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Revealing virtual visiting preference: Differentiating virtual and physical space with massive TikTok records in Beijing

Yuyang Zhang [a], Yan Li [a], Enjia Zhang [a], Ying Long [b,*]

[a] School of Architecture, Tsinghua University, Beijing 100084, China

[b] School of Architecture and Hang Lung Center for Real Estate, Key Laboratory of Eco Planning & Green Building, Ministry of Education, Tsinghua University, Beijing 100084, China

A R T I C L E I N F O

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A B S T R A C T

With the growing penetration of information and communication technologies, social media platforms have become one of the most frequently used virtual spaces in daily life, producing spatiality with new logic and structure. However, few studies have examined the difference of visiting preferences in virtual space due to the lack of proper benchmarks constructed from physical space. The quantity of geo-tagged views, likes, comments, shares embedded in TikTok filming locations was used to measuring virtual and physical visiting activities (VVAs, PVAs), providing a perfect opportunity to clarify the virtual visiting differences. Built environment components are regarded as the objects of reference and their relationships with VVAs and PVAs were examined separately, and virtual visiting preferences were revealed as the following three main points: 1. VVAs are less associated with the built environment, due to people's indirect perception of physical elements. 2. Components that people are more familiar with in physical space and could shape impressive public city images, such as landmarks and urban nodes, are dramatically enhanced in virtual space. 3. Components that could be easily perceived in physical space but hard to present through visual medium, such as functional diversity, are far less critical in virtual space.

1. Introduction

Location-based social media platforms (SMPs), including Instagram, Twitter, Flickr, Foursquare, Facebook, and Sina Weibo, emerged and developed with the information and communications technology, allowing users to share presences at everyday locations (Chorley, Whitaker, & Allen, 2015). These SMPs are creating a new kind of spatiality (Ash, 2009; Ash, Kitchin, & Leszczynski, 2018), which could be defined as virtual spaces (Kellerman, 2014) that allow users to create digital representations of physical locations, complementing physical space through various geo-tagged and real-time logging data (Gordon, Souza, & e Silva A, 2011; Graham & Zook, 2013). Other terms, such as code/spaces (Kitchin & Dodge, 2011), hybrid spaces (De Souza e Silva, 2006), digiplace (Zook & Graham, 2007), net locality (Gordon et al., 2011), virtual community (Hsu, Ju, Yen, & Chang, 2007), and cyberspace (Benedikt, 1991) have also been proposed to delimiting neospatiality, suggesting that it is a new geographical domain with its own logic and structure (Ash et al., 2018). A series of activities (e.g., browsing, commenting, sharing and checking in) could be performed geographically in a virtual space, expressing users' attitudes and experience towards the specific locations, appropriately as a kind of urban activities (Lloyd & Cheshire, 2017). The quantity of different activities on geolocations reflects the popularity of urban amenities and the more "real" perceptions captured in people's minds (Shen & Karimi, 2016).

Previous researchers have demonstrated their interest in investigating virtual space as a particular geographical domain (Kellerman, 2010; Kellerman, 2014). However, due to the data limitation of not having spatial datasets that could simultaneously contain user-generated data in two spaces, many studies have overlooked an important benchmark: our real world – physical space. Meanwhile, the built environment in physical space is also crucial in virtual space. Because they can help users construct public city images in virtual space, ranging from a specific place to the whole city (Lynch, 1960; Santos, Page, Cooper, Ribeiro, & Mota, 2009), which act as essential criteria for people to choose some places for visiting physically. An emerging term, "platform urbanism" (Sadowski, 2020), is used to describe the influence of SMPs in terms of the generally invisible social and technological forces that regulate urban activities (Barns, 2020). Virtual space

* Corresponding author at: School of Architecture, Tsinghua University, Beijing 100084, China.
E-mail address: ylong@tsinghua.edu.cn (Y. Long).

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operates around a predominantly visual understanding of physical space in which various computer-generated environments are visited via screens (Hillis, 1999). That means virtual space produces visiting experiences and activities through a co-production between a human with cognitive ability, an urban physical environment composed of disparate objects, and the intellectual capability that unites this disparate group of entities into a world of holistic experience (Ash et al., 2018).

Hence, visiting experiences and activities in virtual spaces, which we refer to as virtual visiting activities (VVAs), like visiting activities in physical spaces (PVAs), both occur based on the mental representation formed by the perception of the objects/items that can be seen or sensed at certain physical places (Couclelis & Gale, 1986; Saunders, Rutkowski, Genuchten van, Vogel, & Orrego, 2011). The particular spatiality of virtual space could be investigated by comparing the visiting differences between VVAs and PVAs. Some studies treat VVAs and PVAs separately (Kryvasheyeu et al., 2016; Sulis, Manley, Zhong, & Batty, 2018), while others argue those usually coexist (e.g., browsing restaurant reviews before choosing and eating at a restaurant) (Shaw & Yu, 2009; Yu & Shaw, 2008). Since we focus on the differences between the two activities, we separate VVAs and PVAs with the aim of clarifying the visiting preference in virtual space.

In our study, virtual space was derived from TikTok (named Douyin in mainland China), the world's most popular SMP for live video sharing. Video is one of the best virtual forms for perceiving the environments, which can help people in better comprehending an imagined reality (Saunders et al., 2011) and make virtual spaces closer to physical ones. TikTok's virtual space consists of numerous geolocations (known as filming locations herein), and each of these locations contains five geo-tagged tags that present the numbers of videos filmed here, and the corresponding views, likes, comments, and shares towards the videos, reflecting some extent the popularity of the built environment through physical experience and virtual video images. In here, PVAs were measured based on numbers of geo-targeted videos at the specific area. VVAs were measured based on digital behavior connected with those videos, including the numbers of geo-tagged views, likes, comments, and shares. Existing studies evaluate TikTok videos or media video content and conduct empirical studies from different perspectives, including media production and consumption (Lin & Polaniecki, 2009), media geography (Adams, 2011), and travel experiences (Du, Liechty, Santos, & Park, 2020). However, herein, we pay particular attention to only the filming locations and quantities of corresponding geo-tagged tags attached to them rather than the videos themselves. We empirically examined the area within the Fifth Ring Road of Beijing, the most prosperous area in China and an ideal geographical area for this research with 201,600 TikTok filming locations. The main contributions of this study are threefold: First, we introduced appropriate datasets to differentiate and depict VVAs and PVAs; Second, we explored the particular spatiality of virtual space by adopting physical space as a benchmark; Third, we focused on the differences between VVAs and PVAs based on the visiting preferences of the built environment. The remainder of the paper is structured as follows. Section 2 reviews the literature on this topic to better illustrate the research gap. Then the dataset and methodology are described exhaustively in Section 3, and the regression results are presented in Section 4. Finally, Section 5 concludes with theoretical contributions and suggestions for future research.

2. Literature review

There is currently a great interest in studying SMPs worldwide because of the increasing availability of multiple geo-tagged data, including geo-tagged images, videos, and texts, which are closely associated with daily experience and reflect users' behavior, emotions, and perceptions of these places (Huang, Obracht-Prondzynska, Kamrowska-Zaluska, Sun, & Li, 2021).

The number of geo-tagged images, records, comments, and check-ins was used to reflect human activities in physical space. Paldino, Bojic, Sobolevsky, Ratti, and González (2015) analyzed the number of geo-tagged Flickr photography and adopted it as a proxy for individuals' spatial preference. The number of geo-tagged twitter records was used to represent the distribution of residents in London (Sulis et al., 2018) and to map the intensity of people's reactions to a disaster (Kryvasheyeu et al., 2016). The number of geo-tagged Weibo records was used to represent the level of social prosperity in Beijing (Long & Huang, 2019) and Shenzhen (Wu, Ye, Ren, & Du, 2018), and to map neighborhood vibrancy (Lu, Shi, & Yang, 2019). Liu et al. (2018) considered the number of reviews about shops from Dianping.com as the physical visiting volume. Wang, Liu, Wang, and Fu (2021) used densities of geo-tagged check-ins to measure consumer activities. Meanwhile, other studies used such data to describe virtual space through the quantity of geo-tagged data. Zook, Graham, and Shelton (2011) and Graham and Zook (2011) used the number of geo-tagged Flickr photos to represent the human distribution in cyberspace. To sum up, numerous existing studies have used SMPs geo-tagged data to study human activities, human distribution, and aggregation patterns. They typically regard the data as being generated from one space—either the physical or the virtual—and thus ignore the complex interactives of two spaces beneath the SMPs geo-tagged data.

Simultaneously, many researchers are interested in quantitatively examining the associations between the built environment and geo-tagged SMP data, which are employed to represent the distribution of human activities and as a proxy of urban vibrancy. Ye, Li, and Liu (2018) studied the relationship between urban morphology and the presence of small catering businesses from Dianping.com and showed that "block" and "strip" typologies were positively associated with catering activities. Long and Huang (2019) found that mixed-use land, access to amenities, and transportation facilities were related to geo-tagged Weibo records. Lu et al. (2019) claimed that facility diversity and public transport accessibility indicators could enormously increase Weibo geo-tagged check-ins in a given neighborhood. Xia, Yeh, and Zhang (2020) declared that a high land use mix had a distribution pattern similar to the Dianping geo-tagged check-ins. Lu et al. (2019) summarized six categories of the built environment that were found to be closely related to human activities, i.e., urban density, function, accessibility, form, location, and landscape. In summary, the human activities represented by geo-tagged data are associated with many built environment components. However, few studies attempted to reveal the role of the built environment components in both physical space and virtual space, and compare their different performances.

3. Methodology

3.1. Study area and basic spatial unit

This study aimed to address the above research gap with Beijing's Fifth Ring Road as the study area, which is the core area of Beijing, covering approximately 710 km^2. This area has the highest population density and the largest proportion of job openings and economic, cultural, and recreational activities (Fig. 1). Streets, which were listed as one of five significant elements in Lynch's (1960) city images, are selected as our basic spatial unit for the affluence data and low effect of MAUP (Modifiable Areal Unit Problem) (Zhu, Wang, Wu, & Liu, 2017). In this study, 16,790 streets with street-level spatial data within the Fifth Ring Road were included.

3.2. Research design and models

Since our research focused on comparing visiting preferences of physical and virtual spaces, there were two dependent variables: VVAs and PVAs. The reference, built environment components were considered as independent variables. We built two groups of models to examine the associations and verify the robustness. In addition, we excluded the streets without VVAs or PVAs. In Model I, we built an

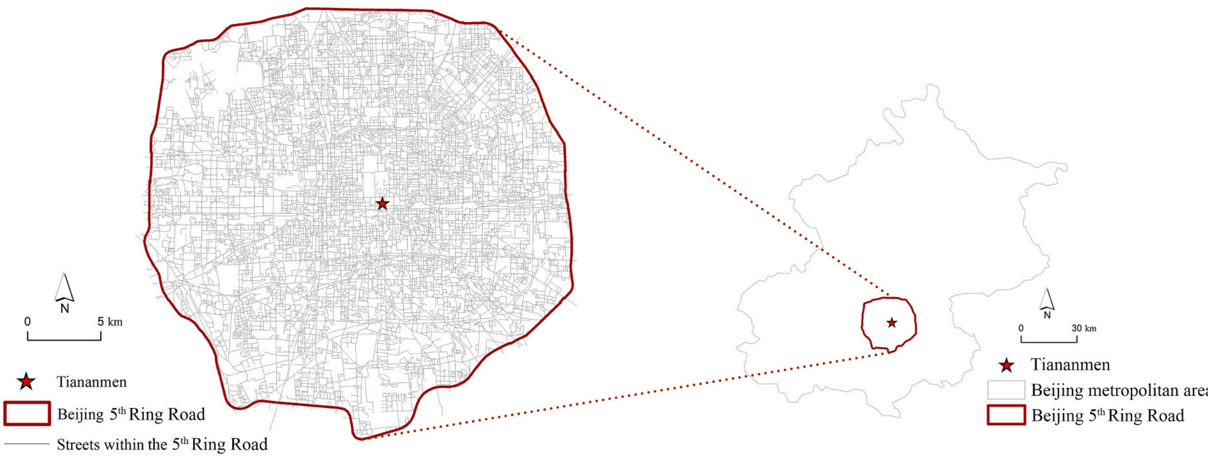

Fig. 1. The study area.

ordinary least squares (OLS) regression model for exploring the impact and explanatory power of the built environment components within the Fifth Ring Road. In Model II, we built two OLS regression models to further reveal and verify the results using different dependent variables and geographical areas.

The conceptual framework is shown in Fig. 2. The descriptions of

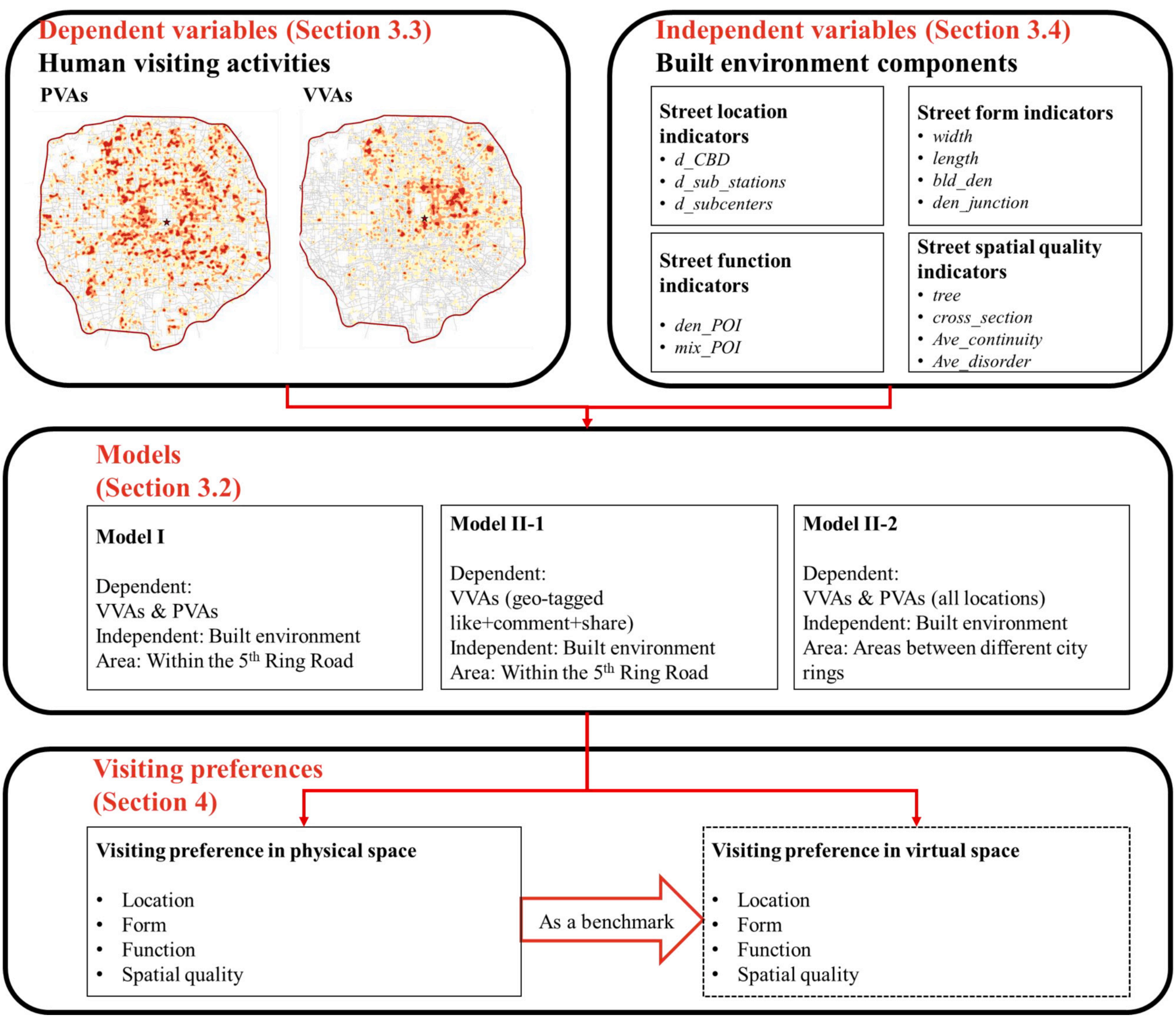

Fig. 2. Conceptual framework.

human visiting activities (dependent variables) and built environment (independent variables) would be respectively described in Section 3.3 and Section 3.4 in detail.

3.3. Dependent variables

TikTok is a significant, famous short video filming and sharing SMP worldwide, which can be used to create short dance, lip-sync, comedy, and talent videos. Based on our close cooperation with TikTok on the evaluation project of online and offline activities in Beijing, we acquired the anonymous TikTok filming locations for free but confidentially from Beijing Microlive Vision Technology Co., Ltd. in May 2019. For the ethical considerations, we need to declare that the anonymous locations were all open access, and five geo-tagged tags, including the quantities of geo-tagged video, views, likes, comments, and shares, were all user-generated. There were 201,600 filming locations within the Fifth Ring Road, and >30 billion videos were uploaded from these locations. Not all TikTok videos were uploaded with geo-tagged tags, implying that the location of geo-tagged videos is where users are willing to attach feelings to the videos.

We acquired the dependent variables through 4 steps (Fig. 3):

(1) 201,600 filming locations were identified within the Fifth Ring Road.
(2) A 50-meter buffer zone was generated for each street within the Fifth Ring Road.
(3) The filming locations within the buffer zones were calculated.

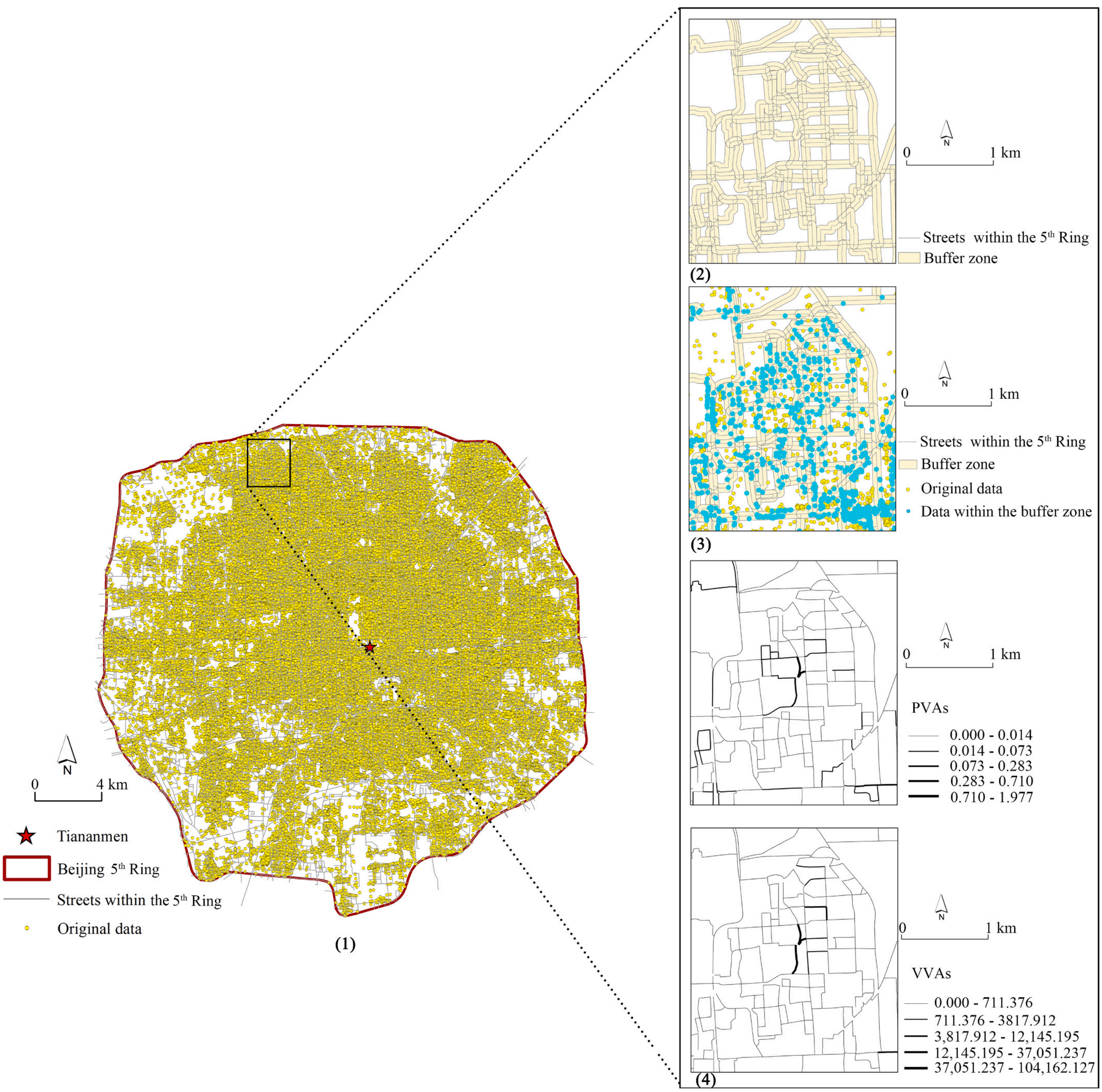

Fig. 3. Measurement process of dependent variables.

(4) Each street had values for virtual activities and physical activities. VVAs were calculated as the number of geo-tagged views, likes, comments, and shares per square meter within the 50-meter buffer of the street. PVAs were calculated as the number of geo-tagged videos per square meter within the 50-meter buffer of the street.

Furthermore, we conducted a kernel density estimation (KDE) of VVAs and PVAs at both POI and street levels (Fig. 4). The results displayed similar geographical distribution characteristics for each space across two levels. Higher densities of VVAs were clustered around the city centers in the northeastern part of the city, while higher densities of PVAs were relatively even across the city. The correlation between VVAs and PVAs at POI and street levels was also examined. The results were 0.826 at the street level, and 0.718 at the POI level, and both results were statistically significant at the 0.01 level. The strong correlations affirmed our choice of employing the built environment as a reference.

3.4. Independent variables

Since we tried to compare the spatial preferences between two visiting activities, we selected the built environment components that could promote visiting activities, including location, form, function, and spatial quality. All variables were measured at the street level to serve as a perfect scale to clarify the differences between VVAs and PVAs. The data for independent variables included Tencent street view images and GIS data of building footprints, road networks, and points of interest (POI) from Amap, the leading navigation company in China. The specific descriptions of independent variables are provided in Table 1.

4. Results

The logarithmic forms of VVAs, PVAs, and *den_POI* were calculated for the regression models to achieve normal distributions. Before the OLS regression, we used Pearson correlation, and variance inflation factor (VIF) tests to test the regression model's reliability and avoid multicollinearity effects. The correlation test results showed that the correlation coefficients between all independent variables were <0.8. According to the VIF test, the values for all the variables are <2. That means the multicollinearity of the model is not very severe, and the model is relatively reliable.

4.1. Model I regression results

Model I was conducted using OLS regression method to compare the effects of built environment components on VVAs and PVAs. The

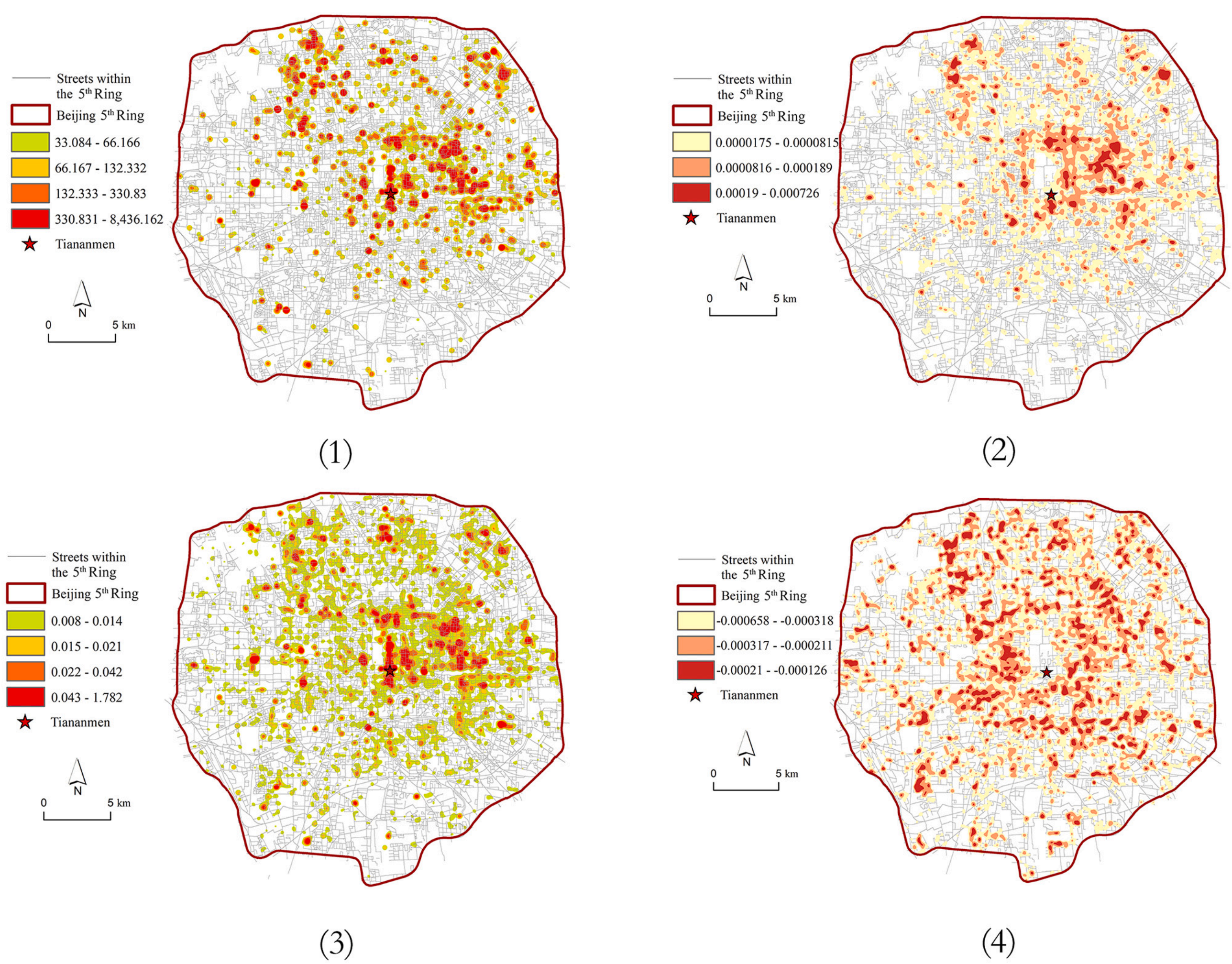

Fig. 4. KDE results of the virtual and physical visiting activities (VVAs and PVAs)
(1) KDE result for VVAs at the POI level
(2) KDE result for VVAs at the street level
(3) KDE result for PVAs at the POI level
(4) KDE result for PVAs at the street level

Table 1
Description of independent variables.

Name	Description	Data source	Min.	Max.	Mean	Std. deviation	Unit
Street location indicators							
d_CBD	The Euclidean distances from the midpoint of each street to CBD (the most prosperous business area in Beijing)	Amap	55.645	22425.351	10310.963	5124.622	m
d_sub_stations	The Euclidean distances from the midpoint of each street to the nearest subway station.	Amap	0.041	6295.862	981.393	860.538	m
d_subcenters	The Euclidean distances from the midpoint of each street to the nearest subcenters that were extracted from Huang, Liu, Zhao, and Zhao (2017), including Zhongguancun, Sanlitun, Wudaokou, Wangjing, etc.	Amap	5.527	12561.914	3764.345	2395.539	m
Street form indicators							
width	The width of each street segment.	Amap	2.000	78.000	35.297	18.707	m
length	The length of each street segment.	Amap	70.003	2948.729	248.947	181.192	m
bld_den	Number of buildings per square meter within 50-m buffer of the street	Amap	0.000	0.166	0.0230	0.00169	Buildings/ m^2
den_junctions	Number of junctions per square meter within 1-km buffer of the street junction	Amap	0.000	0.0000630	0.0000320	0.0000120	Junctions/ m^2
Street function indicators							
den_POI	Number of POIs per square meter within 50-m buffer of the street	Amap	0.000	0.0541	0.00207	0.00286	POIs/m^2
mix_POI	The POIs mix degree was calculated using the method of Liu and Long (2016).	Amap	0.000	2.553	1.447	0.633	–
Street quality indicators							
Tree	The street view images were acquired using the method of Tang and Long (2019). The data were also applied to calculate *Ave_disorder*. The average value of the tree proportions in all the street view images on the street.	Tencent map	0.000146	0.841	0.194	0.128	–
Ave_continuity	The average street wall continuity value of both sides of the street by using the method of Harvey, Aultman-Hall, Troy, and Hurley (2017).	Amap	0.000	0.996	0.335	0.232	–
cross_section	The average cross-sectional proportion value of both sides of the street using the method of Harvey et al. (2017). Considering that cross-sectional proportions (width/height) between 1 and 2 are ideal in the urban design rules according to Ashihara (1983), we converted the cross_section to a binary variable, where the ratio between the ideal range was converted to 1, and the other scale values were converted to 0.	Amap	0.000	25.500	0.378	0.556	–
Ave_disorder	The spatial disorder would result in the decline of neighborhoods (Grubesic, Wallace, Chamberlain, & Nelson, 2018). Thus, we introduced a platform for three people to manually measure the degree of spatial disorder by using the four-direction street view images. The system included five main categories of indicators for evaluating the built environment: residential, commercial, environment, road, and other infrastructure. There were also 19 secondary categories under the five categories. Each street-level spatial disorder score was the average value of the manually evaluated scores for all observation points on the corresponding street (Chen & Long, 2021).	Tencent map	0.000	31.500	2.311	3.531	–

coefficients in the regression results below were standardized; the bolded variables were statistically significant (<0.05) (Table 2 and Fig. 5).

4.1.1. *The built environment had a stronger explanatory value for urban PVAs (R^2 0.313) than VVAs (R^2 0.269)*

Video producers may be inspired by surrounding built environment components to record and upload their geo-tagged video, but video consumers expressed their attitudes based on the perception they formed from the built environment in the video image. The indirect perception pattern may contribute VVAs to presenting a weaker but approximate association. The results confirmed the previous theories (Castells, 1996; Castells, 2004; Zook, 2008) that virtual space cannot be detached from a physical space with a well-defined social culture, physical environment, and functional characteristics. However, even for PVAs, their explanatory power (R^2) was not as high as in most studies found in the literature review. This result may be attributed to the fact that the visiting activities were caused by the filming locations as well as by the people and their behavior presented in the video.

4.1.2. *Landmarks, urban nodes, and main roads had more influential power in virtual space*

As to the location indicators, all the regression coefficients for VVAs were higher than those for PVAs, especially for CBD. Simply put, people in virtual space were more interested in the landmarks, which might be attributed to breaking through geographical limitations (top-down browsing mode provided easy access to those places). Landmarks are places that people are more likely to think of first, which indicated that an increased search frequency for the names of landmarks or nodes influenced the increased browsing of videos filmed at their surrounding locations in the physical world. Meanwhile, the videos taken around landmarks may include distinctive urban landscapes; thus, the favor of people towards these locations could be influenced by the effect of the landmarks' images.

For the form indicators, three indicators—*width*, *length,* and *den_-juctions*—had higher coefficients in the VVAs regression. A long and wide street surrounded by a higher street junction density indicates that the street is the main road rather than a road far from city centers or subcenters. Similar to the location indicators, these streets are more visible and familiar.

Table 2
Regression coefficients for the area within the Fifth Ring Road.

Model I	Variables	VVAs	PVAs
Location indicators	*d_cbd*	**−0.140*****	**−0.097*****
	d_sub_stations	**−0.065*****	**−0.055*****
	d_subcenters	**−0.016****	0.002
Form indicators	*width*	**0.029*****	**0.018****
	length	**0.063*****	−0.006
	bld_den	0.007	**0.032****
	den_junctions	**0.029****	−0.003
Function indicators	*Ln(den_poi)*	**0.328*****	**0.334*****
	mix_poi	**0.086*****	**0.146*****
Spatial quality indicators	*tree*	**0.021****	0.010
	Ave_continuity	**0.076*****	**0.100*****
	cross_section	**0.015****	**0.018****
	Ave_disorder	**−0.058*****	**−0.039*****
	N	14,876	14,876
	Adjusted R^2	0.269	0.313

Notes: All coefficients have been standardized for cross comparison, and coefficients in bold indicate significance at the 0.05 level. *, **, and *** refer to significance levels for the two-tailed tests at $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively. These notes also apply to the following tables.

4.1.3. The functional mix level that might be distinctly perceived from the truth could be far less critical in virtual space

For the function variables, *Ln (den_POI)* was of roughly equal significance for both VVAs and PVAs, and their coefficients were much higher than that of *mix_POI*. Surprisingly, the coefficient of *mix_POI* in the VVAs regression was much lower. The advantages of a high functional use mix include promoting active traveling and forming a community sense within the physical space (Song, Merlin, & Rodriguez, 2013), thereby stimulating visiting activities. However, the functional diversity was relatively an abstract concept, as a mismatch existed between the object and perceived land use mix (Gebel, Bauman, Sugiyama, & Owen, 2011). That means the functional diversity complicates users' ability to build perception from video images and is thus less beneficial for increasing VVAs.

4.1.4. The more visually apparent factors that could affect spatial quality may be more important in virtual space

For the spatial quality variables, two variables, *tree,* and *Ave_disorder*, were with higher coefficients in the VVAs regression, which were directly measured from the images and could be presented on the video. On the contrary, Ave_continuity and cross_section had lower coefficients in the VVAs regression. These two variables could be perceived from the video images, but not in a direct way, as they were three-dimensional variables, and the perception required extra reflections.

4.2. Model II regression results

As there could be potential biases in solely looking at the results of Model I, we also examined other dependents (Model II-1) and at other geographical areas (Model II-2). Since geo-tagged likes, comments, and shares more represented the positive attitude than geo-tagged browsing, we excluded the quantities of geo-tagged browsing from VVAs. Fig. 6 showed that most results of Model II-1 were consistent with the results of the VVAs regression in Model I, and the R^2 was 0.257. Thus, we can confirm the accuracy of the VVAs regression of Model I.

To further verify the visiting preference in virtual space, we conducted a series of OLS regression models (Model II-2) using the geographical areas between four city ring roads as our research areas. The results suggested that the image of urban districts could be reflected in virtual space. Table 3 presented that the explanatory power of every PVAs model was higher than that of the VVAs model. Except for VVAs regression between the 3rd and 4th Rings, all the R^2 gradually decreased as the research area moved to the urban periphery, presenting an apparent concentric pattern, which indicated that visiting activities were more associated with the built environment at central areas in both virtual and physical spaces. Fig. 7 demonstrated that the overall preference for VVAs and PVAs was consistent across most geographical areas in Beijing. However, there were similar particular performances in VVAs and PVAs for the area within the 2nd Ring Road, the historical area of Beijing built in the Ming and Qing Dynasties, which could be attributed to the special urban morphology.

5. Conclusions and discussion

5.1. Conclusions

Currently, virtual space hosted by SMPs has become a prominent place for users to interact with people and the world. In this context, why people visit a place in virtual space becomes a crucial issue for specifying the new spatiality of virtual space and benefiting the future development of both virtual and physical-virtual integrated spaces. We aim to address this issue by analyzing the spatial preferences of human visiting activities in virtual space and comparing them with those in physical space.

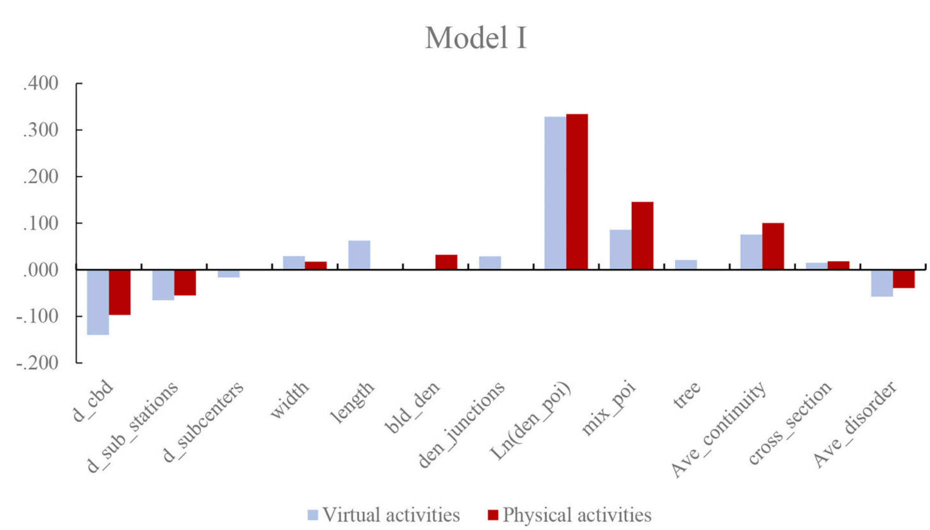

Fig. 5. Regression coefficients for Model I.
Notes: All coefficients were standardized for cross comparison, and variables not statistically significant are not presented in the figure. These notes also apply to the following figures.

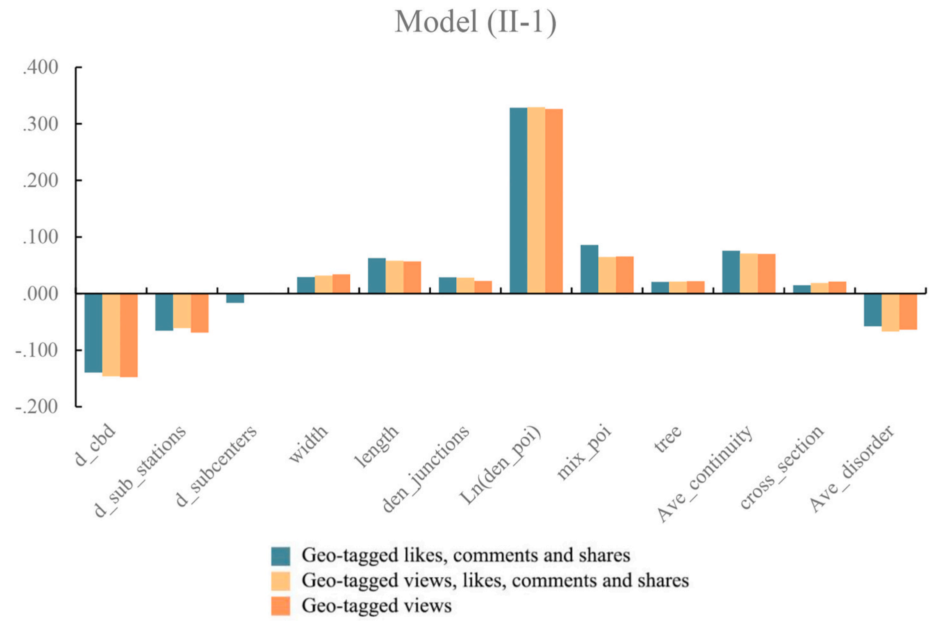

Fig. 6. Regression coefficients for Model II-1.

Table 3
The statistical descriptions for Model II-2.

Dimension	Dependent variable	N	Adjusted R^2
VVAs	Within 2nd Ring	2283	0.286
	2^{nd}_3^{rd}	3136	0.259
	3^{rd}_4^{th}	3465	0.227
	4^{th}_5^{th}	5992	0.251
PVAs	Within 2^{nd} Ring	2283	0.330
	2^{nd}_3^{rd}	3136	0.324
	3^{rd}_4^{th}	3465	0.302
	4^{th}_5^{th}	5992	0.265

TikTok, a popular video-sharing SMP with geo-tagged data generated from both virtual space and corresponding physical space, offered us a valuable spatial dataset enabling us to comprehensively and comparatively investigate visiting preference in virtual space. Our findings are summarized as follows.

First, the VVAs are less associated with the built environment than PVAs, which might be attributed to the indirect perception of physical elements for VVAs. However, the close association between these two human visiting activities also clarifies that virtual space is not detached from physical space. Some elements have similar performance in both spaces; for example, improving functional density is the most efficient way to promote visiting activities. Second, the role of some markable components, which can shape impressive public city image in the real world, such as landmarks, urban nodes, and main roads, is dramatically enhanced by the social network in virtual space. It might be because the top-down exploratory mode flattened distance and broke the geographical limit. Functional diversity, which people could generate mismatched perception in an unfamiliar physical place but has an important purpose, could be far less critical in virtual space. The difficulty of perceiving the diversity of functions in virtual space through the visual medium might be one reason for explaining the result. The components that affect the spatial quality and could be directly seen and perceived in the video may impact visiting activities in virtual space. Finally, the images of urban districts are typically reflected in virtual space, thus further suggesting the inseparable relationship between virtual and physical space.

5.2. Theoretical contributions and potential applications

We differentiated and depicted VVAs and PVAs by introducing appropriate datasets. SMPs geo-tagged data appear in various forms, such as geo-tagged videos, check-ins, and comments, which could be considered interactions between VVAs and PVAs. Nevertheless, most of the data in the existing research comes from the active uploader, showing the willingness of people to share a specific place, which can be used to reflect the preference for PVAs. In this study, five geo-tagged tags embedded in TikTok data were categorized into PVAs and VVAs for further comparing their associations with built environment components. Specifically, the filming (bottom-up content production) based on users' personal experience in physical space was used to measure PVAs. The other four tags - views, likes, comments, and shares (top-down content consumption)- influenced by the contents presented in virtual space, were used to depict VVAs.

Our conclusions could somehow reveal how humans build perception from the urban built environment in virtual space, as human activities are conducted based on the mental representations of certain places (Santos et al., 2009). The urban built environment is one of the most critical environments shaping humans' psychological images of cities. For example, people's perception of safety in the urban built environment has long been emphasized in public health, where its association with crime and walking perspectives was discussed (Cho, Rodríguez, & Khattak, 2009; Hong & Chen, 2014). Our findings indicated that people could build a perception of urban environments from more visually apparent components. It is hard for them to perceive the intangible meanings embedded in the environment, which may explain why visiting activities present a more aggregated distribution pattern in virtual space.

Our conclusions respond and complement The Image of City theory proposed by Kevin Lynch (1960). The theory is related to forming a mental image from the physical urban environment, i.e., conceptualizing a city image as a combination of five distinct built environment elements: paths, edges, districts, nodes, and landmarks. A recent study (Huang et al., 2021) clarified that "districts", "landmarks", and "paths" in citizens' perceptions summarized from the virtual world were similar to those in the real world in Poland, which is also consistent with our findings. In virtual space, the geographic scopes of districts match those in physical space, landmarks are identical with those in physical space

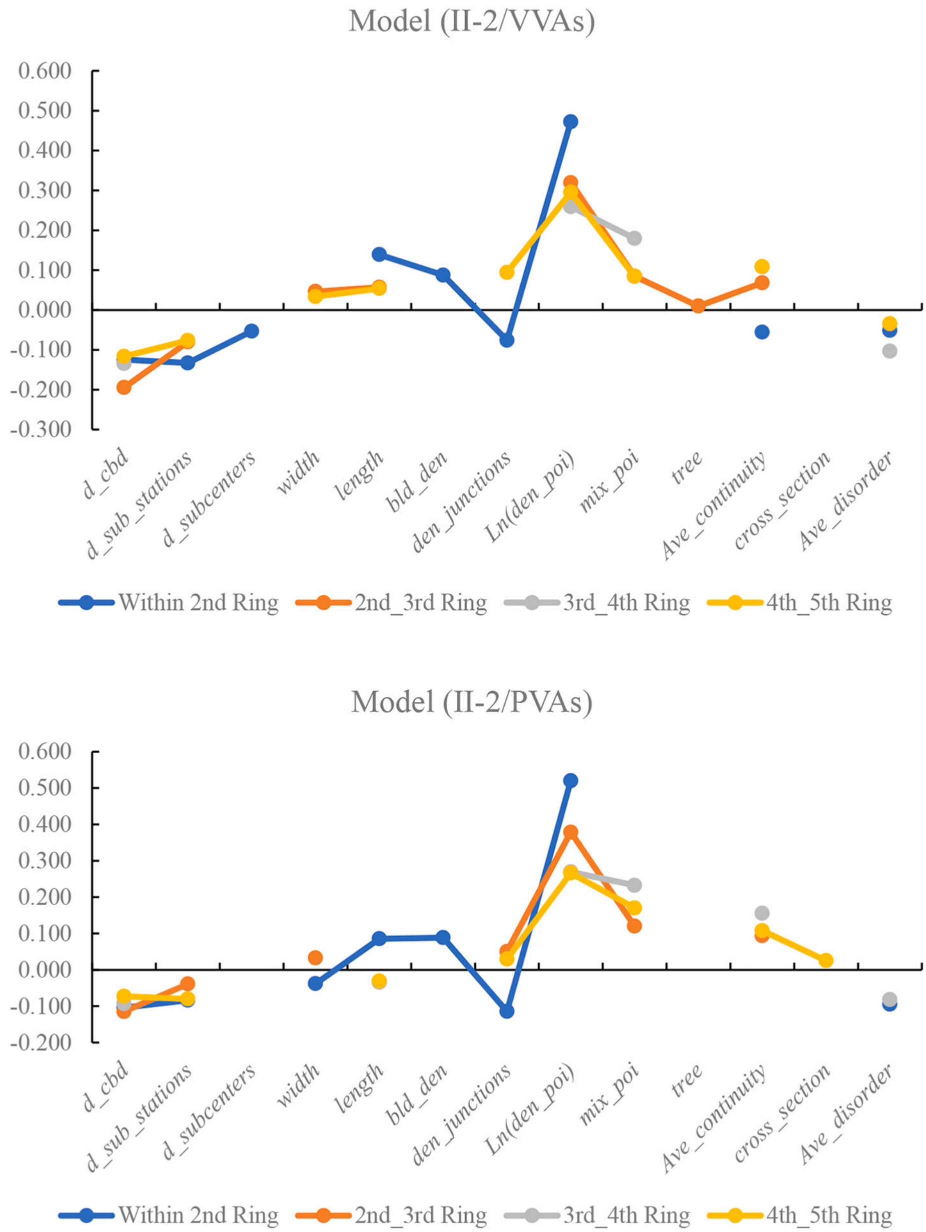

Fig. 7. Regression coefficients for Model II-2.

and with more influential power, and streets have similar levels of visiting activities to those in physical space. In addition, our findings regarding landmarks statistically confirm the *Familiarity* component in virtual space and place theory (Saunders et al., 2011), which proposed that familiarity (e.g., knowing a place name and having observed, visited, or passed by the place frequently) stimulates the experience of presence that fosters the illusion of a place.

Based on our findings, we can take advantage of the associations between VVAs and PVAs to operate and manage human distribution and aggregation in both spaces. For instance, by encouraging users to publish videos of some places to shift people's attention to certain places in virtual space, we can enhance their impressions and, in turn, increase the opportunities for them to visit corresponding places in physical space. Conversely, if a store wants to gain more attention online, it could choose a proper physical location in the city, such as the main road near the city center or the subcenter, or a long and wide street with numerous similar stores.

Moreover, our findings could enlighten the future development of Metaverse and its infrastructure digital twins. Metaverse, initially defined by Neal Stephenson (Stephenson, 1992), is an iteration of the internet, a world of interconnected virtual communities where people can meet, work, and play. Our findings suggested that the future development of Metaverse should enhance the shaping of landmarks and famous places due to more visiting activities performed there. Important built environment components in the central area should be expressed in detail, such as the names, street infrastructures, and real-time information of essential roads and buildings. The functional facilities could be displayed in points, with different functional categories denoted by different colors.

5.3. Potential bias and future directions

There are limitations in this research framework that require further exploration in future studies. First, a proportion of geo-tagged videos browsed by users were pushed by the recommendation system of TikTok other than spontaneous choice, which is not entirely consistent with the naturalist visiting process in physical space. However, we excluded geo-tagged browsing from VVAs in model II-2 to largely eliminate its impact.

Second, although there might be a delay between users' filming and uploading time, the findings from our study are still convincing. Because users can select the location where they are filmed when uploading their videos, even if they are no longer there. Third, this research was limited to the filming locations and quantities of five types of geo-tagged data. The human activities are not only attracted by the urban places or the built environment. Future studies can obtain the locations where users browse, like, comment, and share videos and explore more information extracted from videos, images, or texts to conduct in-depth research. Finally, our dataset was mainly formed by Chinese users, and there might be potential differences between user behaviors on Douyin versus the international version of TikTok. In the future, we hope that more empirical studies will be conducted using the dataset from the international version of TikTok.

CRediT authorship contribution statement

Yuyang Zhang: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Yan Li:** Conceptualization, Writing – review & editing. **Enjia Zhang:** Conceptualization, Writing – review & editing. **Ying Long:** Conceptualization, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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