons for the video types.

Tukey HSD							
Dependent Variable	**(I) Video Type**	**(J) Video Type**	**Mean Difference (I-J)**	**Std. Error**	**Sig.**	**95% Confidence Interval**	
						Lower Bound	**Upper Bound**
View Count	Entertainment	Sport	1,133,731.0802	777,467.78398	0.770	−1,160,268.3037	3,427,730.4641
		Travel and Event	1,119,576.2946 *	262,878.64937	0.000	343,925.5575	1,895,227.0317
		People and Blog	1,125,327.8333 *	284,779.24448	0.002	285,057.1175	1,965,598.5491
		News and Politics	975,491.9188	347,105.55338	0.074	−48,679.0398	1,999,662.8774
		Education and Science	1,100,783.0888	391,002.55643	0.073	−52,910.5330	2,254,476.7106
		Others	1,134,624.4533	761,717.05111	0.751	−1,112,900.7586	3,382,149.6652
	Sport	Entertainment	−1,133,731.0802	777,467.78398	0.770	−3,427,730.4641	1,160,268.3037
		Travel and Event	−14,154.7856	777,228.16498	1.000	−2,307,447.1488	2,279,137.5775
		People and Blog	−8403.2469	784,906.14358	1.000	−2,324,350.2827	2,307,543.7889
		News and Politics	−158,239.1614	809,605.27502	1.000	−2,547,063.5479	2,230,585.2250
		Education and Science	−32,947.9914	829,374.12263	1.000	−2,480,102.4144	2,414,206.4316
		Others	893.3730	1,056,026.18438	1.000	−3,115,021.4806	3,116,808.2267

Table 3. *Cont.*

Tukey HSD							
Dependent Variable	**(I) Video Type**	**(J) Video Type**	**Mean Difference (I-J)**	**Std. Error**	**Sig.**	**95% Confidence Interval**	
						Lower Bound	**Upper Bound**
	Travel and Event	Entertainment	−1,119,576.2946 *	262,878.64937	0.000	−1,895,227.0317	−343,925.5575
		Sport	14,154.7856	777,228.16498	1.000	−2,279,137.5775	2,307,447.1488
		People and Blog	5751.5387	284,124.41535	1.000	−832,587.0358	844,090.1132
		News and Politics	−144,084.3758	346,568.50766	1.000	−1,166,670.7253	878,501.9736
		Education and Science	−18,793.2058	390,525.88192	1.000	−1,171,080.3500	1,133,493.9384
		Others	15,048.1587	761,472.47571	1.000	−2,231,755.4081	2,261,851.7255
	People and Blog	Entertainment	−1,125,327.8333 *	284,779.24448	0.002	−1,965,598.5491	−285,057.1175
		Sport	8403.2469	784,906.14358	1.000	−2,307,543.7889	2,324,350.2827
		Travel and Event	−5751.5387	284,124.41535	1.000	−844,090.1132	832,587.0358
		News and Politics	−149,835.9145	363,460.81535	1.000	−1,222,264.7709	922,592.9419
		Education and Science	−24,544.7445	405,591.54114	1.000	−1,221,284.6798	1,172,195.1908
		Others	9296.6199	769,307.71805	1.000	−2,260,625.6425	2,279,218.8824
	News and Politics	Entertainment	−975,491.9188	347,105.55338	0.074	−1,999,662.8774	48,679.0398
		Sport	158,239.1614	809,605.27502	1.000	−2,230,585.2250	2,547,063.5479
		Travel and Event	144,084.3758	346,568.50766	1.000	−878,501.9736	1,166,670.7253
		People and Blog	149,835.9145	363,460.81535	1.000	−922,592.9419	1,222,264.7709
		Education and Science	125,291.1700	451,539.08507	1.000	−1,207,021.7621	1,457,604.1022
		Others	159,132.5345	794,491.92076	1.000	−2,185,098.3318	2,503,363.4007
	Education and Science	Entertainment	−1,100,783.0888	391,002.55643	0.073	−2,254,476.7106	52,910.5330
		Sport	32,947.9914	829,374.12263	1.000	−2,414,206.4316	2,480,102.4144
		Travel and Event	18,793.2058	390,525.88192	1.000	−1,133,493.9384	1,171,080.3500
		People and Blog	24,544.7445	405,591.54114	1.000	−1,172,195.1908	1,221,284.6798
		News and Politics	−125,291.1700	451,539.08507	1.000	−1,457,604.1022	1,207,021.7621
		Others	33,841.3644	814,627.61193	1.000	−2,369,801.9483	2,437,484.6772
	Others	Entertainment	−1,134,624.4533	761,717.05111	0.751	−3,382,149.6652	1,112,900.7586
		Sport	−893.3730	1,056,026.18438	1.000	−3,116,808.2267	3,115,021.4806
		Travel and Event	−15,048.1587	761,472.47571	1.000	−2,261,851.7255	2,231,755.4081
		People and Blog	−9296.6199	769,307.71805	1.000	−2,279,218.8824	2,260,625.6425
		News and Politics	−159,132.5345	794,491.92076	1.000	−2,503,363.4007	2,185,098.3318
		Education and Science	−33,841.3644	814,627.61193	1.000	−2,437,484.6772	2,369,801.9483

Table 3. *Cont.*

Tukey HSD							
Dependent Variable	**(I) Video Type**	**(J) Video Type**	**Mean Difference (I-J)**	**Std. Error**	**Sig.**	**95% Confidence Interval**	
						Lower Bound	**Upper Bound**
Like Count	Entertainment	Sport	7398.2209	4,289.68349	0.599	−5258.9355	20,055.3772
		Travel and Event	7533.5302 *	1450.43464	0.000	3253.8723	11,813.1881
		People and Blog	7349.8283 *	1571.27131	0.000	2713.6292	11,986.0273
		News and Politics	5294.6672	1915.15712	0.083	−356.2027	10,945.5370
		Education and Science	6652.8486 *	2157.35912	0.034	287.3367	13,018.3606
		Others	7297.0814	4202.77872	0.592	−5103.6534	19,697.8162
	Sport	Entertainment	−7398.2209	4289.68349	0.599	−20,055.3772	5258.9355
		Travel and Event	135.3094	4288.36139	1.000	−12,517.9460	12,788.5647
		People and Blog	−48.3926	4330.72469	1.000	−12,826.6453	12,729.8600
		News and Politics	−2103.5537	4467.00230	0.999	−15,283.9076	11,076.8002
		Education and Science	−745.3722	4576.07705	1.000	−14,247.5625	12,756.8180
		Others	−101.1395	5826.63125	1.000	−17,293.2197	17,090.9407
	Travel & Event	Entertainment	−7533.5302 *	1450.43464	0.000	−11,813.1881	−3253.8723
		Sport	−135.3094	4288.36139	1.000	−12,788.5647	12,517.9460
		People and Blog	−183.7020	1567.65829	1.000	−4809.2404	4441.8365
		News and Politics	−2238.8631	1912.19397	0.905	−7880.9898	3403.2637
		Education and Science	−880.6816	2154.72906	1.000	−7238.4333	5477.0701
		Others	−236.4488	4201.42928	1.000	−12,633.2019	12,160.3043
	People and Blog	Entertainment	−7349.8283 *	1571.27131	0.000	−11,986.0273	−2713.6292
		Sport	48.3926	4330.72469	1.000	−12,729.8600	12,826.6453
		Travel and Event	183.7020	1567.65829	1.000	−4441.8365	4809.2404
		News and Politics	−2055.1611	2005.39738	0.948	−7972.2942	3861.9720
		Education & Science	−696.9796	2237.85393	1.000	−7299.9999	5906.0406
		Others	−52.7469	4244.66028	1.000	−12,577.0575	12,471.5638
	News and Politics	Entertainment	−5294.6672	1915.15712	0.083	−10,945.5370	356.2027
		Sport	2103.5537	4467.00230	0.999	−11,076.8002	15,283.9076
		Travel and Event	2238.8631	1912.19397	0.905	−3403.2637	7880.9898
		People and Blog	2055.1611	2005.39738	0.948	−3861.9720	7972.2942
		Education and Science	1358.1814	2491.36980	0.998	−5992.8637	8709.2266
		Others	2002.4142	4383.61428	0.999	−10,931.8946	14,936.7231
	Education and Science	Entertainment	−6652.8486 *	2157.35912	0.034	−13,018.3606	−287.3367
		Sport	745.3722	4576.07705	1.000	−12,756.8180	14,247.5625
		Travel and Event	880.6816	2154.72906	1.000	−5477.0701	7238.4333
		People and Blog	696.9796	2237.85393	1.000	−5906.0406	7299.9999
		News and Politics	−1358.1814	2491.36980	0.998	−8709.2266	5992.8637
		Others	644.2328	4494.71308	1.000	−12,617.8846	13,906.3502

Table 3. *Cont.*

Tukey HSD							
Dependent Variable	**(I) Video Type**	**(J) Video Type**	**Mean Difference (I-J)**	**Std. Error**	**Sig.**	**95% Confidence Interval**	
						Lower Bound	**Upper Bound**
	Others	Entertainment	−7297.0814	4202.77872	0.592	−19697.8162	5103.6534
		Sport	101.1395	5826.63125	1.000	−17,090.9407	17,293.2197
		Travel and Event	236.4488	4201.42928	1.000	−12,160.3043	12,633.2019
		People and Blog	52.7469	4244.66028	1.000	−12,471.5638	12,577.0575
		News and Politics	−2002.4142	4383.61428	0.999	−14,936.7231	10,931.8946
		Education and Science	−644.2328	4494.71308	1.000	−13,906.3502	12,617.8846
Comment Count	Entertainment	Sport	399.7862	354.55697	0.920	−646.3710	1445.9433
		Travel and Event	406.6881 *	119.88337	0.012	52.9598	760.4164
		People and Blog	365.1875	129.87093	0.074	−18.0102	748.3851
		News and Politics	−106.2006	158.29427	0.994	−573.2643	360.8631
		Education and Science	321.3022	178.31309	0.547	−204.8291	847.4335
		Others	312.9086	347.37400	0.973	−712.0544	1337.8717
	Sport	Entertainment	−399.7862	354.55697	0.920	−1445.9433	646.3710
		Travel and Event	6.9019	354.44770	1.000	−1038.9328	1052.7366
		People and Blog	−34.5987	357.94917	1.000	−1090.7649	1021.5675
		News and Politics	−505.9868	369.21298	0.818	−1595.3880	583.4144
		Education and Science	−78.4840	378.22838	1.000	−1194.4861	1037.5181
		Others	−86.8775	481.59095	1.000	−1507.8616	1334.1065
	Travel and Event	Entertainment	−406.6881 *	119.88337	0.012	−760.4164	−52.9598
		Sport	−6.9019	354.44770	1.000	−1052.7366	1038.9328
		People and Blog	−41.5006	129.57231	1.000	−423.8172	340.8159
		News and Politics	−512.8887 *	158.04935	0.020	−979.2297	−46.5477
		Education and Science	−85.3859	178.09571	0.999	−610.8757	440.1040
		Others	−93.7794	347.26246	1.000	−1118.4134	930.8545
	People and Blog	Entertainment	−365.1875	129.87093	0.074	−748.3851	18.0102
		Sport	34.5987	357.94917	1.000	−1021.5675	1090.7649
		Travel and Event	41.5006	129.57231	1.000	−340.8159	423.8172
		News and Politics	−471.3881	165.75293	0.067	−960.4593	17.6832
		Education and Science	−43.8853	184.96626	1.000	−589.6474	501.8769
		Others	−52.2788	350.83565	1.000	−1087.4558	982.8982
	News and Politics	Entertainment	106.2006	158.29427	0.994	−360.8631	573.2643
		Sport	505.9868	369.21298	0.818	−583.4144	1595.3880
		Travel and Event	512.8887 *	158.04935	0.020	46.5477	979.2297
		People and Blog	471.3881	165.75293	0.067	−17.6832	960.4593
		Education and Science	427.5028	205.92021	0.367	−180.0862	1035.0918
		Others	419.1092	362.32067	0.910	−649.9555	1488.1740

Table 3. *Cont.*

Dependent Variable	(I) Video Type	(J) Video Type	Tukey HSD Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
	Education and Science	Entertainment	−321.3022	178.31309	0.547	−847.4335	204.8291
		Sport	78.4840	378.22838	1.000	−1037.5181	1194.4861
		Travel and Event	85.3859	178.09571	0.999	−440.1040	610.8757
		People and Blog	43.8853	184.96626	1.000	−501.8769	589.6474
		News and Politics	−427.5028	205.92021	0.367	−1035.0918	180.0862
		Others	−8.3936	371.50337	1.000	−1104.5528	1087.7657
	Others	Entertainment	−312.9086	347.37400	0.973	−1337.8717	712.0544
		Sport	86.8775	481.59095	1.000	−1334.1065	1507.8616
		Travel and Event	93.7794	347.26246	1.000	−930.8545	1118.4134
		People and Blog	52.2788	350.83565	1.000	−982.8982	1,087.4558
		News and Politics	−419.1092	362.32067	0.910	−1488.1740	649.9555
		Education and Science	8.3936	371.50337	1.000	−1,087.7657	1,104.5528

Based on the observed means. The error term is mean square (error) = 5331865.410. * The mean difference was significant at the 0.05 level.

3.2.2. Sentiment Analysis of Beijing's Architectural Heritage Relevant Videos

To understand the attitudes that the YouTube videos portrayed towards Beijing's destination image and issues they were concerned about, this study investigated the video descriptions via sentiment analysis using MeaningCloud. The sentiment of 2237 video descriptions were divided into strong negative, negative, neutral, positive, and strongly positive. The sentiment analysis result is illustrated in Figure 3.

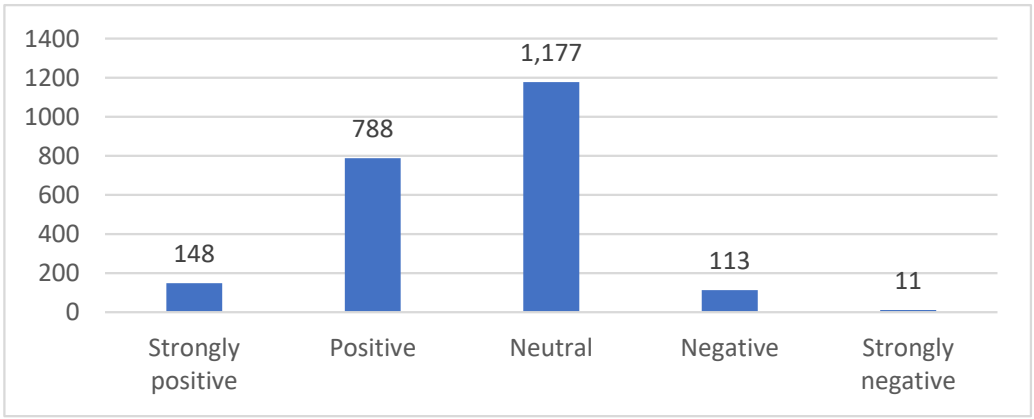


Figure 3. Sentiment distribution of video description.

The result in Figure 3 reflects that 94.46% of the video descriptions were neutral, positive, and strongly positive. This illustrates that people's perceptions of videos related to Beijing's architectural heritage as a tourist spot were neutral (1177), positive (788), and strongly positive (11). This implies that video viewers might obtain positive/neutral messages regarding Beijing's architectural heritage.

3.2.3. Viewer's Social Network Analysis

To understand how YouTube video viewers perceive Beijing's destination image and their social interactions when watching videos, this study conducted a social network analysis.

Social network analysis measures and visualises informal and formal relationships to discover what promotes or hinders knowledge flows binding interacting units [85]. The rise of social media has offered a chance to build large social networks essential for communicating information, ideas, and influence in which typic phenomena in real-life are word-of-mouth effects [86].

Step one was an investigation of the relationships among YouTube viewers. In the network, the cluster called community, refers to a group of nodes connecting closely. This study used NodeXL to mine YouTube users' comments and analyse the social networks of these comments and then conducted a sentimental analysis of the video comments via MeaningCloud, as per Yao, Li, and Song [73]. Nodes (i.e., "vertices" or "entities") refer to a social structure or content, virtual physical location, event, or individual, for instance, an institution, organisation, or country [87]. The Clauset–Newman–Moore algorithm, a widely used algorithm for analysing large networks and community classification [88], was used to characterise the network. This greedy heuristic method is ideal for quickly discovering communities [89], which seek to examine all nodes pair by pair to identify which two nodes can be merged as a cluster after first assuming that all nodes are independent clusters [90].

Clauset–Newman–Moore algorithm

$$Q = \frac{1}{2m}\sum_{vw}\left[A_{vw} - \frac{k_v k_w}{2m}\right]\sum_{i}\delta(c_v, i)\delta(c_w, i)$$

Algorithm 1 applied after the data visualisation was the Harel–Koren fast multiscale layout algorithm, which aims to generate a graph [91]. The algorithm is as follows.

Algorithm 1: Harel–Koren fast multiscale layout algorithm

Layout (G (V, E))
Goal: Find L, a nice layout of G
1. Compute the all-pairs shortest distance ($d_v \times v$)
2. Set up a random layout L
3. $k \leftarrow Threshold$
4. while $k \leq |v|$ do
   4.1 $Centers \leftarrow \boldsymbol{K-Centers}(G(V,E),k)$
   4.2 $\boldsymbol{LocalLayout}(d_{Centers \times Centers},\ L(Centers))$
   4.3 $for\ every\ v \in V do$
      4.3.1 $L(v) \leftarrow L(center(v) + \xi)$
   4.4 $k \leftarrow k{\cdot}Ratio$
5. *end*

Calculating via these two algorithms, the multiple clusters of video viewers was organised as shown in Figure 4, and the data results are in Table 4. Figure 4 presents the inactive network clusters of video commenters visualised using the Harel–Koren fast multiscale layout algorithm. Table 4 details a graphic metric of video commentors on YouTube and interprets Figure 4 via the index and value. Figure 4 and Table 4 reflect video commenters' social networks, in other words, their interactive behaviour, when watching these videos.

According to the above data results, there were 22,677 vertices in the networks composed of Beijing's architectural heritage tourism video commenters. Among them, 20,867 were unique edges, and 4367 were edges with duplicates. The average geodesic distance signifies the average number of paths that one node uses to reach the others [92]. In this study, the average geodesic distance was 10.042648, meaning that 10 people were needed to reach others via 10 people. This exceeded the value defined by Guare [93] in the six degrees of separation, where everyone is linked to everyone else by a chain of six or fewer people [94]. Compared with this value in other knowledge sharing cases in social media, for example, the value 3.6 for francophone users and 3.2 for English speaking users in Twitter when sharing occupational safety knowledge [95], such a result coincides with Yao, Li, and Song's [73] finding that YouTube users' viewing behaviour showed less crossviews and comments.

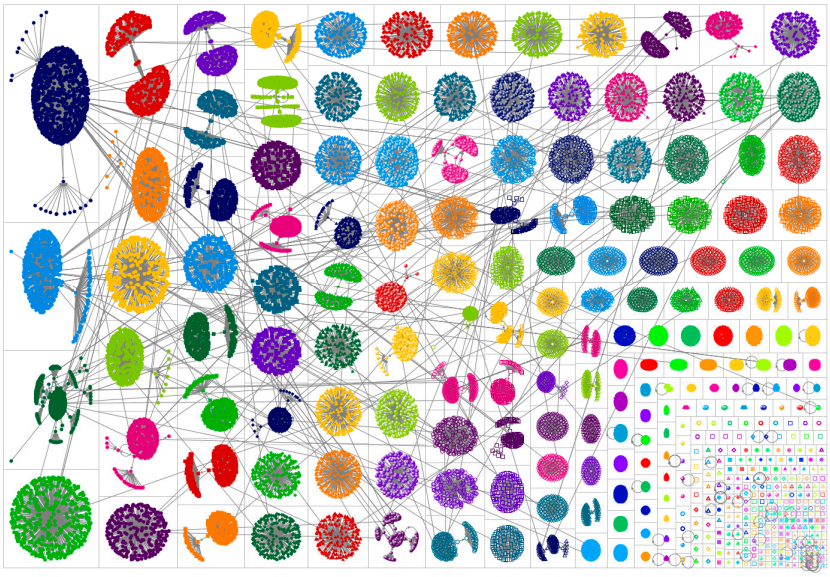


Figure 4. Inactive network clusters of the video commenters visualised using the Harel–Koren fast multiscale layout algorithm.

Table 4. Graph metrics of the video commentors on YouTube.

Graph Type	Directed
Vertices	22,677
Unique Edges	20,867
Edges With Duplicates	4367
Total Edges	25,234
Self-Loops	108
Reciprocated Vertex Pair Ratio	4.45474×10^{-5}
Reciprocated Edge Ratio	8.90908×10^{-5}
Connected Components	361
Single-Vertex Connected Components	12
Maximum Vertices in a Connected Component	15,492
Maximum Edges in a Connected Component	17,381
Maximum Geodesic Distance (Diameter)	30
Average Geodesic Distance	10.042648
Graph Density	4.36561×10^{-5}
Modularity	0.875765

This revealed a discursive connection among the video commenters on YouTube. Moreover, the modularity determines the fitness of the groups in a network. It counts the number of edges that split from one group to join another [92]. The number in this study was 0.875765. The higher the degree of modularity, the lower the group's quality [96]. Therefore, this social network's average geodesic distance and modularity value proved that the interaction among these YouTube commenters was loose. Referencing research by Yao et al. [97], this result could be interpreted that the commenters of these videos were unwilling to visit different clusters to discuss Beijing's tourist architectural heritage.

3.2.4. Semantic Analysis of YouTube Users' Comments

To understand the perceptions and attitudes of YouTube commenters towards Beijing's destination image, the first step involved a sentiment analysis with MeaningCloud. The distribution of 25,234 comments' sentiment is presented in Figure 5. The video descriptions and comments' sentiments were divided into 5 categories: N+ (strongly negative), N (negative), Neu (neutral), P (positive), and P+ (strongly positive). Figure 5 reflects the commentors' perceived emotional (affective) image. It illustrates that most were neutral comments, and 53.85%, and 36.79% were a positive or strongly positive sentiment. These statistics reflects that when watching videos, most YouTube viewers held a positive or neutral attitude towards Beijing's architectural heritage. In line with the video contents, negative comments were substantially fewer, meaning that YouTube viewers do not receive much negative messages by reading the comments.

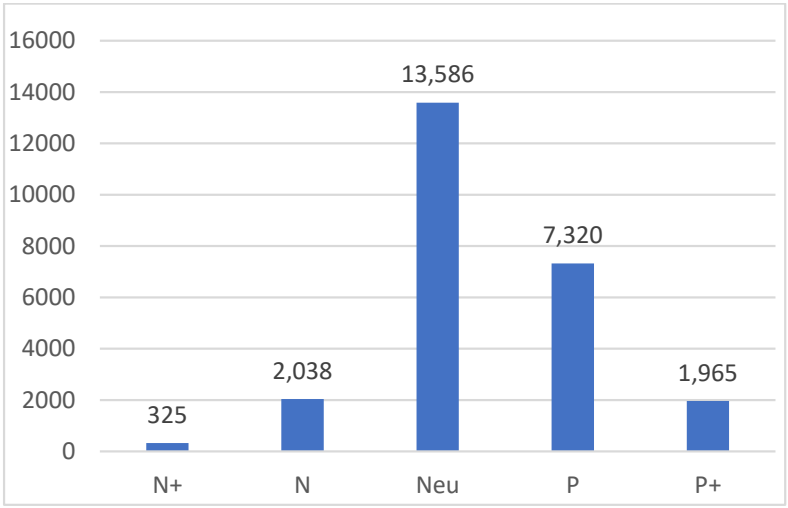


Figure 5. Sentiment distribution of YouTube users' comments.

Meanwhile, further comment content analysis via keyword in context (KWIC) was conducted to understand viewers' views. Nowadays, multilingual scenarios in social media are expected. In this study, the comments contain many different languages. To analyse French speakers' attitudes more accurately towards Beijing's architectural heritages, a Markov chain-based method was used to identify the languages in the comments. Markov chains are widely applied in the financial industry and data science, such as for handwriting recognition, spam filtering, and text generation. A Markov chain is a stochastic process with a set of states shifting from one state to another. These transitions are decided by probabilities, which depend on the current state of the Markov chain [98,99]. A Markov chain-based method can identify the language through the maximum likelihood decision rule. Empirical studies proved that compared with the N-gram method, this method could recognise languages with a fast speed and lower error rate [100].

After the analysis, 134 languages were found in the comments, and 13,518 (approximately 55%, ranked no. 1) were French. This result shows that Beijing's classic architecture has aroused broad interest on YouTube. Based on the previous sentiment analysis, we believed that the classic architecture in Beijing was neutrally or positively perceived worldwide, and it was concluded that a video of classic architecture is an effective tool to promote the image of Beijing as a destination.

Next, simple word frequency was analysed, and the 10 most frequent and meaningful French keywords in the video comments were found. Then, this study investigated the keyword in context (KWIC) to better understand these French comments. This study extracted five contextual words to the specific keyword's left and right. For each frequent keyword in the video comments, this study picked the top 10 meaningful contextual words according to their scores. The formula used to calculate the score is shown below. "l_i"

and "r_i" refer to the frequency with which the contextual word appears before or after the keyword, and the formula is shown below.

$$f(\omega) = \sum_{i=1}^{5} \frac{(l_i + r_i)}{i}$$

KWIC calculated the number of contextual words to the left and right of the keywords and the total count. The higher the score, the higher the correlation between the contextual word and the keyword. The KWIC analysis result reflects the cognitive–emotional image perceived by the commentors. Table 5 lists the context of these keywords, and Appendix A (Table A1) provides detailed information. Table 5 lists the most frequent and meaningful French keywords mentioned in the video comments, contextual words, number of times that the contextual words appeared on the right- and left-hand sides of the French keywords, and the score, which indicates the correlation between the French keywords and contextual words.

Table 5. The 10 meaningful contextual words.

Keywords in French (English)	Contextual Words	Number of Times That the Contextual Words Appear on the Left-Hand Side of the French Keywords	Number of Times That the Contextual Words Appear on the Right-Hand Side of the French Keywords	Total Frequency	Correlation Score between French Keywords and Contextual Words
Merci (Thanks)	Beaucoup (a lot)	19	166	185	163.550
	Vidéo (video)	104	186	290	105.467
	Avoir (have)	79	131	210	80.983
	Seigneur (lord)	22	76	98	73.9983
	Amen (amen)	63	20	83	42.550
	Infiniment (infinitively)	3	43	46	42.167
	Grand (great or big)	45	5	50	41.867
	Bon (good)	60	53	113	41.067
	Beau (beautiful)	39	76	115	39/050
	Chef (Chief)	11	39	50	37.893
Vidéo (video)	Super (super)	120	21	151	121.833
	Merci (thanks)	187	104	291	105.667
	Avoir (have)	118	143	261	81.383
	Bon (good)	79	27	106	74.283
	Beau (beautiful)	75	15	90	65.583
	Faire (make or do)	86	47	133	49.367
	Superbe (superb)	45	11	56	47.183
	Excellent (excellent)	35	10	45	35.187
	Voir (watch or see)	47	17	64	23.300
	Adorer (adore)	42	16	58	23.050

Table 5. *Cont.*

Keywords in French (English)	Contextual Words	Number of Times That the Contextual Words Appear on the Left-Hand Side of the French Keywords	Number of Times That the Contextual Words Appear on the Right-Hand Side of the French Keywords	Total Frequency	Correlation Score between French Keywords and Contextual Words
Pouvoir (can)	Avoir (have)	136	65	201	131.117
	Faire (make or do)	18	133	151	102.200
	Dire (say or tell)	12	59	71	41.633
	Voir (watch or see)	13	44	57	33.517
	Aller (go)	13	23	36	20.267
	Mettre (put)	4	22	25	17.983
	Vidéo (video)	16	29	45	13.983
	Regarder (watch or look)	6	14	20	12.900
	Trouver (find)	1	18	19	12.417
	Parler (talk or speak)	5	13	18	10.350
Bon (good)	Très (very)	200	26	226	184.333
	Vidéo (video)	30	78	108	75.483
	Film (film)	18	64	82	63.050
	Continuation (continuation)	3	48	51	48.522
	Merci (thanks)	54	62	116	41.933
	Humeur (humour)	0	41	41	41.000
	Journée (day or daytime)	2	39	41	39.083
	Courage (courage)	5	38	43	37.317
	Moment (moment)	2	26	29	25.483
	Travail (job or work)	3	27	30	25.017
Beau (beautiful)	Très (very)	149	22	171	143.533
	Vidéo (video)	14	76	90	65.533
	Trop (too)	45	4	49	40.550
	Merci (thanks)	76	41	117	39.450
	Film (film)	10	17	27	18.600
	Image (image or photo or picture)	2	19	21	18.167
	Français (French)	3	17	20	17.283
	Pays (country)	2	16	18	15.783
	Histoire (history)	9	15	24	14.917
	Super (super)	16	7	23	14.876

Table 5. *Cont.*

Keywords in French (English)	Contextual Words	Number of Times That the Contextual Words Appear on the Left-Hand Side of the French Keywords	Number of Times That the Contextual Words Appear on the Right-Hand Side of the French Keywords	Total Frequency	Correlation Score between French Keywords and Contextual Words
Aimer (love)	Bien (well)	23	64	87	81.050
	Beaucoup (much)	15	53	68	63.400
	Vidéo (video)	15	28	43	13.633
	Film (film)	7	25	32	11.950
	Savoir (know)	3	13	16	10.983
	Voir (watch or see)	3	13	16	7.783
	Merci (thanks)	8	20	28	9.317
	Aller (go)	5	9	14	6.733
	Histoire (history)	4	15	19	6.540
	Chine (China)	3	10	13	4.533
Film (film)	Bon (good)	64	17	81	62.800
	Voir (watch)	16	46	62	25.167
	Beau (beautiful)	17	10	27	18.600
	Super (super)	18	6	24	16.183
	Merci (thanks)	11	19	30	14.883
	Aimer (love)	25	7	32	11.950
	Regarder (watch)	21	5	26	11.333
	Adorer (adore)	18	9	27	10.250
	Meilleur (better)	13	10	23	9.433
	Magnifique (magnificent)	15	5	20	9.350
Chine (China)	Muraille (wall)	64	1	65	32.083
	Aller (go)	21	7	28	11.850
	Voir	11	10	21	8.533
	Grand (great or big)	16	5	21	7.017
	Vif (live or vivid or bright)	8	3	11	5.700
	Histoire (history)	15	2	17	5.633
	Bon (good)	2	11	13	5.317
	Merci (thanks)	1	12	13	4.767
	Pays (country)	6	10	16	4.717
	Aimer (louve)	10	3	13	4.533

Table 5. *Cont.*

Keywords in French (English)	Contextual Words	Number of Times That the Contextual Words Appear on the Left-Hand Side of the French Keywords	Number of Times That the Contextual Words Appear on the Right-Hand Side of the French Keywords	Total Frequency	Correlation Score between French Keywords and Contextual Words
Super (super)	Vidéo (video)	30	116	146	116.833
	Intéressant (interesting)	3	45	48	42.000
	Merci (thanks)	30	48	78	32.050
	Bien (well)	16	19	35	18.933
	Cool (cool)	3	17	20	18.400
	Film (film)	6	18	24	16.183
	Beau (beautiful)	7	16	23	14.867
	Bon (good)	14	14	28	14.217
	Episode (episode)	2	12	14	12.583
	Format (format)	5	13	18	11.750
Grand (great or big)	Muraille (wall)	0	59	59	56.200
	Merci (thanks)	6	49	55	46.867
	Chose (thing)	1	13	14	13.200
	Bravo (bravo)	3	14	17	12.900
	Pays (country)	3	15	18	11.783
	Chine (China)	5	16	21	7.017
	Ville (city)	3	7	10	6.783
	Homme (people or man)	1	6	7	6.250
	Maître (master)	1	6	7	6.200
	Beau (beautiful)	5	8	13	5.183

Through KWIC, this study found that the most frequent word was "merci (thanks)", which shows that audiences were grateful when they watched these videos to acquire Beijing's information. Many positive adjectives, such as "grand (great)", "bonne (good)", "beau (beautiful)", and "aime (love)", were found, which reflects the audiences' good impression of Beijing's architectural heritage and the city where it was situated. Meanwhile, words such as "magnifique (magnificent)" and adorer (adore) indicate that Beijing's classic architecture clips were also popular with audiences. In addition, "the Great Wall" was frequently mentioned, and it can be inferred that the Great Wall is a symbol widely recognised by the French with a positive attitude. However, we also found that "Chine (China)" was most frequently mentioned while "Beijing" was absent, which shows that when people watched these videos, they associated these architectural heritages to China rather than Beijing itself, another frequent word "pays (country)" also corroborated this finding.

4. Discussion

4.1. General Discussion

Destination image (Table A2 in Appendix B) has been crucial in destination choice, brand differentiation, and marketing [6]. Architectural heritage shapes a destination's image. It significantly motivates visits to specific destinations [24]. The destination image in people's eyes has constantly been changing [8], while the architectural heritage, culture, and history cannot be rewritten, as these resource endowments have historically been relatively

stable. Social media provides a convenient platform for the international communication of destination images. Applying Gerbner's cultivation theory, this paper analysed both the projected destination image and perceived destination image of Beijing on YouTube. The result found that architectural heritage can shape Beijing's destination image via social media, which has far-reaching significance, contributes to the communication of the architectural heritage of Beijing, and proposes helpful suggestions for shaping Beijing's destination image in the digital era.

To answer the first research question, by MANOVA analysis, this paper found that among Beijing architectural heritage-related tourism videos, the entertainment-type videos fascinated the most viewers. YouTube users considered Beijing architectural heritage-related tourism clips as entertainment videos. At the same time, the sentiment analysis of the video descriptions showed that YouTube video uploaders generally held a positive or neutral attitude towards Beijing's architectural heritage-related tourism videos. This result shows that these videos exhibited a neutral or complimentary projected online destination image of Beijing.

To answer the second question, the sentiment analysis found that 94.46% of video descriptions held a neutral or positive sentiment, the comment results corroborated that 90.64% of viewers held a neutral or positive sentiment. Approximately 53.84% of viewers held a neutral attitude towards Beijing's architectural heritage-related tourism videos, and approximately 36.79% held a positive or strongly positive sentiment attitude towards Beijing's architectural heritage-related tourism videos. This result reflects that architectural heritage-related tourism videos can indeed cultivate people's perceived destination images. YouTube viewers hardly received negative information from architectural heritage clips.

In addition, the KWIC analysis found that although this research focused on Beijing and its architectural heritages when watching these videos, francophone people tended to connect architecture with the country rather than the city. Among many architectural heritages, the Great Wall was not the first but the most widely recognised by francophones. This result presents that the architectural heritage did not only portray the destination image but impacted the destination country's image to be stronger. Moreover, the KWIC analysis showed that the videos (or TV series) with architectural heritage elements fascinated them and shaped a positive image, which further connects the destination image to the destination country image.

The answers to the first and second questions illustrate the consistency of the projected and perceived destination image, therefore indicating the cultivation effect of these YouTube videos. This finding suggests the necessity of enhancing the role of architectural heritage to shape a better destination image, since it effectively impacts the destination image [46]. As Costa and Carneiro [24] stated, in addition to investigating the general image of the destination, it is essential to examine the image of specific elements of the tourism destination, such as its architectural heritage, and to investigate how visitors learn about this heritage, as it is one of the primary attractions of many destinations.

To answer the final question regarding the clusters that developed in the YouTube videos networks, the social network analysis showed that although users crosswatched some videos on Beijing's architecture and left comments, the mediating distance between users was long, and no positive interactions were found. In addition, users were less willing to leave their clusters to discuss with other clusters. This showed that Beijing's architecture videos lacked the means to stimulate users' interactions. This finding suggests the needs to improve users' interaction to better communicate and cultivate Beijing's destination image, since information and knowledge sharing often requires users' extensive interaction on social media [101].

4.2. Contributions and Implication

This study expanded the research on Beijing's architectural heritage via online social media analysis, and it is significant to online destination image studies and development, offering practical and academic insights.

Firstly, this study provides a comprehensive understanding of Beijing's architectural heritage online destination image based on French YouTube videos' content and comments. It overcame the sample size problems of surveys and qualitative interviews. At the same time, this study used big data mining and analysis, which enhanced the validity and reliability of the research results [46]. This study contributes to local governments regarding how social media projects the destination image and how users perceive the destination information via YouTube videos.

Secondly, this study applied a mixed approach that combined big data mining, social networks analysis by algorithm, KWIC analysis, and semantic analysis by natural language processing, including word cloud and sentiment analyses, which innovated the statical research method in the architectural heritage study and saving costs. In contrast, it is easier to gather and process unstructured text [102], generating a complete and pellucid result. Therefore, this study enriched the research method in online architectural heritage relevant destination image study.

Thirdly, as for policy and managemental enlightenment, this study proposes that the tourism agencies of Beijing cooperate with opinion leaders for destination country image building. In addition, online celebrities should be invited to close the distance with users by sharing their own stories. Sharing experiences, tourism-related suggestions, and expressing emotions can effectively motivate users to comment, like, and forward [103]. On the other hand, the research results also show that when watching architectural heritage tourism in Beijing, viewers tended to associate it with the country with such architectural heritage. Therefore, organisations or agencies that wish to improve the destination country image may choose an appropriate city or cities as representation. Another finding of this study was that videos containing architectural heritage should be actively used for international communication, because they can create a positive attitude among audiences and indirectly enhance the image of a city or even a country.

4.3. Limitation and Future Works

This study also has some limitations. Firstly, this study focused only on YouTube, and there are many social media platforms worth investigating. Thus, it is recommended to include more social media platforms in the future.

Secondly, this study only investigated Beijing, and many other heritage sites in other cities such as Rome were not included. Thus, in the future, it is suggested to extend the target area to other territories or compare several cities in the same country.

Thirdly, this study investigated only Beijing's architectural heritage tourism relevant videos in French as a pilot study. Videos in other languages, such as English, Chinese, German, Korean, Japanese, and Spanish, can be studied in the future. In addition, this study conducted only KWIC analyses for comments in French, while 134 languages were found in the comments. Thus, it is recommended that future research could investigate videos in other languages or compare videos and comments of different languages to understand better the cultivation effect of the projected and perceived architectural heritage relevant to the online destination image in different languages.

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Appendix A. Detail of KWIC

Table A1. Detail of KWIC.

Keyword in French (English)	Contextual Words (L = Count on the Left of Keyword, R = Count on the Right of Keyword)												
	Contextual Words	**L5**	**L4**	**L3**	**L2**	**L1**	**R1**	**R2**	**R3**	**R4**	**R5**	**Score**	**Count**
Merci (Thanks)	Beaucoup (a lot)	3	8	3	4	1	154	1	0	5	6	163.550	185
	Vidéo (video)	18	15	16	38	17	2	2	112	49	21	105.467	290
	Avoir (have)	30	19	20	10	0	30	9	32	28	32	80.983	210
	Seigneur (lord)	1	3	7	6	5	56	4	9	6	1	73.983	98
	Amen (amen)	3	9	11	24	16	2	7	1	4	6	42.550	83
	Infiniment (infinitively)	0	1	0	0	2	38	2	2	1	0	42.176	46
	Grand (great or big)	4	0	3	0	38	1	0	2	0	2	41.867	50
	Bon (good)	17	12	18	10	3	7	7	14	10	15	41.074	113
	Beau (beautiful)	7	6	12	11	3	2	4	33	25	12	39.050	115
	Chef (Chief)	1	1	1	6	2	29	2	3	4	1	37.983	50
Vidéo (video)	Super (super)	5	3	5	8	99	5	15	5	1	5	121.833	151
	Merci (thanks)	22	49	112	2	2	17	38	16	15	18	105.667	291
	Avoir (have)	41	27	43	4	3	10	11	36	48	38	81.383	261
	Bon (good)	4	10	3	2	60	0	8	7	5	7	74.283	106
	Beau (beautiful)	8	5	4	3	55	0	3	6	4	2	65.583	90
	Faire (make or do)	12	11	24	39	0	2	11	14	11	9	49.367	133
	Superbe (superb)	2	1	0	2	40	2	5	1	2	1	47.183	56
	Excellent (excellent)	0	1	4	1	29	1	6	1	0	2	35.187	45
	Voir (watch)	4	6	14	23	0	0	4	1	2	10	23.300	64
	Adorer (adore)	2	4	3	33	0	0	0	6	3	7	23.050	58
Pouvoir (can)	Avoir (have)	23	10	7	26	70	26	12	7	7	13	131.117	201
	Faire (make or do)	9	2	3	3	1	68	44	15	4	2	102.200	151
	Dire (say or tell)	4	6	2	0	0	24	19	14	2	0	41.633	71
	Voir (watch or see)	7	3	2	1	0	20	14	9	0	1	33.517	57
	Aller (go)	3	2	1	2	5	9	1	4	4	5	20.267	36
	Mettre (put)	2	1	0	1	0	14	3	4	0	0	17.983	25
	Vidéo (video)	4	1	4	7	0	0	1	12	8	8	13.983	45

Table A1. *Cont.*

Keyword in French (English)	Contextual Words (L = Count on the Left of Keyword, R = Count on the Right of Keyword)												
	Contextual Words	**L5**	**L4**	**L3**	**L2**	**L1**	**R1**	**R2**	**R3**	**R4**	**R5**	**Score**	**Count**
	Regarder (watch or look)	2	0	4	0	0	9	3	2	0	0	12.900	20
	Trouver (find)	0	0	1	0	0	7	9	1	1	0	12.417	19
	Parler (talk or speak)	2	1	1	1	0	6	4	2	0	1	10.350	18
Bon (good)	Très (very)	12	8	7	7	166	1	2	9	6	8	184.333	226
	Vidéo (video)	8	5	8	8	1	60	2	2	10	4	75.483	108
	Film (film)	5	6	4	2	1	54	3	2	1	4	63.050	82
	Continuation (continuation)	0	0	1	2	0	47	0	0	0	1	48.522	51
	Merci (thanks)	15	10	15	7	7	3	10	19	12	18	41.933	116
	Humeur (humour)	0	0	0	0	0	41	0	0	0	0	41.000	41
	Journée (day or daytime)	0	1	0	1	0	38	0	1	0	0	39.083	41
	Courage (courage)	1	0	1	2	1	33	2	1	1	1	37.317	43
	Moment (moment)	1	1	0	0	1	23	1	1	0	1	25.483	29
	Travail (job or work)	2	0	1	0	0	23	1	1	1	1	25.017	30
Beau (beautiful)	Très (very)	6	5	6	2	130	1	6	7	3	5	143.533	171
	Vidéo (video)	2	3	6	3	0	55	3	4	5	9	65.533	90
	Trop (too)	2	3	2	2	36	1	0	1	0	2	40.550	49
	Merci (thanks)	12	25	33	4	2	3	11	12	6	9	39.450	117
	Film (film)	3	1	5	1	0	15	0	1	1	0	18.600	27
	Image (image or photo or picture)	0	0	1	0	1	16	0	1	2	0	18.167	21
	Français (French)	1	1	1	0	0	16	1	0	0	0	17.283	20
	Pays (country)	0	1	0	0	1	14	0	1	0	1	15.783	18
	Histoire (history)	4	1	1	3	0	11	0	1	2	1	14.917	24
	Super (super)	2	1	1	1	11	1	0	1	1	4	14.876	23
Aimer (love)	Bien (well)	4	1	3	0	15	64	0	0	0	0	81.050	87
	Beaucoup (much)	0	0	0	0	15	45	6	0	0	2	63.400	68
	Vidéo (video)	5	6	4	0	0	0	9	9	6	4	13.633	43
	Film (film)	4	1	2	0	0	1	10	10	2	2	11.950	32
	Savoir (know)	2	0	1	0	0	8	4	0	1	0	10.983	16
	Voir (watch or see)	1	2	0	0	0	6	5	1	1	0	7.783	16
	Merci (thanks)	2	3	3	0	0	2	2	5	6	5	9.317	28
	Aller (go)	1	0	0	2	2	1	1	4	2	1	6.733	14
	Histoire (history)	1	1	2	0	0	0	3	10	2	0	6.540	19
	Chine (China)	0	1	2	0	0	0	4	2	3	1	4.533	13

Table A1. *Cont.*

Keyword in French (English)	Contextual Words (L = Count on the Left of Keyword, R = Count on the Right of Keyword)												
	Contextual Words	**L5**	**L4**	**L3**	**L2**	**L1**	**R1**	**R2**	**R3**	**R4**	**R5**	**Score**	**Count**
Film (film)	Bon (good)	4	1	2	3	54	1	2	4	5	5	62.800	81
	Voir (watch)	2	3	7	34	0	0	4	1	3	8	25.167	62
	Beau (beautiful)	0	1	1	0	15	0	1	5	1	3	18.600	27
	Super (super)	2	3	0	3	10	2	2	1	0	1	16.183	24
	Merci (thanks)	2	1	8	0	0	8	3	2	4	2	14.883	30
	Aimer (love)	2	2	10	10	1	0	0	2	1	4	11.950	32
	Regarder (watch)	1	0	0	20	0	0	0	1	0	4	11.333	26
	Adorer (adore)	2	2	1	13	0	0	1	2	3	3	10.250	27
	Meilleur (better)	2	0	1	0	7	1	1	0	0	1	9.433	13
	Magnifique (magnificent)	1	1	0	0	3	4	2	0	2	2	9.350	15
Chine (China)	Muraille (wall)	0	0	1	63	0	0	0	0	1	0	32.083	65
	Aller (go)	2	3	3	13	0	2	0	0	4	1	11.850	28
	Voir (watch or see)	0	4	4	3	0	2	2	3	2	1	8.533	21
	Grand (great or big)	1	3	11	0	1	0	0	3	0	2	7.017	21
	Vif (live or vivid or bright)	1	0	0	7	0	1	2	0	0	0	5.700	11
	Histoire (history)	3	0	9	3	0	0	0	1	0	1	5.633	17
	Bon (good)	0	2	0	0	0	2	2	2	3	2	5.317	13
	Merci (thanks)	0	1	0	0	0	0	6	2	1	3	4.767	13
	Pays (country)	1	1	4	0	0	0	1	4	2	3	4.717	16
	Aimer (love)	1	3	2	4	0	0	0	2	1	0	4.533	13
Super (super)	Vidéo (video)	5	1	5	15	4	95	8	5	3	5	116.833	146
	Intéressant (interesting)	1	0	0	1	1	39	0	0	2	4	42.000	48
	Merci (thanks)	2	3	15	8	2	5	13	15	8	7	32.050	78
	Bien (well)	6	4	5	1	0	13	0	2	2	2	18.933	35
	Cool (cool)	1	0	0	0	2	16	0	0	0	1	18.400	20
	Film (film)	1	0	1	2	2	10	3	0	3	2	16.183	24
	Beau (beautiful)	4	1	1	0	1	11	1	1	1	2	14.867	23
	Bon (good)	2	3	4	4	1	6	3	1	2	2	14.217	28
	Episode (episode)	0	1	0	0	1	11	0	1	0	0	12.583	14
	Format (format)	0	1	1	2	1	7	2	2	2	0	11.750	18

Table A1. *Cont.*

Keyword in French (English)	Contextual Words (L = Count on the Left of Keyword, R = Count on the Right of Keyword)											
	Contextual Words	L5	L4	L3	L2	L1	R1	R2	R3	R4	R5	Score	Count
Grand (great or big)	Muraille (wall)	0	0	0	0	0	55	1	0	2	1	56.200	59
	Merci (thanks)	2	0	2	0	2	42	0	3	0	4	46.867	55
	Chose (thing)	1	0	0	0	0	13	0	0	0	0	13.200	14
	Bravo (bravo)	1	0	2	0	0	11	1	1	0	1	12.900	17
	Pays (country)	0	0	3	0	0	9	1	1	3	1	11.783	18
	Chine (China)	2	0	3	0	0	1	0	11	3	1	7.017	21
	Ville (city)	1	1	0	1	0	5	1	1	0	0	6.783	10
	Homme (people or man)	0	1	0	0	0	6	0	0	0	0	6.250	7
	Maître (master)	1	0	0	0	0	6	0	0	0	0	6.200	7
	Beau (beautiful)	2	1	0	1	1	1	1	1	4	1	5.183	13

Appendix B. Glossary of Terms

Table A2. Glossary of Terms.

Term	Definition	Reference
Architectural heritage	Immovable cultural heritage, including historical buildings, monuments, and archaeological sites	UNESCO [22]
Destination image	The set of beliefs, ideas, and impressions that people have of a destination of place	Baloglu and McCleary [47]
Cultivation theory	How a much more comprehensive range of messages gradually influence the public, as they are exposed to media messages daily	Potter [68]
Open APIs (open application programming interfaces)	Open APIs promote interoperability via the provision of the data-sharing tools required to create widely used web apps, enable seamless social media service integration, and give rise to developer ecosystems that are mutually beneficial and build on top of social media platforms	Bodle [71]
NodeXL	An open-source graph visualisation tool that supports social network structure analysis from Microsoft	NodeXL [72]
Clauset–Newman–Moore algorithm	A widely used algorithm for analysing large networks and community classification	Vieira, Xavier, Ebecken, and Evsukoff [88]
Harel–Koren fast multiscale layout algorithm	Algorithm enables both multiscale graph representation and locally good layout	Yao, Li, Song, and Crabbe [91]

Table A2. *Cont.*

Term	Definition	Reference
Nodes (i.e., vertices)	A social structure or content, virtual physical location, event, or individual, for instance, an institution, organisation, or country	Hansen, Shneiderman, and Smith [87]
Edge(s)	Link or connection that occurs when two vertices collaborate or exchange information	NodeXL [92]
Average geodesic distance	Average number of paths that one node reaches the others	NodeXL [92]
Modularity	Index that determines the fitness of the groups in a network	NodeXL [92]
KWIC (keyword in context)	Extracting co-occurrence words from the text	Ängsal, Brodén, Fridlund, Olsson, and Öhberg [76]

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