The Spatial Dynamics of Cafés as Everyday Urban Spaces: Exploring Socialscapes through Streetscapes

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Abstract
Cafés have emerged as vital cultural and social anchors in contemporary cities, increasingly located in alleyways and residential neighbourhoods rather than traditional commercial centres. Focusing on Seoul's Hongdae district, this study uses semantic segmentation and deep learning applied to Street View Images to examine how streetscape attributes—both visual (e.g. enclosure, openness) and perceptual (e.g. liveliness, beauty)—influence café location patterns. Results reveal a shift away from conventional accessibility-based location towards environments that offer sensory richness and walkable appeal. These findings underscore the evolving role of cafés as everyday cultural spaces shaped by experiential consumption and image-based sharing. Accordingly, urban planners should consider streetscapes as active elements of lived heritage and place identity, rather than passive infrastructure.

1.Introduction

Modern consumer culture has expanded beyond the consumption of goods to encompass the commodification of space, emphasising the image and aesthetic distinctiveness of retail environments. Brands have adopted experience-oriented retail strategies, such as flagship stores and pop-up stores, or employed omni-channel approaches that integrate online and offline platforms. Offline stores, in particular, are being restructured as spaces where consumers can engage with brand identity and share their experiences with others. These experience-centred spaces have become a key foundation for consumer engagement, enabling them to share information through online communities or social network services (SNS), and visit cafés based on recommendations from others. Furthermore, location-based information on social media enables consumers to indirectly experience places they have not yet visited (Yuksel et al., 2016), thereby influencing their spatial preferences and consumption behaviour. In South Korea, retailers are making strategic location decisions that prioritise residential neighbourhoods over commercial centres, largely due to lower rents and improved access to spatial information. This tendency reflects a growing interest in individual consumer preferences, sense of place, and spatial experiences. Previously overlooked places and cafés have started to attract attention from consumers. Some of these areas—though not originally designed as commercial zones—are gradually recognised as commercial spaces, while others actively contribute to enhancing the perceived attractiveness of their surrounding urban space.

Among business sectors, the food and beverage (F&B) industry—particularly cafés, restaurants, and pubs—clearly exemplifies these spatial and cultural shifts. Cafés, in particular, are relatively easy to open with limited capital and preparation time, and are perceived as carrying lower risks compared to other food-related businesses, leading to greater locational flexibility. Moreover, as the millennial generation increasingly values experience and social sharing (Ryu et al., 2022), cafés are gaining recognition as places for unique experiences and social interaction. In South Korea, the café industry has expanded rapidly since the entry of the global franchise Starbucks in 1999. In Seoul, the number of operating cafés doubled from 8,638 in 2010 to 17,721 in 2019, making it one of the most active sectors for new business openings. Additionally, cafés are often among the first establishments to enter neighbourhoods undergoing a commercialisation process—including those associated with gentrification—and are known to attract external visitors, thereby demonstrating pronounced shifts in spatial distribution. With their rapid proliferation and flexible locational behaviour, cafés have thus played a leading role in shaping new commercial geographies across urban space.

While geographic location remains an important factor in retail location decisions, cafés have recently demonstrated patterns that diverge from traditional retail location models. In the past, cafés were typically concentrated in areas with high physical accessibility, such as near subway stations or along major boulevards. In contrast, newly opened cafés tend to be smaller in scale and more locally situated. Unlike conventional stores, these cafés position themselves as places offering distinctive experiences, enabling consumers to perceive their surroundings as unique and appealing, thereby overcoming less favourable locational conditions. This phenomenon is difficult to explain using traditional retail location theories, such as Christaller's (1933) central place theory, which suggests that new spatial patterns may emerge—patterns that are not solely based on conventional economic-geographic factors such as accessibility, land price, agglomeration, or population density, but are instead shaped by changing consumer behaviours. However, most of the previous literature on café locations has focused on these traditional indicators (Gautama Himawan and Rahadi, 2020; Kim et al., 2015; Ko and Chiu, 2006; Sevtsuk, 2014; Zhao et al., 2023), often overlooking the influence of experiential attributes and visual appeal on location decisions.

In urban space, cafés have established themselves not merely as providers of food and beverages, but as everyday places of social and cultural interaction. They serve as places for optional activities (Gehl, 2013), and contribute to the vitality of public space (MacCormac, 1983). Zukin (1998) interpreted cafés not as simple consumption spaces, but as symbolic places that represent a new form of urban lifestyle. Similarly, Banerjee (2001) argued that public life becomes more enriched in third places such as cafés. According to Oldenburg (1999), third places refer to diverse public spaces beyond the domains of home and work, where people voluntarily and informally gather with the expectation of enjoyment. In South Korea, cafés have become representative examples of spatial consumption, functioning not as venues for the physical acquisition of goods at a specific moment in time, but as experiential places consumed and possessed through use. In this sense, cafés enable consumers to indirectly express their personal tastes and lifestyles through experiential consumption. Increasingly, people visit cafés not for the products themselves, but for the atmosphere of the surrounding area or the store. Ultimately, consumers have come to pay attention not only to the physical attributes of a place, but also to the emotional atmosphere and image it conveys.

Pedestrians' perceptions of place are shaped by the physical environment of the streetscape and the interactions among individual storefronts. Environmental elements that constitute the street function as part of the service setting that supports better customer experiences and contributes to the overall atmosphere of a café. At the same time, they offer personalised experiential spaces, allowing consumers to perceive a distinctive and appealing ambiance. A favourable service environment experienced at the time of use can trigger consumer behaviour and enhance customer satisfaction (Koo et al., 2023b). This, in turn, can attract potential customers, making it essential to understand the role of streetscape and walkability in shaping the attractiveness of commercial spaces in relation to café locations. Accordingly, this study examines the spatial dynamics of café location shifts in an area where traditional and emerging retail districts coexist, and analyses the influence of streetscape and walkability. Furthermore, it aims to assess the limitations of traditional theories in explaining café location decisions and to explore the evolving role of cafés in urban space.

The structure of this study is as follows. Section 2 reviews the relevant literature and theoretical background. Section 3 outlines the study area, data, and methodology. Section 4 presents the spatial patterns and influencing factors of café location shifts. Section 5 discusses the empirical findings, and Section 6 concludes the study.

2.Literature review

2.1.Retail location theories

Traditional retail location theories assume that retailers make location decisions that minimise transportation costs for consumers while maximising proximity to both competing and complementary stores. For example, Christaller (1933), in his central-place theory, posited that each retail store is equidistant from others selling the same goods and that stores offering more diverse products possess market areas of varying sizes. Later, Lösch (1938) modified this framework by excluding the concept of product range and instead focusing on the minimum market area required to maximise production value. In contrast, Hillier (1997) introduced the concept of movement in his movement-economic theory, emphasising that the fundamental logic of urban structure lies in movement itself. Ultimately, he emphasised that spatial advantages—such as streets with high pedestrian or vehicular traffic—are inherently more valuable.

More recently, the rising rents that often accompany commercial revitalisation have driven retailers to make location decisions in areas with relatively lower physical accessibility to reduce operational costs. In this context, producers increasingly choose locations with lower rents compared to commercial centres, thereby seeking greater economic efficiency. From this perspective, Smith (1979) proposed the rent-gap theory, suggesting that commercialisation occurs when disparities in rent emerge, even among areas with similar accessibility. Ley (1997), on the other hand, argued that when artists move into low-rent areas, they foster a consumption culture centred on aesthetic value.

Today, retail locations are increasingly chosen by consumers based not only on convenience but also on the unique characteristics of a district and the physical environment and atmosphere surrounding the store. Walkable streets provide positive sensory stimuli, contributing to more enjoyable and satisfying service experiences (Koo et al., 2023b). Building on this idea, Bitner (1992) introduced the concept of the 'servicescape', combining service and landscape to describe the physical environment in which the service experience takes place. The servicescape includes both the interior and exterior of a facility, as well as its surroundings, allowing consumers to indirectly perceive service quality and product value even prior to direct service engagement (Turley and Milliman, 2000).

2.2.Walkability and retail location

The built environment of a retail district plays a crucial role in attracting potential consumers, making walkability a key factor in determining the location and operation of retailers (Duncum, 2007; Handy et al., 2002). Streets serve not only as corridors for movement but also as social spaces that connect buildings and human activities (Carmona, 2021). Streets with high connectivity or those designed to encourage pedestrian movement tend to experience greater levels of foot traffic, which in turn contributes to drawing potential consumers (Sevtsuk, 2020).

Previous studies examining the built environment of retail districts from a street network perspective have employed Urban Network Analysis (UNA) to demonstrate that street-level accessibility and connectivity significantly influence the location and performance of retailers (Jeong and Yoon, 2017; Kang, 2016; Sevtsuk, 2014). For example, Sevtsuk (2014) analysed pedestrian accessibility from surrounding facilities and highlighted the importance of network-based measures such as the gravity index for public transit and building-level expected betweenness. Kang (2016) demonstrated that in pedestrian accessibility, betweenness and straightness are key predictors of retail sales in Seoul. From the perspective of urban spatial structure, Harvey et al. (2017) investigated cities such as Boston, New York, and Baltimore to explore how built features—such as street width and length—can be used to evaluate streetscape structure. Streetscapes enclosed by buildings or walls were found to contribute to perceived safety and imageability, offering more immediate stimuli for pedestrians and enhancing the effect of visual complexity.

2.3.Streetscape and retail location

Most literature on streetscape and retail location has primarily measured walkability from the perspective of pedestrian accessibility. However, walkability extends beyond accessibility to encompass pedestrians' perceived safety, aesthetic quality, and enjoyment of the environment at the landscape level (Koo et al., 2023b; Shields and Gomes da Silva, 2023). The architectural organisation of streetscape influences how pedestrians experience and perceive the space, contributing to increased safety, comfort, and enjoyment. Specifically, previous studies have assessed streetscape characteristics based on elements such as enclosure (Ewing and Handy, 2009; Harvey et al., 2017), openness (Ewing et al., 2013), and greenery (Li et al., 2018; Zhang et al., 2018). These micro-scale streetscape characteristics of walkability directly or indirectly influence pedestrian perception and emotion, shaping a human-scale environment that supports commercial activity by enhancing pedestrians' feelings of safety and comfort (Hahm et al., 2019). In previous literature, these features have been quantified through two-dimensional GIS-based analyses or extracted from street-level images using qualitative methods to identify visual factors (Ewing et al., 2006; Harvey et al., 2017; Hong et al., 2010; Purciel et al., 2009).

More recently, urban planning research has increasingly turned to machine learning techniques using street-level imagery, such as Google Street View, to estimate walkable environments from a human-eye perspective. Compared to two-dimensional GIS-based methods, Street View Images (SVIs) provide a more accurate representation of the built environment as it is experienced by pedestrians (Koo et al., 2022). For example, several studies have used semantic segmentation techniques to identify visual components of the streetscape from the perspective of pedestrian perception (Kim and Woo, 2022; Koo et al., 2023a; Lee et al., 2022). Common models include PSPNet, UPerNet, and HRNet, which have been applied in various studies to classify fine-grained visual features of the street environment. Furthermore, Dubey et al. (2016) proposed a Convolutional Neural Network (CNN)-based deep learning model that predicts six emotional responses to urban environments using the Place Pulse 2.0 dataset provided by MIT. This dataset contains 110,998 images collected from 56 cities across 28 countries and includes over 1.17 million pairwise comparisons evaluating six dimensions of perceived streetscape quality: Safe, Lively, Beautiful, Wealthy, Depressing, and Boring (Figure 1). Using this dataset, it becomes possible to identify how different SVIs elicit varying perceptions among pedestrians. In addition, Zhang et al. (2018) developed a deep learning model to predict emotional responses to streetscapes in specific study areas such as Beijing and

Shanghai. They examined the relationship between qualitative perceptual evaluations derived from image-based predictions and quantitative visual attributes obtained through semantic segmentation.

Figure 1. Example of Place Pulse 2.0 data collection

2.4.Café location

Cafés have been considered both spaces for community engagement (Ferreira et al., 2021) and indicators of gentrification (Zukin et al., 2009). Accordingly, previous studies on café locations have primarily focused on factors related to business performance, such as accessibility, economic viability, competitiveness, demographic characteristics, and store characteristics (Gautama Himawan and Rahadi, 2020; Kim et al., 2015; Ko and Chiu, 2006; Sevtsuk, 2014; Zhao et al., 2023). Table 1 provides an overview of these studies.

Table 1. Literature on café locations

Authors (Year)	Key variables	Findings related to location
Ko and Chiu (2006)	Accessibility, Physical characteristics	Key factors influencing customer satisfaction, ranking professional service, reasonable pricing, food quality, environment, other food drink, and promotion.
Sevtsuk (2014)	Accessibility, Competitions, Demographics, Store characteristics	Spatial clustering is a key determinant of retail location patterns, with restaurants exhibiting a tendency to be situated near similar stores. Additionally, proximity to subway stations is a significant positive factor influencing the store's location.
Kim et al. (2015)	Accessibility, Economic conditions, Competitions, Demographics, Store characteristics	Retail sales benefit from closer proximity to subway stations and a higher density of similar stores. Higher sales are observed in locations with lower footprint area but greater building volume.
Gautama Himawan and Rahadi (2020)	Accessibility, Physical characteristics	The built environment and ambiance of a café strongly influence customer satisfaction and revisit intention. Location and accessibility are critical factors in customers' choice of a particular café.
Zhao et al. (2023)	Accessibility, Economic conditions, Competitions	In Beijing's major urban centres, cafés tend to cluster in central business districts or along high streets.

However, today's consumers are increasingly willing to visit cafés with a desirable atmosphere, even if the locations are not physically accessible. As a result, the widespread use of digital platforms such as social media has brought about noticeable shifts in location patterns, even for stores situated outside traditionally optimal areas. Based on these insights, this study aims to examine how micro-scale environmental factors enhance the perceptual quality of streetscape while simultaneously making the pedestrian experience more enjoyable. In particular, aesthetic streetscapes increase the attractiveness of the walking experience and thus play a critical role in encouraging pedestrian flows. Given that such flows often translate into consumer footfall, it is essential to investigate how walkable and visually distinctive streetscapes are associated with café location decisions.

Accordingly, this study explores the shifting patterns of café locations and investigates the role of streetscape and walkability in this process. Specifically, it employs a deep learning model to objectively evaluate physical streetscape conditions while also incorporating subjective pedestrian perceptions. By analysing new patterns in café locations, this study contributes to understanding not only the spatial transformation of retail districts and urban form but also the socio-cultural shifts driven by experiential consumption.

3.Methodology

3.1.Study area

This study focuses on the Hongdae retail district, one of the major commercial centres in Seoul, South Korea (Figure 2). The study area encompasses seven administrative districts (dong): Seogyo-dong, Seogang-dong, Hapjeong-dong, Mangwon-1-dong, Mangwon-2-dong, Seongsan-1-dong, and Yeonnam-dong. The term 'Hongdae' refers to the area surrounding Hongik University, which has developed into a central retail district around the campus. Covering an area of 8.15 km², the district includes six subway stations along two lines: Hongik University, Hapjeong, Mapo-gu Office, Mangwon, Sangsu, and Gwangheungchang. The district is characterised by human-scale streetscapes and a mixture of residential and commercial zones, which allows for the observation of retail activity not only within designated commercial zones but also in adjacent residential zones.

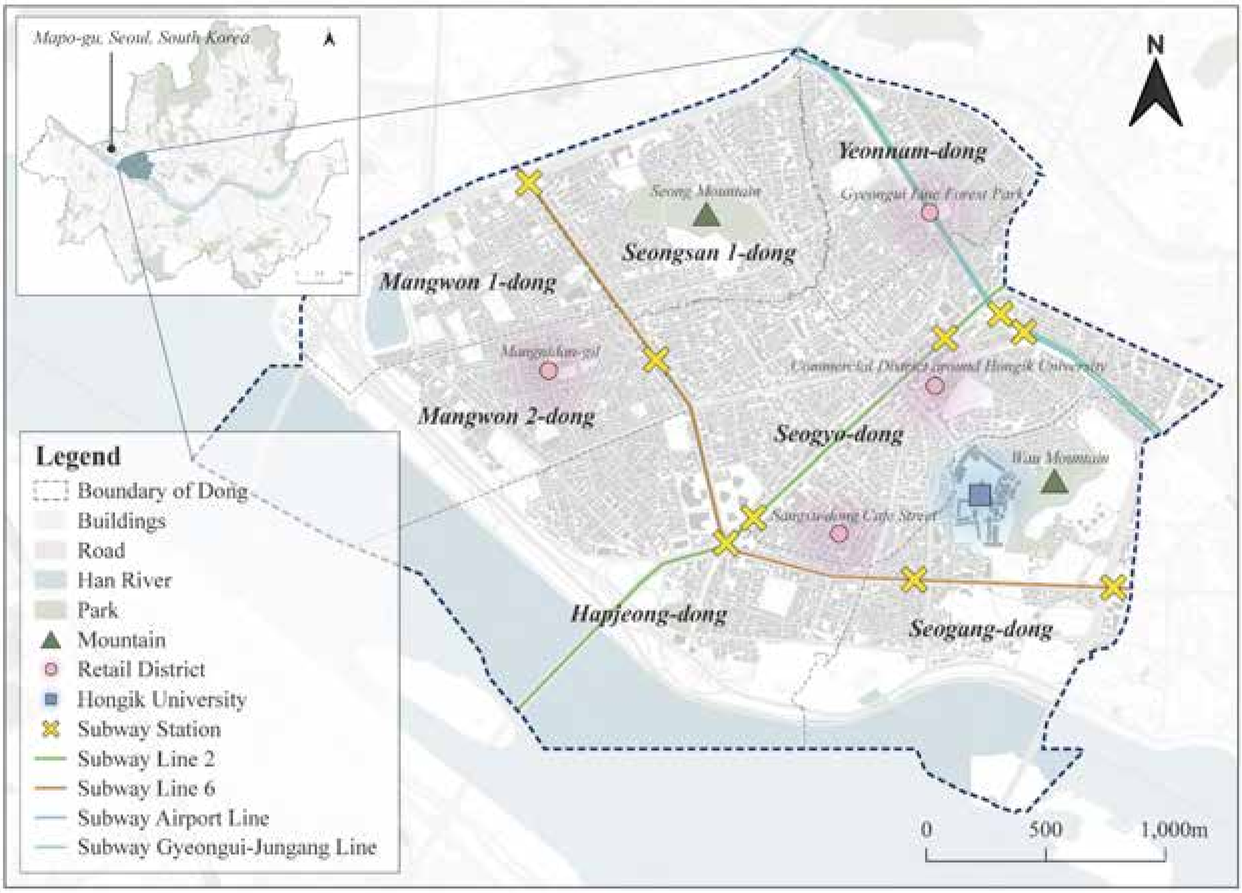

Figure 2. Study area

The Hongdae retail district began to take shape in 1955 with the establishment of the College of Fine Arts at Hongik University. As studios and galleries catering to art students began to cluster in the area, it gradually evolved into a culturally significant street. Over time, the area experienced continued retail growth as small shops became concentrated, and commercial businesses gradually penetrated residential zones, giving rise to newly developed retail districts (Hahm et al., 2017).

In the 2000s, foot traffic increased significantly due to two major factors: the 2002 Korea–Japan World Cup and the implementation of the Walkable Street Development Project, part of the broader Street Environment Improvement Project. These developments led to an influx of cafés, pubs, and restaurants into the university-centred retail district, solidifying its position as a central commercial district. In the early 2010s, the opening of new subway lines such as the Incheon Airport Railroad and Gyeongui Line improved accessibility from other cities such as Incheon and Gimpo. As a result, the area experienced gentrification driven by rising rents, which forced many young artists to relocate to nearby neighbourhoods such as Hapjeong-dong. This migration led to the emergence of new street-level retail districts, such as the so-called 'Sangsu-dong Café Street'.

In 2015, the Gyeongui Line Forest Park, an urban regeneration project that transformed an abandoned railway line into a linear park, was completed near Yeonnam-dong. It has been popularly dubbed 'Yeontral Park'—a reference to New York City's Central Park—due to its central location and the perceived improvement it brought to the surrounding residential and retail environment. The development of this green space contributed to another wave of retail expansion along the park corridor. That same year, the Beautiful Signage Street Project, a signage improvement initiative, was implemented to enhance the visual aesthetics of streets near the retail district. In 2016, the western part of Mangwon-dong—adjacent to the Mangwon Market—gained popularity and has been labelled as 'Mangnidan-gil'. The name was inspired by Gyeongnidan-gil, a well-known street-level retail district in South Korea. As the area attracted increasing attention on social media, it began to emerge as a new hotspot for younger consumers and independent retailers.

More recently, the broader Hongdae retail district has seen a rapid increase in foreign visitors, prompting the launch of the Cultural Tourism Destination Development Project for Walkable Street, a tourism initiative aimed at enhancing pedestrian-friendly cultural attractions. Figure 3 illustrates the spatial transformation of the study area over time.

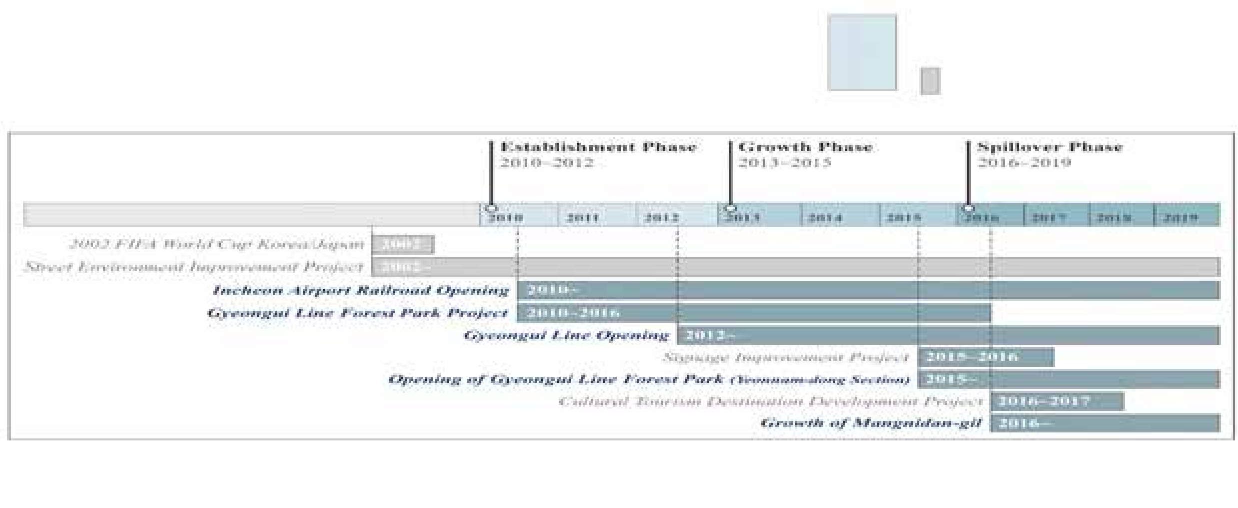

Figure 3. Evolution of study area

3.2.Definition of analysis periods

Due to limitations in the availability of SVIs prior to 2010, and in order to exclude the economic disruptions caused by COVID-19, the temporal scope of the analysis was set from 2010 to 2019. To examine the spatial shifts in café locations, it was necessary to define specific phases that reflect the evolution of spatial and commercial dynamics. This periodisation also helps to control for potential outliers in the annual opening data of cafés.

Based on the evolution of the Hongdae retail district, the study defines three distinct analytical phases. The Establishment Phase (2010–2012) corresponds to the initial formation of café clusters centred in Seogyo-dong, adjacent to Hongik University. The Growth Phase (2013–2015) is characterised by spatial expansion into surrounding areas along the edge of the core, while the Spillover Phase (2016–2019) captures the transformation of retail activity extending beyond major boulevards into previously overlooked alleyways.

3.3.Measuring network-based walkability using UNA

The built environment that influences retail location decisions includes two key forms of accessibility: proximity to public transportation and specific facilities, and network-based accessibility derived from the street structure. In this study, three indicators were calculated using UNA: accessibility to subway station exits, accessibility to parks, and betweenness. UNA is a network-based spatial analysis method that incorporates buildings into the analytical framework; in this study, it was implemented using Rhinoceros 3D.

The Gravity Index quantifies accessibility by incorporating spatial resistance between origins and destinations. It captures the cumulative gravitational pull that destinations exert on a given origin within a specified network radius. The index assumes that accessibility increases when more destinations are located within the radius, when those destinations have greater weights (e.g. size or attractiveness), and when the network distance to them is shorter (Sevtsuk, 2020). The formula is given as follows:

$$Gravity[i]^r = \sum_{j \in G-i; d[i,j] \leq r} W[j]^\alpha / e^{\beta * d[i,j]} \tag{1}$$

where *W[j]* is the weight of destination *j*, indicating its size or attractiveness; *d[i,j]* is the shortest distance between origins *i* and destination *j* within the network radius r; α is a parameter that adjusts the influence of destination weight; and β is the distance decay coefficient that determines how accessibility decreases as distance increases.

The Betweenness measures the degree to which a building lies on the shortest paths between other buildings. A higher betweenness value indicates greater accessibility and ease of movement. As a probabilistic measure of how often a specific location is traversed within the street network, it serves as a proxy for estimating pedestrian flow (Figure 4). The formula is defined as follows:

$$Betweenness[i]^{r,dr} = \sum_{j,k \in G-i; d[j,k] \leq r*dr} (n_{jk}[i]/n_{jk}) W[j] \tag{2}$$

where n_{jk} [i] is the total number of shortest paths from origin j to destination k that pass by observer building i, $n_{jk}$is the total number of shortest paths from origin j to destination k, W[j] is the weight of origin j, and dr is the detour ratio, allowing for slight deviations from the shortest path, with j and k located within the network radius r of one another.

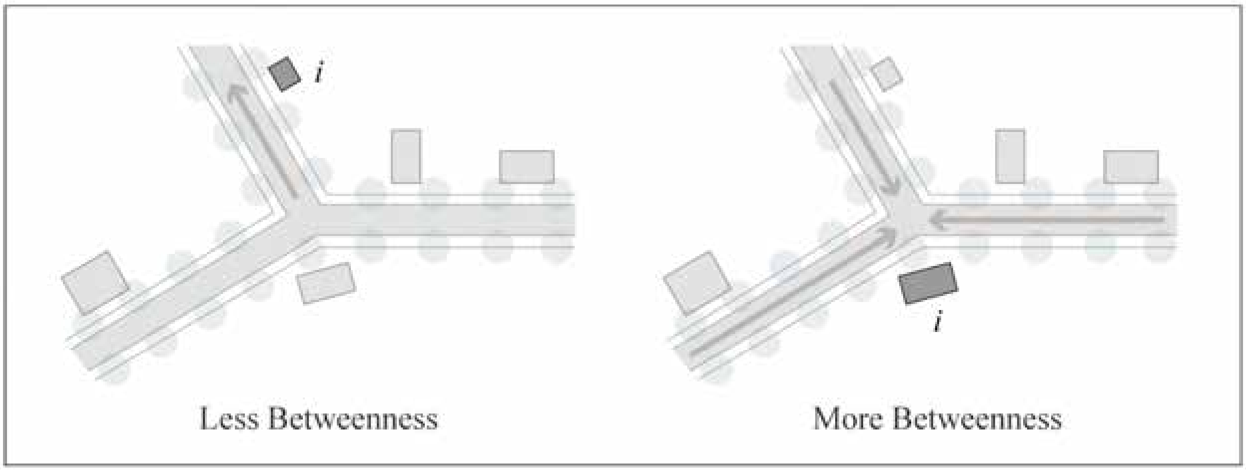

Figure 4. Example of betweenness (Adapted form Sevtsuk, 2014)

For the calculation of the Gravity Index, the network radius was set to 600 metres, which corresponds to a typical walking distance of 5–10 minutes. The distance decay coefficient was set to 0.00217, following the walking distance-based value reported in Handy and Niemeier (1997). Betweenness was computed based on the full network of buildings within the study area. To account for differences in building size within the Hongdae retail district, each building was weighted by its volume. Accordingly, the resulting Betweenness values reflect the estimated volume of movement associated with each building, assuming that larger buildings generate more pedestrian flow than the smaller ones (Sevtsuk, 2014).

Given that urban structures such as roads and buildings tend to evolve gradually over long periods (Casali and Heinimann, 2019), it was assumed that the spatial configuration remained relatively stable during the analysis period. Therefore, spatial network data from 2019 were used for all time periods. For subway accessibility, changes were incorporated starting from the Growth Phase to reflect the opening of the Gyeongui–Jungang Line at Hongik University Station in 2012.

3.4. Measuring streetscape characteristics using SVIs

This study employed SVIs to extract streetscape characteristics as perceived by pedestrians. SVIs enable the quantification of pedestrians' subjective perceptions of the physical environment (Lee et al., 2022; Seo et al., 2021; Yin and Wang, 2016). This approach reduces statistical distortions and data biases, thereby improving measurement precision and enhancing the generalisability of results.

SVIs for the study area were collected using the Naver Street View (NSV) API. Naver is a leading Korean internet portal that provides both mapping and Street View services. In this study, a total of 21,101 panoramic 360° images were collected by generating points at 20-metre intervals along the road network in the study area. For visual attributes, full 360° panoramic images were used to assess the overall street environment. For perceptual attributes, only the front-facing portions of the panoramic images were extracted, as these reflect the visual field most relevant to pedestrians and were used as input for streetscape perception modelling (Figure 5). The SVIs used in the analysis correspond to the years 2010, 2014–2015, and 2016–2017. NSV data for the year 2013 were not available, as imagery for that year was not provided by the platform. In addition, the 2015 and 2017 images were included to supplement spatial gaps left by incomplete coverage in earlier years.

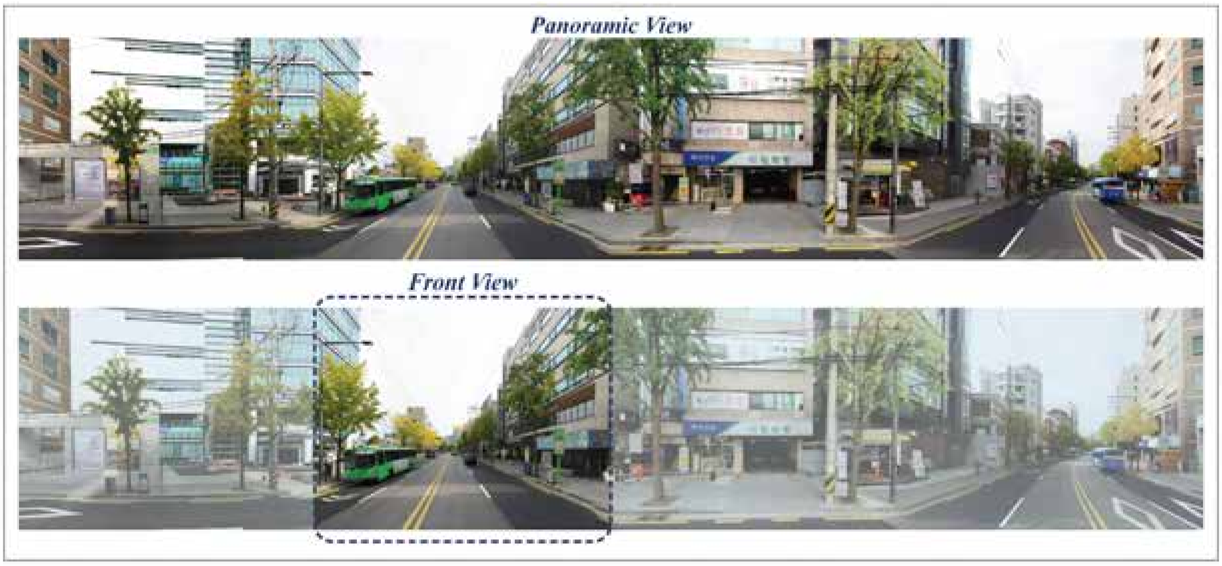

Figure 5. Example of a panoramic and front views extracted from SVIs

To extract the visual attributes of streetscape characteristics, this study employed a computer vision technique known as semantic segmentation. Semantic segmentation is a pixel-wise image classification method that distinguishes between multiple categories—such as buildings, trees, and sky—within a given dataset. We used the HRNet-V2-W48 model pre-trained on the ADE20K dataset to apply this technique. The pixel proportions of physical streetscape elements identified in each image were adopted as visual attributes perceived by pedestrians. Four indicators were ultimately computed: Enclosure, Openness, Pavement, and Greenness. Enclosure refers to the proportion of buildings and walls relative to roads; Openness indicates the proportion of sky area; Pavement reflects the proportion of sidewalks relative to road area; and Greenness quantifies the proportion of visible greenery such as trees, grass, and plants (Figure 6).

Figure 6. Visual attributes extracted from a SVI using semantic segmentation

To measure pedestrians' perceptions of the streetscape, we trained a CNN model to predict perceptual attributes based on SVIs. In this study, we adopted VGG16 and applied transfer learning using a model pre-trained on the ImageNet dataset. For training data, we used the Place Pulse 2.0 dataset, a large-scale visual perception survey conducted by MIT Media Lab, which captures people's impressions of urban environments via an online platform. From the Place Pulse dataset, we extracted three positive perceptual dimensions—Safe, Lively, and Beautiful—as quantifiable street scores for each image. Other perceptual labels were excluded to ensure objectivity and reliability. First, the Wealthy dimension was excluded, as it tends to reflect high-income residential zones or areas with large boulevard-style street trees, which are not easily generalisable in typical retail districts. Second, the Depressing and Boring dimensions were excluded as negative emotional attributes, which may conflict with the selected positive attributes. Moreover, these mental health-related indicators are less applicable in the South Korean context, and difficult to interpret within retail environments.

Each variable was calculated as the average value of images within a 100-metre radius, to reflect the contextual streetscape characteristics of the surrounding area. During this process, 86 samples lacking image coverage within the 100-metre buffer were removed from the analysis due to missing data. Figure 7 illustrates the three stages of the machine learning-based analysis using SVIs conducted in this study.

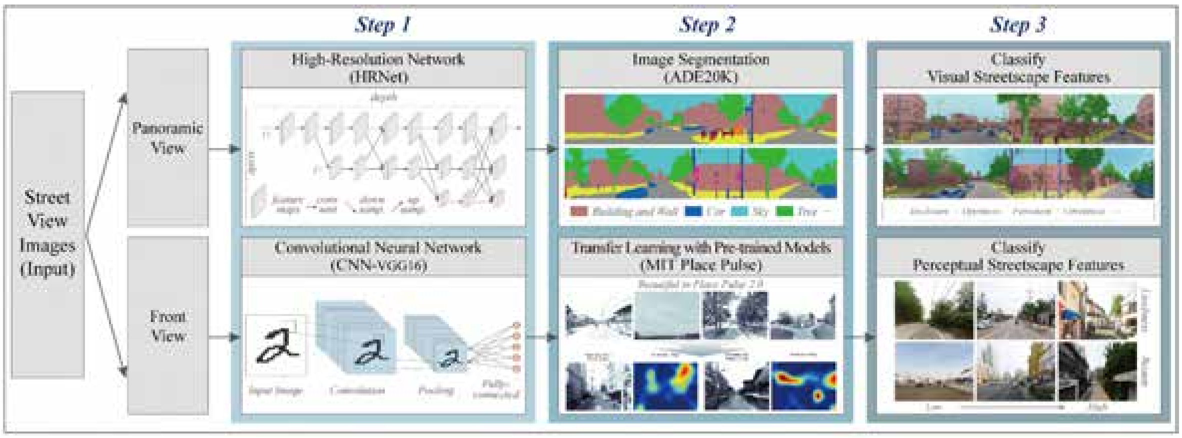

Figure 7. SVI-based process for classifying visual and perceptual streetscape features

3.5.Data

Point-of-interest (POI) data on cafés from 2010 to 2019 were collected from the Statistical Geographic Information Service (SGIS) using Python-based web crawling. From these data, we identified store openings, closures, and operational status for each year to construct the dependent variable: a binary indicator of store opening (0 or 1). Store opening was operationally defined as the appearance of a café in year t that did not exist in year t–1 (Figure 8).

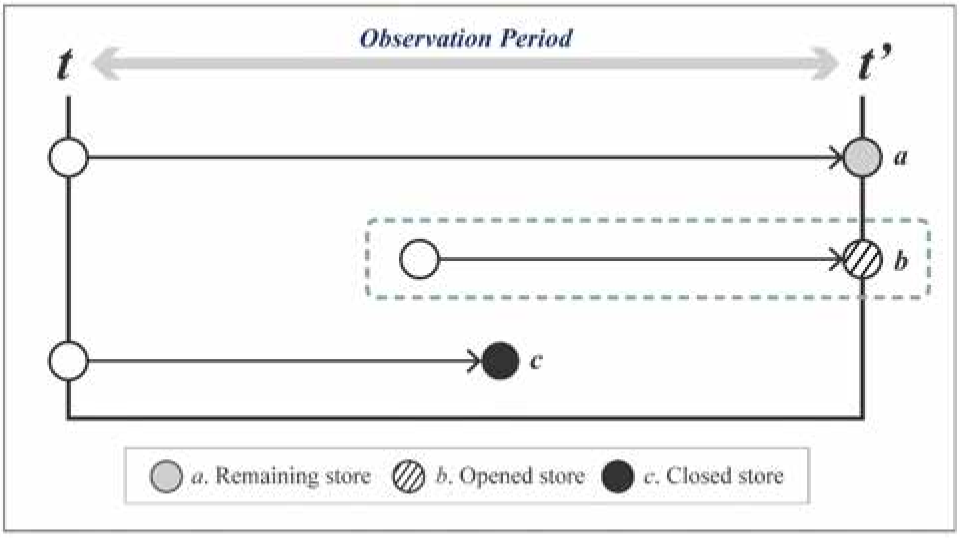

Figure 8. Classification of store status

To assess the prior presence of stores and café clustering before the time of opening, we used POI data from 2010, 2013, and 2016. Clustering was calculated using UNA with a network radius of 100 metres to capture the degree of competitive clustering as experienced by pedestrians.

Additional data on location factors were collected from various sources commonly used in previous studies. Information on building characteristics—including building footprint, building volume, building height, and parcel area—was obtained from the Ministry of Land, Infrastructure and Transport (MOLIT). Average land prices were collected from the Seoul Open Data Plaza and averaged for each analysis period. Population density and the number of millennial residents were retrieved from SGIS. Because population data prior to 2015 were only available in 5-year intervals, data for the Growth Phase were collected based on the 2015 census. Definitions of all variables used in the analysis and their data sources are summarised in Table 1.

Table 2. Description of variables

Variable				Description of variables	Source
Dependent variable			Open	Binary variable indicating whether a café newly opened (1=Yes; 0=No)	SGIS
Independent variable	Walkability characteristics		Subway	Spatial accessibility to subway entrance in the radius (gravity, r=600m)	MOLIT
	Park		Spatial accessibility to park in the radius (gravity, r=600m)		
	Betweenness		Connectivity between all buildings in the radius (r=n, weighted by volume)		
	Road width		Width of the road adjacent to the building (m)		
	Streetscape characteristics	Visual attributes	Enclosure	Average ratio of building and wall area to road in the radius (r=100m)	NSV
			Openness	Average ratio of sky area to road in the radius (r=100m)	
			Pavement	Average ratio of sidewalk area to road in the radius (r=100m)	
			Greenness	Average ratio of tree and plant area to road in the radius (r=100m)	
		Perceptual attributes	Safe	Average perceived level of safety of streetscape in the radius (r=100m)	
			Lively	Average perceived level of liveliness of streetscape in the radius (r=100m)	
			Beautiful	Average perceived level of beauty of streetscape in the radius (r=100m)	

	Store characteristics Agglomeration	Occupied	Binary variable indicating whether the store was already occupied in the previous year (1=Yes; 0=No)	SGIS
		Spatial proximity to other operating cafés in the radius (gravity, r=100m)		
Control variable	Built environment characteristics Building height Parcel area Land price	Building footprint	Footprint area of the building (m^2)	MOLIT
		Height of the building (m^2)		
		Area of the land parcel (m^2)		
		Average land price during the analysis period (won)	SODP	
	Demographic characteristics Millennials Employees	Residents	Residential population density in the census district	SGIS
		Number of millennials (aged 20–39) in the census district		
		Number of workers in the census district		

3.6.Research methods

To investigate the spatial distribution of café locations, we employed Kernel Density Estimation (KDE), a point pattern analysis method. KDE is a non-parametric technique that estimates the probability density of point distributions across space using point data. Unlike statistical clustering methods such as K-means, KDE accounts for spatial dependence and is particularly effective for identifying the spatial diffusion of events and visualising clusters of point features (Anderson, 2009; Węglarczyk, 2018). Due to its strengths, KDE has been widely used in various fields, including traffic accident and crime hotspot analysis, as well as studies of spatial utilisation patterns (Cai et al., 2013; Chainey et al., 2008; Xie and Yan, 2008; Yu et al., 2015). In this study, KDE was applied to the opening data of cafés during the Establishment, Growth, and Spillover Phases to examine spatial shifts in location patterns over time.

Subsequently, a binary logistic regression model was used to identify the determinants of café openings for each phase. Logistic regression is one of the simplest probabilistic modelling techniques and is used to estimate the likelihood of a binary outcome based on a set of independent variables. Rather than predicting whether an event will occur, it estimates the probability of its occurrence (Jin and Lee, 2017). The predicted value of the dependent variable is expressed as a probability between 0 and 1. If the predicted value exceeds a threshold (typically 0.50), the event is considered likely to occur. The logistic function is formulated as follows:

$$\ln\left(p\left(y=1\middle|x_1,\cdots,x_p\right)/\left(1-p\left(y=1\middle|x_1,\cdots,x_p\right)\right)\right)=\beta_0+\beta_1x_1+\cdots+\beta_px_p \tag{3}$$

where ln *ln(p/(1-p))* represents the logit, *p/(1-p)* is the odds, β_p is the regression coefficient, and x_p is the independent variable.

$$Odds = p_i/(1-p_i) = \exp\left(\textstyle\sum_{j=1}^{k}\beta_j x_{ij}\right) = \exp(\beta_1 x_1)\exp(\beta_2 x_{i2})\cdots\exp(\beta_k x_{ik}) \tag{4}$$

where p_i represents the probability that event *i* occurs, β_k is the regression coefficient, and x_{ik} is the independent variable.

The odds indicate the ratio of the probability that an event occurs to the probability that it does not. When an independent variable x_{ik} increases by one unit, the odds ratio (OR) is given by exp(β_j), which quantifies the multiplicative change in odds. If the coefficient β_j is negative, the OR will be less than 1, indicating a decrease in odds as the independent variable x_{ik} increases. Based on this model, we examined the factors influencing café openings across the three temporal phases, thereby analysing the spatial dynamics of location shifts in the Hongdae retail district.

4.Results

4.1.Shifting patterns of café locations

Figure 9 presents the KDE results for café openings in the Hongdae retail district and reveals a pattern of spatial diffusion over time. During the Establishment Phase, openings were concentrated around Hongik University and Hongdae Station on Subway Line 2. Densely clustered openings appeared along Wausan-ro and the 'Walkable Street' near Hongdae, which had already established themselves as central commercial districts by the early 2000s. Several openings also occurred along higher-order boulevards such as Yanghwa-ro and Dongmak-ro.

In the Growth Phase, new openings emerged primarily around Hapjeong Station (Line 2) and Sangsu Station (Line 6). In particular, the alleyways adjacent to Hongdae Solnae-gil and the 'Sangsu-dong Café Street'—located roughly one block away from major boulevards—saw an increase in activity. This spatial relocation may reflect displacement due to commercial saturation or gentrification.

In the Spillover Phase, a significant increase in opening density was observed in the residential area of Yeonnam-dong near the Gyeongui Line Forest Park, suggesting a newly emerging location pattern. Additionally, opening density rose around Mangnidan-gil, indicating the expanding boundary of the Hongdae retail district. Notably, opening clusters during the Growth and Spillover Phases exhibited a linear pattern along the street network, suggesting that retail development and relocation tend to follow the structure of the street grid. Unlike the earlier phases, openings in Yeonnam-dong and Mangwon-dong extended beyond boulevards and into inner-block alleyways, highlighting the spatial shift into non-central areas.

The KDE results across the three temporal phases demonstrate an evolving spatial distribution of café locations. Unlike earlier periods, when cafés were concentrated in core commercial centres, recent openings have increasingly occurred in non-commercial or decentralised locations. These findings suggest a shift in the preferred locational attributes of cafés. To further investigate this trend, we apply binary logistic regression to quantify the factors that influence location decisions.

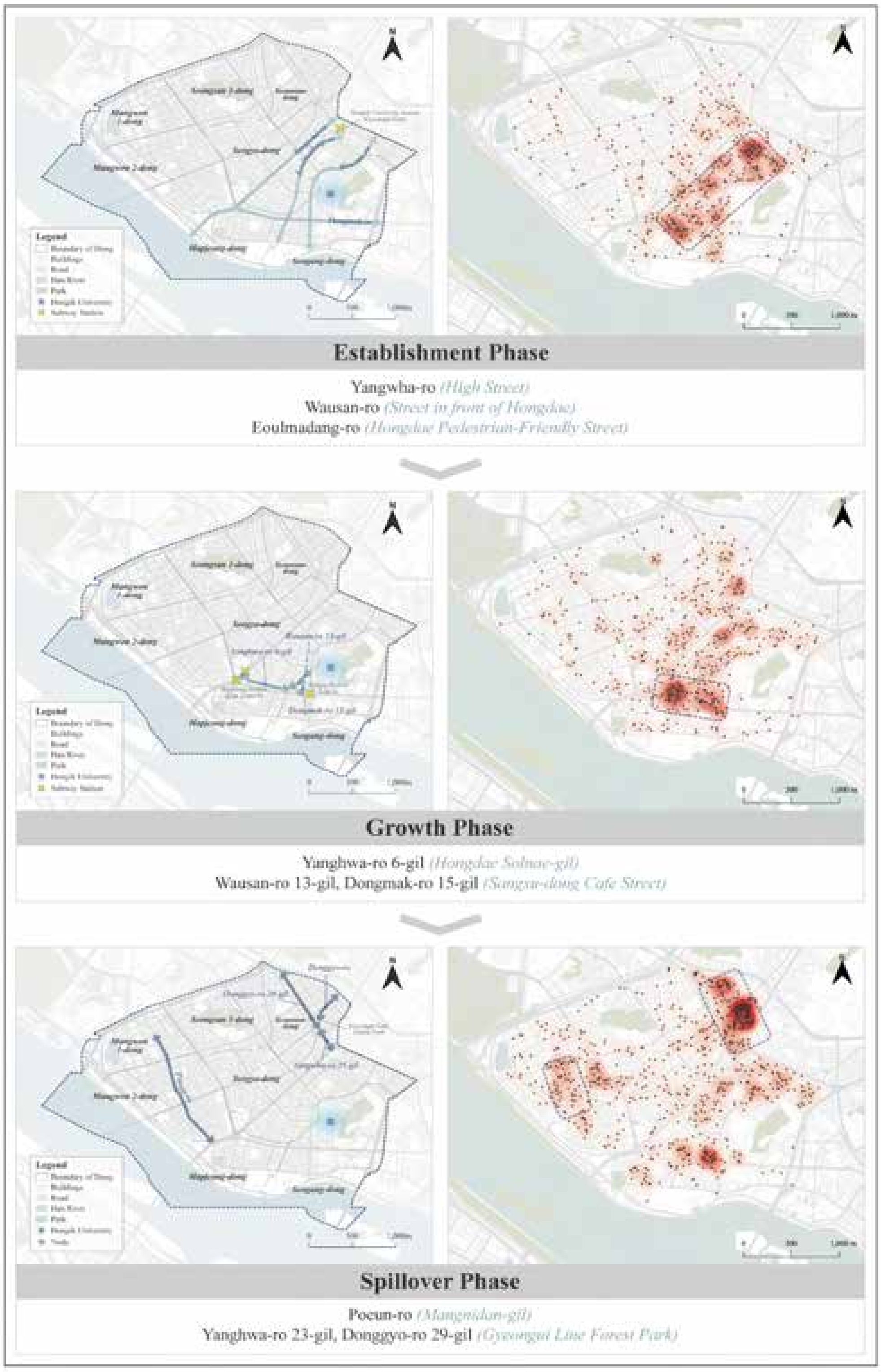

Figure 9. KDE of café openings by phase

4.2.Descriptive statistics

Descriptive statistics for the dependent and explanatory variables used in the binary logistic regression models are presented in Table 2. The unit of analysis is the individual building, and all variables were aggregated accordingly. Buildings deemed unsuitable for retail district analysis—such as apartments, schools, gas stations, and parking lots—were excluded from the sample. The final dataset includes a total of 13,439 buildings. Some variables were log-transformed or rescaled to improve normality prior to analysis.

Table 3. Descriptive statistics

	Model 1		**Model 2**		**Model 3**	
Variables	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Dependent variable						
Open	0.03	0.17	0.03	0.18	0.05	0.22
Independent variables						
Walkability characteristics						
Subway (gravity, 600m)	0.93	1.08	1.13	1.25	1.13	1.25
Park (gravity, 600m)	1.14	0.47	1.14	0.47	1.14	0.47
Betweenness (weight=building volume, r=n, log)	11.97	1.16	11.97	1.16	11.97	1.16
Road width	6.06	4.46	6.06	4.46	6.06	4.46
Streetscape characteristics						
Visual attributes						
Enclosure (r=100m)	838.96	564.68	742.79	287.71	835.18	299.62
Openness (r=100m)	17.99	3.97	16.10	3.49	15.28	3.32
Pavement (r=100m)	26.00	24.45	25.43	8.54	26.05	8.35
Greenness (r=100m)	7.19	4.43	10.23	5.31	9.80	4.94
Perceptual attributes						
Safe (r=100m)	0.26	0.09	0.40	0.11	0.38	0.09
Lively (r=100m)	0.74	0.10	0.80	0.08	0.81	0.07
Beautiful (r=100m)	0.16	0.07	0.23	0.09	0.22	0.08
Control variables						
Store characteristics						
Occupied	0.03	0.16	0.05	0.21	0.06	0.24
Agglomeration (gravity, r=100m)	0.87	1.78	1.42	2.29	1.88	2.37
Built environment characteristics						
Building footprint (log)	4.69	0.55	4.69	0.55	4.69	0.55
Building height (log)	2.43	0.55	2.43	0.55	2.43	0.55
Parcel area	14.84	0.36	15.00	0.37	15.37	0.36
Land price (log)	269.86	601.76	269.86	601.76	269.86	601.76
Demographic characteristics						
Residents	11.06	0.72	10.97	0.76	10.94	0.79
Millennials	71.33	46.58	58.27	25.31	60.21	27.88
Employees	6.26	1.78	6.34	1.81	6.60	1.70
Observations	13,439		13,439		13,439	

Note: Model 1 corresponds to the Establishment Phase (2010–2012), Model 2 to the Growth Phase (2013–2015), and Model 3 to the Spillover Phase (2016–2019).

4.3.Factors influencing café location choices

The Log Likelihood Ratio (LR) test results indicate that all three models are statistically significant ($p<0.001$). The Nagelkerke R^2 values were 0.23 for the Establishment Phase, 0.15 for the Growth Phase, and 0.11 for the Spillover Phase. However, it is widely recognised that R^2 values in logistic regression tend to be relatively low and vary depending on the distribution of the dependent variable (Cohen et al., 2009). Moreover, the Nagelkerke R^2 should not be interpreted in the same manner as R^2 in Ordinary Least Squares (OLS) regression, as the two statistics are not directly comparable (Azen and Traxel, 2009; Hu et al., 2006). To further assess the goodness-of-fit of the models, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values were also examined. Table 3 summarises the overall model accuracy.

Table 4. Model fit statistics for the three phases

Statistic	Model 1	Model 2	Model 3
Log likelihood	-1,405.53	-1,741.58	-2,413.44
LR chi^2(df)	746.58(20)***	538.98(20)***	491.43(20)***
Nagelkerke R^2	0.23	0.15	0.11
AIC	2,853.05	3,525.15	4,868.88
BIC	3,010.68	3,682.78	5,026.50

*: $p<0.1$, **: $p<0.05$, ***: $p<0.01$

The binary logistic regression results for the Establishment Phase are presented in Table 4. All variance inflation factor (VIF) values were below the conventional threshold of 10, indicating that multicollinearity was not a concern. Neither walkability nor the visual attributes of streetscape characteristics had a statistically significant effect on the probability of café openings.

By contrast, among the perceptual attributes of the streetscape, Lively—reflecting pedestrian perception of vibrancy—was negatively associated with the likelihood of opening (OR = 0.18). Regarding traditional location factors, both prior presence of cafés (OR = 9.49) and agglomeration (OR = 1.13) were positively associated with the odds of opening. In terms of building characteristics, larger footprint was associated with lower opening probability (OR = 0.79), while greater building height (OR = 1.38), larger parcel (OR = 1.00), and higher average land price (OR = 2.72) were associated with increased odds of opening. As for demographic factors, higher population density (OR = 1.44), larger millennial population (OR = 1.00), and higher number of employees (OR = 1.21) all significantly increased the likelihood of café openings. These results align with previous findings suggesting that the complementary relationships among similar stores contribute to agglomeration economies, and that building characteristics and population-based retail demand are critical for the efficient operation and location decisions of retailers (Porter, 1996; Sevtsuk, 2014; Small and Song, 1994; Teller et al., 2016; Um et al., 2009; Wu et al., 2021).

Table 5. Binary logistic regression results for the Establishment Phase

Variables	Model 1 (Establishment Phase)		
	OR	**z**	**VIF**
Constant	4.40e-11***	-7.85	-
Dependent variables			
Walkability characteristics			
Subway (gravity, r=600m)	1.09	1.64	1.39
Park (gravity, r=600m)			
1.24			
1.59			
1.12			
Betweenness (weight=building volume, r=n, log)	1.02	0.42	1.33
Road width	1.01	1.22	1.27
Streetscape characteristics			
Visual attributes			
Enclosure (r=100m)	0.99	-0.69	5.49
Openness (r=100m)	1.00	0.21	1.63
Pavement (r=100m)	1.00	0.28	4.48
Greenness (r=100m)	0.99	-0.00	3.47
Perceptual attributes			
Safe (r=100m)	4.24	1.12	3.67
Lively (r=100m)	0.18*	-1.77	2.59
Beautiful (r=100m)	0.13	-1.12	4.41
Control variables			
Store characteristics			
Occupied	9.49***	15.48	1.14
Agglomeration (gravity, r=100m)	1.13***	5.33	1.61
Built environment characteristics			
Building footprint (log)	0.79**	-2.11	1.46
Building height (log)	1.38***	2.73	1.31
Parcel area	1.00**	2.17	1.27
Land price (log)	2.72***	6.17	1.88
Demographic characteristics			
Residents (log)	1.44***	2.89	1.86
Millennials	1.00***	2.73	1.41
Employees (log)	1.21***	2.99	2.24
Number of observations	13,439		
Log likelihood	-1,405.53		
LR chi^2(df)	746.58(20)***		
Nagelkerke R^2	0.23		
AIC	2,853.05		
BIC	3,010.68		

*: p<0.1, **: p<0.05, ***: p<0.01

The logistic regression results for the Growth Phase are presented in Table 5. All VIF values were below the threshold of 10, indicating no multicollinearity issues. Compared to the Establishment Phase, the Growth Phase revealed a notable shift in the influence of locational factors, particularly in terms of walkability and streetscape characteristics.

Café openings were more likely to occur in areas with greater accessibility to subway stations (OR = 1.11) and nearby parks (OR = 1.27). Among the visual attributes of streetscape characteristics, higher Enclosure was associated with a slight decrease in opening probability (OR = 0.99), while higher Greenness also reduced the likelihood of opening (OR = 0.95). Conversely, a higher Pavement had a positive effect on opening probability (OR = 1.02). These findings support the interpretation that micro-scale visual streetscape factors enhance pedestrian visual preferences, thereby increasing the attractiveness of retail locations, in line with the results of Koo et al. (2023b).

Among the perceptual attributes, Lively continued to show a negative association (OR = 0.13), whereas Beautiful exhibited a strong positive association with café openings (OR = 9.89). In contrast, several traditional location factors—such as building footprint, parcel area, and millennial population—lost their statistical significance during this period. This suggests that, as the retail district expanded, large-scale parcels and fixed demographic groups such as young adult residents became less influential, while other commercial and spatial factors emerged as more influential in location decisions.

Table 6. Binary logistic regression results for the Growth Phase

	Model 2 (Growth Phase)		
Variables	**OR**	**z**	**VIF**
Constant	$1.22e\text{-}09^{***}$	-6.40	-
Dependent variables			
Walkability characteristics			
Subway (gravity, r=600m)	1.11^{**}	2.59	1.59
Park (gravity, r=600m)	1.27^{**}	2.06	1.10
Betweenness (weight=building volume, r=n, log)	0.95	-1.01	1.32
Road width	0.99	-0.68	1.27
Streetscape characteristics			
Visual attributes			
Enclosure (r=100m)	0.99^{**}	-2.10	3.35
Openness (r=100m)	0.99	-0.38	1.75
Pavement (r=100m)	1.02^{**}	2.45	1.68
Greenness (r=100m)	0.95^{*}	-1.96	4.62
Perceptual attributes			
Safe (r=100m)	0.86	-0.12	7.01
Lively (r=100m)	0.13^{*}	-1.79	3.04
Beautiful (r=100m)	9.89^{*}	1.69	6.16
Control variables			
Store characteristics			
Occupied	4.64^{***}	11.74	1.16
Agglomeration (gravity, r=100m)	1.05^{***}	2.76	1.72
Built environment characteristics			
Building footprint (log)	0.97	-0.30	1.47
Building height (log)	1.48^{***}	3.69	1.31

Parcel area	0.99	-0.71	1.17
Land price (log)	2.17***	4.79	2.18
Demographic characteristics			
Residents (log)	1.45***	3.13	2.09
Millennials	1.00	1.59	1.16
Employees (log)	1.31***	4.38	2.39
Number of observations	13,439		
Log likelihood	-1,741.58		
LR chi^2(df)	538.98(20)***		
Nagelkerke R^2	0.15		
AIC	3,525.15		
BIC	3,682.78		
*: $p<0.1$, **: $p<0.05$, ***: $p<0.01$			

The binary logistic regression results for the Spillover Phase are summarised in Table 6. All VIF values were below 10, indicating no multicollinearity concerns. While the influence of traditional retail location attributes remained similar to the previous phase, the impact of walkability and streetscape characteristics shifted notably.

Accessibility to subway entrances (OR = 0.89) and wider roads (OR = 0.98) were associated with decreased probabilities of café openings. This suggests that improved access to spatial information has weakened the traditional locational advantages of highly accessible central areas. Meanwhile, higher Enclosure (OR = 1.27) and higher Openness (OR = 1.09) were positively associated with opening likelihood, whereas higher Pavement was negatively associated (OR = 0.98). These findings align with Nasar's (1990) study, which argued that people prefer open spaces with clearly defined boundaries, rather than simply wide-open areas.

In addition, Lively, one of the perceptual attributes of streetscape, was positively associated with café openings (OR = 14.15). This reflects the fact that areas with slower pedestrian speeds and frequent foot traffic—such as alleyways with small-scale spatial units and multiple storefronts—are perceived as more vibrant (Gehl, 2013; Kickert and Talen, 2022; Yun and Choi, 2013), and play a crucial role in retail operation and location decisions. Overall, these results suggest that under the rise of experiential consumption, consumers increasingly value the emotional and aesthetic appeal of surrounding environments. As a result, visually and perceptually attractive areas—as experienced by pedestrians—are becoming more important in café location decisions.

Table 7. Binary logistic regression results for the Spillover Phase

	Model 3 (Spillover Phase)		
Variables	**OR**	**z**	**VIF**
Constant	1.25e-09***	-6.73	-
Dependent variables			
Walkability characteristics			
Subway (gravity, r=600m)	0.89***	-2.88	1.57
Park (gravity, r=600m)	1.17*	1.73	1.08
Betweenness (weight=building volume, r=n, log)	0.99	-0.10	1.33
Road width	0.98*	-1.91	1.27
Streetscape characteristics			
Visual attributes			
Enclosure (r=100m)	1.00***	4.89	3.21
Openness (r=100m)	1.09***	5.78	1.67

Pavement (r=100m)	0.98**	-1.97	2.08
Greenness (r=100m)	1.01	0.79	5.56
Perceptual attributes			
Safe (r=100m)	0.42	-0.79	5.51
Lively (r=100m)	14.15**	2.42	3.25
Beautiful (r=100m)	2.89	0.77	7.42
Control variables			
Store characteristics			
Occupied	6.10***	16.60	1.13
Agglomeration (gravity, r=100m)	1.06***	3.49	1.76
Built environment characteristics			
Building footprint (log)	0.89	3.37	1.47
Building height (log)	1.30***	-0.92	1.32
Parcel area	0.99	-1.28	1.16
Land price (log)	1.73***	2.96	2.42
Demographic characteristics			
Residents (log)	1.38***	3.17	1.98
Millennials	1.00	0.53	1.23
Employees (log)	1.14***	2.73	2.53
Number of observations	13,439		
Log likelihood	-2,413.44		
LR chi^2(df)	491.43(20)***		
Nagelkerke R^2	0.11		
AIC	4,868.88		
BIC	5,026.50		
*: p<0.1, **: p<0.05, ***: p<0.01			

5.Discussion

The spatial shift in café locations in the Hongdae district reflects the evolving nature of urban consumer culture and highlights the growing influence of streetscape quality and place perception on location preferences. Figure 10 illustrates the streetscape characteristics of areas that satisfied the preferred locational conditions for each phase. In the early stages, location decisions were primarily shaped by traditional characteristics of commercial centres, such as accessibility and centrality. However, as the core area became increasingly saturated and experiential consumption gained prominence, new locations—such as surrounding alleyways—emerged as preferred sites. These findings align with previous research suggesting that during commercialisation, retail districts tend to expand into adjacent areas with relatively lower rents or land prices once the core becomes saturated (Ley, 1997; Smith, 1979; Zukin, 1987). Furthermore, beyond traditional location characteristics, spatial features closely tied to consumers' experiences of place should be considered as increasingly important in café location decisions.

More specifically, the results can be interpreted in two ways. First, the relationship between café locations and walkability differed by phase. During the Growth Phase, openings were concentrated near subway stations and parks, reflecting a continued preference for traditional commercial centres with high transit accessibility and public amenities. These results align with prior studies that emphasise the positive impact of public transportation on retail activity by serving as anchors of pedestrian flow (Lee and Kwon, 2016; Wu et al., 2021; Yoshimura et al., 2021) and highlight how parks attract consumers and generate synergies with surrounding businesses (Sim, 2019). However, in the Spillover Phase, locations with lower subway accessibility and narrower street widths became more favoured. This suggests that café location decisions were no longer dependent on minimising distance to a fixed destination or locating in walkability-optimised central areas.

Second, the visual and perceptual quality of streetscapes had a significant influence on café location decisions, and this influence varied by phase. During the Establishment Phase, cafés tended to locate along major boulevards with relatively low perceived vibrancy. As the retail district expanded, new openings increasingly concentrated along pedestrian-friendly streets and eventually shifted towards narrower, human-scale alleyways. In particular, during the Spillover Phase, vibrant and visually attractive streets—as perceived by pedestrians—became preferred locations for café openings. While wide streets may appear empty even when populated, narrow streets with clear visibility of building facades are perceived as more active. Cafés located along such streets not only contribute to perceived safety and imageability (Harvey et al., 2017), but also enhance the spatial appeal by encouraging optional activities such as lingering and spending time (Gehl and Svarre, 2013). This shift in location—from closed boulevards with limited social interaction to open alleyways that support informal encounters—ultimately contributes to neighbourhood transformation and strengthens the vitality of the broader urban space. Moreover, as cafés begin to cluster along pedestrian-friendly and aesthetically pleasing streets, the resulting streetscapes can promote gradual urban growth and enhanced vibrancy (Cox and Streeter, 2019; Jacobs, 1961; Kickert and Talen, 2022). Outdoor cafés that utilise terraces in highly walkable areas, or shops embedded in alleyways that foster active interaction with the street, serve as extensions of public space (Montgomery, 1997; Sim, 2019). These findings suggest that urban planners should aim to improve the streetscape environment and encourage small-scale commercial activity in alley-based retail districts.

While traditional location attributes have long been considered important in café location decisions, their influence has diminished over time. This result underscores the limitations of traditional location theories and highlights the need for ongoing monitoring of consumer preference shifts—particularly by incorporating streetscape-oriented locational trends.

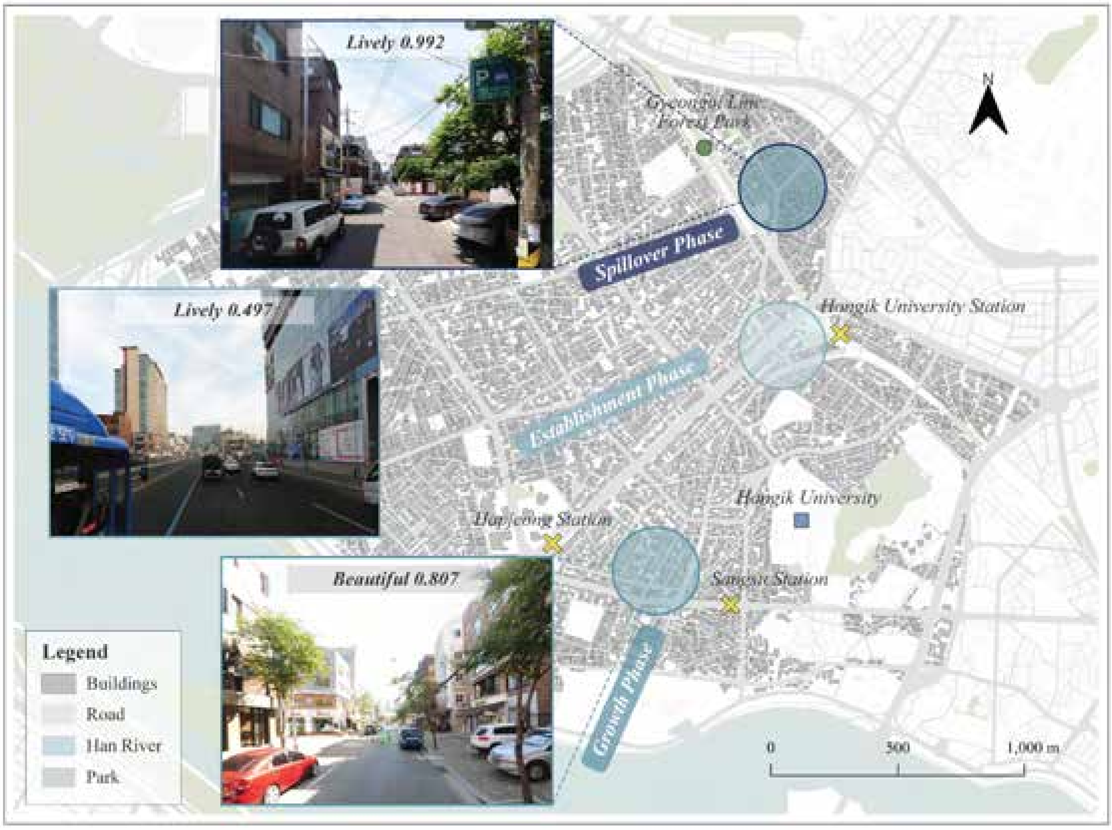

Figure 10. Locational preferences and streetscape indicators by phase

6.Conclusion

This study empirically demonstrates the complex interaction between café location decisions and urban spatial conditions, particularly emphasising the significance of streetscape quality. It highlights the dynamic and interrelated processes through which sense of place, urban culture, and everyday heritage evolve. In the Hongdae retail district, traditional commercial location characteristics were more influential during the Establishment Phase, while walkability became more important during the Growth Phase, and visual and perceptual streetscape characteristics were emphasised during the Spillover Phase. Historically, small-scale retailers such as cafés have tended to locate in highly visible areas—physically central streets with heavy pedestrian and vehicular traffic—to benefit from agglomeration economies or gain competitive advantage. However, in contemporary urban consumer culture, consumption has evolved towards everyday life, and cafés have become key social spaces where individuals share in one another's daily routines (Horton and Kraftl, 2013). Place, as Carmona (2021) notes, is constructed through lived experience; it becomes meaningful as individuals, communities, and societies attach emotions and memories to space. These social activities are embedded in the street, where the streetscape becomes a medium for memory, experience, and emotional resonance.

Moreover, the rise of small-scale experiential spaces, omni-channel retail, and social media has made it possible for people to indirectly experience spaces without physically visiting them, thereby increasing the importance of the environment surrounding a store. User-generated content and information sharing on social media platforms can shape the identity and attachment to place (Farrelly, 2017). In particular, with the growing culture of image-based sharing, users now actively tag locations and upload images in real time, even from lesser-known alleys or newly discovered destinations (Lee et al., 2018). From this perspective, streetscapes that facilitate visual engagement and offer sensory experiences provide retailers with new opportunities to attract consumers (Kickert and Talen, 2022). Therefore, urban planners are encouraged to cultivate a localised sense of place in retail districts by designing environments that offer differentiated experiences for consumers within the everyday urban landscape.

This research not only assesses the continued relevance of traditional commercial location theories, but also highlights the overlooked connection between recent shifts in café locations and streetscape characteristics—an aspect that has received limited attention in previous research. The findings emphasise that, in determining retail locations, the perceived quality of the surrounding service environment has become increasingly important for consumers. Specifically, the study shows that preferred location conditions have changed over time, from both the retailer's and the consumer's perspectives. These results point to the need for long-term monitoring of spatial changes in retail districts to support sustainable commercial operations. Notably, considering the role of cafés in enhancing quality of life and contributing to urban vibrancy, the findings suggest that streetscapes should be viewed not as passive elements, but as active components in evaluating and promoting urban vitality. In this sense, the study offers insights into retail dynamics driven by evolving consumption patterns and the changing role of cafés, moving beyond a mere examination of locational shifts.

There are some limitations that need to be explored in future research. First, as this study focuses on a single case study area, the generalisability of the findings is limited. Future research should expand the analysis to include multiple cities. Second, to ensure consistency across the dataset, the SVIs used in the analysis were collected by vehicle-mounted cameras, meaning that the images were captured from a driver's perspective. In streets with clearly separated roads and sidewalks—such as boulevards—this may lead to discrepancies from the pedestrian point of view. As such, there may be subtle differences between the visual perception captured in the SVIs and the streetscape as experienced by pedestrians. Addressing this limitation in future studies may help to more precisely capture changes in how urban spaces are subjectively perceived.

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