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Examining the Impact of E-Commerce Growth on the Spatial Distribution of Fashion and Beauty Stores in Seoul

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Abstract: E-commerce has dramatically expanded its sales, with people being increasingly customized to online shopping. This study aimed to examine changes in the distribution of retail stores that provide fashion and beauty products and services in terms of the number of online shopping transactions and their spatial characteristics in Seoul. For this purpose, we analyzed location data concerning relevant newly opened and closed offline stores from four subgroups between 2015 and 2019. Though more offline stores were newly opened than closed in that period, the number of stores had overall significantly decreased apart from stores providing beauty services, with significant differences in subgroup spatial distribution patterns. We identified local geographic factors affecting retail stores by applying spatial regression models, and we found that the growth of e-commerce was associated with the related to the survival and closure of fashion and beauty stores. While retail store locations are not immediately responsive to changes due to COVID-19, we expect the prolonged COVID-19 outbreak will further facilitate the spatial transformation that has been stimulated by rise of online retailing. Our findings provide important basic data for establishing location plans and management strategies for future fashion and beauty stores, as well as timely evidence-based data to help direct subsequent academic research.

Keywords: online shopping; retail store; fashion and beauty; survival; COVID-19; spatial characteristics; spatial regression models

1. Introduction

There have been many changes in the lifestyles of people with the development of information and communication technology and the generalization of the internet and mobile phones. One representative example concerns changes in consumption behavior in relation to the various goods and services that form parts of daily life. As online purchases became possible, a diversification of purchase channels began to move away from previous transaction methods towards direct electronic visits and purchases [1–3]. In particular, online transactions increased due to the expansion of smartphone use, greater transaction convenience due to simpler payment systems, and the strengthening of online retailer promotions [4,5]. Online transactions are not limited in time and space, and consumer purchases are expected to continuously expand because of the convenience of reducing the time and labor required to purchase and because of price competitiveness compared to offline transactions [6].

Globally, e-commerce is growing at an exponential rate [7]. Worldwide online transaction sales were recently estimated to be $3.5 trillion in 2019 [8]. Korea is ranked fifth in global online transactions, with the domestic online transaction proportion being 25% of total transactions, which is much higher than that of the global average (14.1%) [8]. As the online purchasing culture through COVID-19 became more active, the total amount of transactions in the domestic e-commerce market increased from $121.1 billion in 2019 to $144.4 billion in 2020 [8]. The sales of Coupang, the No. 1 domestic company in e-commerce, surged 3716.4% in sales from $39.7 million in 2014 (according to the domestic...
company evaluation site “CEO Score”) to $12.495.11 million in 2020 [8]. In the case of Amazon, the world’s No. 1 company in this category, sales in 2020 reached $386 billion [9], which was up from 362.2% in 2014 ($82.73 billion). The sales gap between Coupang and Amazon was calculated to have decreased from 268.9 times in 2014 to 32.3 times in 2020.

This rapid expansion of online transactions has led to a relatively rapid contraction of the offline market. While the proportion of sales from offline companies is decreasing, the proportion of online retailers and the gap between online and offline retail sales are increasing every year. In Korea, the proportion of online retail sales among the total retail sales was 30.4% as of December 2020, an increase of 8.3%p from the same month in the last year (22.1%) [8]. On the other hand, offline stores are facing closure due to decreased sales, which is expected to lead to significant changes in local industrial location decision-making, the regional economic environment, and the related job market. While there are various views concerning the outcome of the information revolution, the emergence of e-commerce seems likely to fundamentally change the “rules of the game” of the existing retail industry [1]. In particular, significant changes are likely in the location of commercial facilities that have evolved to allow consumers to trade goods and services more effectively and with greater levels of satisfaction [10–12]. In other words, a commercial location pattern that cannot be explained using current location theory based on physical accessibility facilitated through a transportation network in offline space is likely to emerge [13,14].

With ongoing and accelerating digital innovations occurring in the Fourth Industrial Revolution, changes in purchasing pathways and consumption behavior can be expected to further expand, so it is necessary to closely monitor and continuously analyze the effect of these changes on spatial changes. In particular, from the winter of 2019, as the number of online transactions that allow for non-face-to-face and contactless transactions has exploded in the aftermath of COVID-19, the central axis of consumption has further shifted to the online market [15]. In addition to its effect on public health, COVID-19 has had a major impact on the economy [16–19]. As physical mobility is constrained due to concerns for COVID-19 transmission through human contact, various “ontect” (the compound word ‘ontect’ is used in Korea to refer to online activities occurring in the non-contact market) fields are emerging in consumption, education, finance, healthcare, culture, and business, and the market size is rapidly increasing. Among these, the fastest-expanding market is the consumption sector, which has rapidly grown in recent years, with sales of fashion and beauty-related products and services accounting for a large portion of online shopping transactions [8]. At the same time, this development can now be expected to bring about a significant change in the spatial distribution of stores that sell fashion and beauty-related products and services where they involve offline shopping spaces.

Therefore, this study aimed to analyze the relationship between the survival and location characteristics of retail stores according to changes in the commercial environment, such as the growth of online transactions. We analyzed and predicted the effects of economic and geographic changes in retail redistribution. The focus of this study was on the space change in offline retailing as online retailing grows. In particular, COVID-19 has increased the dependency on or facilitated the shift from brick-and-mortar retailing to online retailing. In this context, we focused on changes in the distribution of retail stores related to fashion and beauty products and services, which currently have the largest number of online shopping transactions in Korea and have shown a sharp increase in recent years. We also examined local geographic factors influencing the survival distribution of offline stores, such as relevant regional demographic and socio-economic indicators. In summary, we sought to analyze changes in the retail environment, including the growth of online transactions, to identify relevant spatial distribution characteristics and changes in fashion and beauty-related offline retail stores, and to determine regional and geographic factors affecting the survival or closure of offline stores.
2. Background

Location is a key factor in the retail business and plays a very important role in determining the absolute and relative value of a store. This is because profits, such as those gained through store sales, and operating expenses, such as rental fees, are determined by location. Therefore, many researchers have analyzed the locational characteristics of retail stores across various case regions and retail industries. With the development of GIS and the use of spatial microdata, the spatial analysis of retail locations has also become more sophisticated [14,20]. In general, retail store locations tend to be distributed in areas with a high demand for purchases or close to transportation facilities, in response to consumer pools comprising floating populations and the need to provide accessibility for consumers [21–23]. It has been shown that a pattern of spatial concentration where these characteristics are most prevalent has emerged [14,24–33].

The location of retail stores generally differs according to the characteristics of the products and services they provide [24,28,34–38]. To account for the differences in the distribution of retail stores based on retail store characteristics, researchers have identified factors affecting the distribution of retail stores to allow for optimal retail store locations [39–47]. Economic factors such as relevant demographic characteristics and industrial activities, as well as physical factors such as the transportation distance to the store and road network structure, have been shown to have a significant effect on retail profits and location. In addition, the location of additional features such as the distribution of cultural facilities and internal operating factors such as product composition and store layout have also been shown to be influential in terms of retail profits and location.

One critical research issue regarding the impact of e-commerce activities concerns how the spatial pattern of physical distribution has changed due to the growth of e-retailing over the long term [13,48]. It has been expected that the spatial redistribution of the retail industry will occur, with numerous retail stores within the retail sector closing and opening according to changes in the retail environment, such as the activation of e-commerce. While multinational and large corporate retailers tend to quickly respond to the changing retail environment and add new online sales channels to complement their existing enterprises, a significant number of small businesses and self-employed retailers are struggling with the changing retail environment [49–51].

Location of commercial facilities such as accommodation, restaurants, and wholesale establishments, which account for approximately half of Korean domestic industry including retail, are highly changeable in terms of short survival periods and high closure rates [8]. Accordingly, as economic losses for individuals and local governments gradually increase, the central government has worked to develop various forms of financial aid and policies to reduce the number of business closures. In response, various studies have also been conducted to better understand how to increase the survival period of commercial facilities and reduce business closures. In particular, since location is a fixed factor that does not change, the importance of locational characteristics has been more emphasized in the long-term survival of commercial facilities [52–61]. Nevertheless, no studies have empirically analyzed the relationship between survival and locational characteristics in retail stores where changes in the commercial environment are noticeable. In situations where retail stores are clustered together, there are locational advantages and disadvantages in relation to concentrations involving the same or similar industry, so it is necessary to consider the locational characteristics of newly opened and closed stores to determine the sustainability of the survival of retailing.

This study had two major differences from previous studies. First, our analysis targeted offline retail stores that provide products and services related to the fashion and beauty sectors, which have not been covered in previous studies. While there have been some studies on fashion and beauty, most have been business studies that analyzed consumers’ store preferences and store operation strategies from a management perspective. Most retail location studies have analyzed wholesale and retail components in combination, or they have selected a single retailer for analysis. There have been previous studies that
analyzed the spatial distribution characteristics related to retail stores, but no studies have analyzed the close relationship between survival characteristics and location characteristics according to the opening and closure of retail stores. Our study is useful in that we analyzed the relationship between survival characteristics and location characteristics by focusing on those retail stores providing fashion and beauty-related products and services with the largest number of online shopping transactions among all the retail industries. We divided these retail stores into four subgroups according to their distinctive characteristics in terms of products and services, and then we analyzed local geographic factors affecting the opening and closure of these stores to determine the key spatial characteristics affecting survival. Second, in terms of spatial scale, this study also differed from other studies in terms of the used spatial polygonal units. We collected location information concerning all retail stores large and small using their addresses, and we collated the relevant information in the form of a spatial point in order to understand the spatial distribution and characteristics of retail stores related to fashion and beauty throughout Seoul. This approach complements spatial analysis results from previous studies and enhances the universality of outcome interpretations. Our approach allowed us to use empirical analysis to generate results that were based on a substantial amount of spatial data and which can more accurately help to predict changes in the retail environment.

3. Methods

3.1. Outline of Analytical Procedures

This empirical analysis first identified spatial clusters (hot spots) by performing a spatial point pattern analysis using the location coordinate data of retail stores related to fashion and beauty. We then aggregated these spatial points and transformed them into spatial polygons to identify local geographic factors affecting distribution among four fashion and beauty subgroups. A spatial point was generated using a geo-coding process based on the longitude and latitude-coordinated location data of relevant retail stores, and then it was visualized using the kernel density estimation (KDE) method, which is a probability density estimation technique used to identify cluster patterns. This point pattern analysis approach was used to compare and describe point patterns and test for significant differences in random spatial patterns [62]. We then tested the statistical significance level using the nearest neighbor ratio (NNR) index. The local geographic factors affecting the relevant retail stores were identified using an ordinary least squares (OLS) regression model, a spatial lag model (SLM), and a spatial error model (SEM) while considering spatial heterogeneity and spatial autocorrelation. Spatial statistical models have been popular methodological techniques in recent empirical research. In building these models, the spatial points of newly opened and closed stores in Seoul from 2015 to 2019 were aggregated and converted to administrative areas (spatial polygons).

The spatiotemporal scope of this analysis focused on fashion and beauty retail stores located in Seoul from 2015 to 2019, with the spatial data derived from publicly available address data in Seoul from the Small Enterprise and Market Service [63]. We also used processed secondary data and microdata from the Korean Statistical Information Service (KOSIS, statistics Korea) for the empirical analysis. As an analysis tool in this study, we first used ArcGIS 10.5 software (ESRI, Redlands, CA, USA) to create an overall map of the spatial points. OLS regression was performed using the SPSS statistics 25 software (IBM SPSS, Armok, NY, USA), and the SLM and SEM were constructed using the GeoDa 1.14 software (The Center for Spatial Data Science, University of Chicago, Chicago, IL, USA). In this case, a spatial weighted matrix, based on first-order Queen’s contiguity, was generated for the SLM and SEM.

3.2. Study Regions and Subjects

Korea has a three-level of administrative unit structure. The highest administrative unit consists of a total of 17 metropolitan cities and provinces, including the capital city of Seoul. Of these, the special city of Seoul is composed of 25 administrative district (gu) as
lower administrative units, which include a total of 424 administrative areas (dong), the lowest administrative units. This study region includes all 424 administrative areas (dong), thus covering all of Seoul (Figure 1).

Figure 1. Case study regions.

Figure 2 shows the spatial distribution of fashion and beauty-related related stores, the subject of this study. While acquiring relevant spatial data, we grouped the retail stores into four subgroups according to specific characteristics in relation to fashion and beauty-related products and services, namely, for fashion-related products: (i) “wearing apparel—clothing” and (ii) “footwear, luggage, and accessories”; and for beauty-related products: (iii) “cosmetics” and (iv) “hair, nails, and skin care—health”.

As of 2019, the total number of fashion and beauty-related stores in Seoul was 68,050. Looking at the spatial distribution by product characteristics, there were 23,531 “wearing apparel—clothing” stores, 6367 stores for “footwear, luggage, and accessories”, 6405 stores for “cosmetics”, and 31,747 stores for “hair, nails, and skin care—health”.

3.3. Analytical Techniques

3.3.1. Kernel Density Analysis

Spatial density was calculated from the distribution of spatial point data by applying a bivariate kernel density function based on the collected spatial data.

Kernel density was estimated using the following Equation (1): when the points \(x_1, x_2, \ldots, x_n\) are events \((n)\), they are distributed independently in the limited space \((S)\).

\[
\hat{f}_n(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \quad h = \left(\frac{4\sigma^5}{3n}\right)^{1/5} \approx 1.06\sigma n^{-1/5}
\]  

(1)
where $K$ is the kernel function as a bivariate probability density function, $h$ is the smoothing parameter as the bandwidth, and $x$ is the location in each fashion and beauty-related store. In our analysis, by applying the quartic function, which is the most widely used option for kernel functions [64], the spatial weights based on the distance from each store location were estimated and the bandwidth ($h$) was calculated by applying Silverman’s rule of thumb [65].

3.3.2. The Nearest Neighbor Ratio (NNR) Index

The NNR index is an analysis method used to determine the distribution pattern of spatial points by measuring the distance between the two nearest points, which involves calculating the average nearest distance from the actual spatial point distribution to the nearest point and then calculating the expected average nearest distance in the point distribution pattern. The expected distance is the average distance between neighbors in a hypothetical random distribution. The average NNR was calculated as the observed average distance divided by the expected average distance.

The observed nearest point distance was calculated using the following Equation (2): $d_{ij} = \min d_{ijr}$, where $d_{ij}$ is the distance between two points $i$ and $j$, the nearest Euclidean distance to any spatial point $i$ is expressed as here the number of spatial points is $n$, and the average nearest distance is $r$. The expected average nearest distance was calculated using the following Equation (3): where $\lambda$ is the estimated spatial point ($n$) per unit area ($A$).

\[
r = \frac{1}{n} \sum_{i=1}^{n} d_i
\]

\[
E(r) = \frac{1}{2\sqrt{\lambda}} \left( \frac{1}{2\sqrt{\pi}} \right)
\]

The NNR index was finally calculated using Equation (4):

\[
NNR = \frac{r}{E(r)}
\]

In our analysis, the NNR index was used to test the statistical significance of the cluster pattern revealed in the spatial point distribution. If the NNR index was less than 1, the pattern exhibited clustering; if the index was greater than 1, the trend was toward dispersion. In addition, the difference between $r$ and $E(r)$ was tested based on the results of calculating the threshold value of standardized normal probability. The z-scores and $p$-values were used as measures of statistical significance. Tests were considered significant at a level of 0.05, where a cluster distribution was identified if the value of the test statistic was less than $-2.58$ or greater than $2.58$.

3.3.3. Spatial Regression Models

Regression analysis is commonly used in the social sciences. Identifying and measuring the relationship between two or more functional attributes through regression analysis can help understand better what is happening in one place and predict where something is likely to happen. Ordinary least squares (OLS) regression is the best known regression technique and is considered the most appropriate starting point for all spatial regression analyses [66]. The spatial error model (SEM) and the spatial lag model (SLM) are forms of OLS regression, but they are estimated while controlling the intrinsic characteristics of spatial data, i.e., they consider spatial dependence and spatial heterogeneity. The SLM is used as an alternative model when the dependent variable has spatial autocorrelation, and the SEM is used when there is spatial autocorrelation in the error term [67]. The SEM and SLM were calculated via Equations (5) and (6), respectively:

\[
y = \rho W_y + \beta x + \epsilon = (I - \rho W)^{-1}(\beta x + \epsilon)
\]
\[
y = \beta x + \varepsilon (\varepsilon = \lambda W \mu + \mu) y = \beta x + (I - \lambda W)^{-1} \varepsilon
\]

where \( y \) is the dependent variable, \( x \) is the independent variable, \( \rho \) is the spatial autoregressive parameter (\( \rho \) for spatial lag), \( W \) is the spatial weighted matrix for the spatial lagged dependent variable, \( \varepsilon \) is an error term, and \((I - \rho W)^{-1}\) is the spatial multiplier effect on adjacent regions. Having spatial dependence in the error term \((\varepsilon)\) in the general linear regression equation \((y = \beta x + \varepsilon)\) enabled the construction of the SEM, where \( \lambda \) is the spatial autoregressive parameter (\( \lambda \) for spatial error), \( u \) is an error term, and \((I - \lambda W)^{-1}\) is the spatial multiplier effect between adjacent regions.

In our analysis, the optimal estimation model was selected from OLS regression, the SEM regression, and the SLM regression to avoid estimation deviations due to spatial effects.

4. Results

4.1. Basic Analysis

Figure 3 shows the annual transaction value of online shopping across a range of products from 2001 to 2020, and Table 1 summarizes the categorized products in which changes occurred around 2018.

![Figure 3. The trend of online shopping transactions (2001–2020). Source: [8].](image)

| Previous (–2017) | Current (2018–) |
|------------------|------------------|
| S/W(CD) | Computer, computer related appliances |
| Integration |  |
| Music CDs and disks · videos · musical instruments | Others |
| Flowers | Household goods |
| Household goods motor vehicle parts and accessories | Household goods |
| Motor vehicle parts and accessories | Motor vehicle parts and accessories |
| Subdivision |  |
| Travel arrangement and reservation services | Travel arrangement and transportation services |
| Culture and leisure services |  |
| Miscellaneous services | E-coupon services |
| | Food services |
| | Miscellaneous services |
The number of online shopping transactions in Korea has sharply increased over the last 20 years, and the total transaction amount was $14.2 billion as of December 2020 [8]. However, as seen in Figure 1, there were considerable differences in the trend of e-commerce transaction values in terms of product group. Books, software, and music CDs—as well as disks, videos, and musical instruments—showed a relatively rapid increase in transaction value compared to other products in the early 2000s, but their transaction value growth has been insignificant in recent years. On the other hand, the online shopping transaction value of clothes, fashion-related goods, travel arrangements and reservation services, and food and beverages have increased rapidly, particularly in recent years. In particular, e-commerce has grown since the emergence of smartphones and mobile services in 2010, and, with the arrival of various platform services such as Coupang in 2013, remarkable growth has also occurred in Korea. In addition, as overseas direct sales and purchases have become available in the online market, the volume of transactions continues to increase, with the amount and proportion of e-commerce in retail channels expected to increase further in the future.

Table 1 shows which product groups are driving the e-commerce market. Products that are currently leading the e-commerce market have been subdivided for greater precision, while those with low transaction volumes have been integrated with other product groups. “Household goods”, “motor vehicle parts and accessories”, “travel arrangement and reservation services”, and “miscellaneous services” are product groups that have increased in transaction value and that could therefore be clearly subdivided. The sectors that have grown rapidly in the online shopping market over the past 20 years are “clothes—fashion-related goods” and “beauty-related goods”, which account for the largest scale and portion in the amount of online shopping transactions. For example, we subdivided “clothes—fashion-related goods” into “wearing apparel—clothing” and “footwear, luggage, and accessories” from 2017, which enabled us to determine the number of transactions for each subgroup. On the other hand, “software (CDs)”, “music CDs and disks—videos—musical instruments”, and “flowers” have been integrated into other product groups from 2018 due to the decline in the value of online shopping transactions in relation to these product groups.

Table 2 shows increasing and decreasing trends in relation to the number of offline retail stores in terms of the four groups in Seoul between 2015 and 2019. Compared to Figure 1, the number of offline stores overall decreased in the retail channels for “wearing apparel—clothing”, “footwear, luggage, and accessories”, and “cosmetics” over the period. However, the number of online shopping transactions has continued to increase since 2015. Only “hair, nails, and skin care—health” stores grew in number, increasing by 27.26% in 2019 compared to 2015.

Table 2. Changes in the number and growth rate of retail stores with fashion and beauty (unit: n, %).

|                     | 2015      | 2019      | 2020      | 2015/2019 | 2019/2020 |
|---------------------|-----------|-----------|-----------|-----------|-----------|
| Wearing apparel—clothing | 27,370    | 23,531    | 21,745    | -14.03    | -7.59     |
| Footwear, luggage, and accessories | 8107      | 6367      | 6117      | -21.46    | -3.93     |
| Cosmetics           | 8612      | 6405      | 5602      | -25.63    | -12.54    |
| Hair, nails, and skin care—health | 24,947    | 31,747    | 32,055    | 27.26     | 0.97      |

Note: The figures for 2020 used aggregated data by sept., not the annual figures, due to data acquisition time.

In retail channels, e-commerce has grown rapidly. However, it was observed that increasing or decreasing trends slightly differed depending on the characteristics of the product group. Product areas such as wearing apparel, clothing, and related products showed the greatest increases, and increases were also observed in household goods, food and beverages, and cosmetics, which are related to daily life. These findings showed that changes in technology and in society, as well as changes in people’s lifestyles, have been reflected in e-commerce, where transactions have increasingly involved lifestyle consumer
goods that are closely related to food, clothing, and shelter. This trend could be expected to affect the opening and closing distribution patterns of offline retail stores.

As shown in Table 2, except for “hair, nails, and skin care—health” stores, a decreasing trend was observed in the number of stores of “wearing apparel—clothing”, “footwear, luggage, and accessories”, and “cosmetics”, but the overall spatial distribution had a broadly similar pattern (Figure 2).

Specifically, we found that there were differences in the number of newly opened and closed offline stores in terms of the fashion and beauty product group between 2015 and 2019. As shown in Table 3, more stores closed than were opened for “wearing apparel—clothing”, “footwear, luggage, and accessories”, and “cosmetics”. Only stores involved with “hair, nails, and skin care—health”, with relatively strong face-to-face service purchasing characteristics, were opened more often than closed over the period.

Table 3. Changes of opening and closure by retail stores with fashion and beauty (2015/2019) (unit: n).

| Product Group                                      | Opening  | Closure  | Variation (2015/2019) |
|---------------------------------------------------|----------|----------|-----------------------|
| Wearing apparel—clothing                         | 11,102   | 36,522   | −25,420               |
| Footwear, luggage, and accessories                | 2680     | 4408     | −1728                 |
| Cosmetics                                         | 3144     | 5290     | −2146                 |
| Hair, nails, and skin care—health                 | 18,610   | 11,888   | 6722                  |

4.2. Spatial Cluster Analysis

We estimated spatial density to identify clusters appearing in the distribution of stores based on the distribution of locations in terms of the four groups of our study. Figure 4 shows a visualization following kernel density analysis of the relevant stores in 2019. Large and small hotspots were found to be distributed around the central business district for each store subgroup. Hotspots also appeared around newly developed urban areas comprising offices, large-scale apartment complexes, industrial complexes, and major nodular areas. Stronger hotspots were observed in relation to beauty-related stores than to fashion-related stores. In particular, “hair, nails, and skin care—health” stores had a high spatial density throughout Seoul.

As of 2019, among the fashion and beauty-related stores in Seoul, “wearing apparel—clothing” stores were distributed at approximately 25 stores per unit area, “footwear, luggage, and accessories” stores and “cosmetics” stores were distributed at approximately 7 stores per unit area, and “hair, nails, and skin care—health” stores were distributed at approximately 33 stores per unit. The number of retail stores related to fashion and beauty products and services was found to be very large and clustered in specific regions. All four groups also formed strong hotspots in more recently developed parts of the central business district. In particular, fashion-related hotspots were found to be highly concentrated around the central business district, and beauty-related hotspots were found to be highly concentrated around the original and new central business district.

We also tested the statistical significance of this cluster pattern by deriving values using the NNR index [68]. As shown in Table 4, the ratio of the average observed value of the shortest distance between the locations of fashion and beauty-related stores in Seoul and the predicted average shortest distance was statistically significant (NNR < 1), with clustering confirmed.
Wearing apparel—clothing  
Footwear, luggage, and accessories  
Cosmetics  
Hair, nails, and skin care—health 

Figure 4. Kernel density analysis results (2019).

Table 4. Nearest neighbor distance statistics results (2019).

|                        | Point (n) | Observed NND (m) | Expected NND (m) | NNR (Index) | Z-Score | p-Value |
|------------------------|-----------|------------------|------------------|-------------|---------|---------|
| Wearing apparel—clothing | 23,531    | 25.95            | 93.29            | 0.28        | -211.84 | 0.00    |
| Footwear, luggage, and accessories | 6367     | 62.79            | 176.06           | 0.36        | -98.21  | 0.00    |
| Cosmetics               | 6405      | 63.23            | 173.79           | 0.36        | -97.40  | 0.00    |
| Hair, nails, and skin care—health | 31,747   | 25.66            | 80.81            | 0.32        | -232.65 | 0.00    |

4.3. Spatial Regression Analysis

We empirically analyzed local geographic factors affecting the spatial distribution characteristics of newly opened and closed fashion and beauty-related stores from 2015 to 2019. After cluster patterns had been confirmed, we could apply OLS regression to evaluate the distribution of newly opened and closed retail stores in terms of the four subgroups. The SLM and SEM were used to estimate spatial heterogeneity and spatial autocorrelation by using the aggregated spatial points of 35,536 newly opened stores and 58,108 closed stores in Seoul from 2015 to 2019 that had been converted to 424 administrative areas.

4.3.1. Collecting Spatial Data

The independent variables of the regression model comprised offline local geographic attributes such as population, industrial and economic activities, transport factors, and land value (Table 5). The spatial unit of the data was composed of the smallest spatial polygon unit and administrative-area data.
Table 5. Variable selection.

| Dimension                  | Variables                                                                 | Data Year | Data Source |
|----------------------------|---------------------------------------------------------------------------|-----------|-------------|
| Dependent variables        | The newly opened and closed fashion and beauty-related stores (n)          | 2019      | [69]        |
|                            | (1) Wearing apparel—clothing; (2) footwear, luggage, and accessories;     |           |             |
|                            | (3) cosmetics; and (4) hairs, nails, and skin care—health                |           |             |
| Independent variables      | Resident population (person)                                              | 2015      | [8]         |
|                            | The average of the daytime population (person)                            |           |             |
|                            | The annual average of passengers in a subway station (person)            | 2019      | [70]        |
| Industrial economic        | Industrial establishments (n)                                             | 2018      | [8]         |
| activities                 | Workers per establishment (person)                                       |           |             |
|                            | Food and beverage stores (n)                                             |           |             |
|                            | Business start-up rate (%)                                               |           |             |
| Physical accessibility     | Private tutoring institutes for adults (n)                               | 2019      | [71]        |
|                            | Average nearest distance to a subway station (m)                         | 2019      | [70]        |
|                            | Average nearest distance to the main road (m)                            | 2019      | [72]        |
|                            | Parking spaces (n)                                                       | 2018      | [69]        |
| Land value                 | Officially assessed individual land price (W)                             | 2019      | [73]        |

First, we structured the spatial data by separating the resident from the active population within the region in terms of demographic attributes to enable the measurement of the consumption strength of fashion and beauty goods and services. The resident population comprised households registered within the administrative areas, and the active population comprised the daytime population (09:00–18:00) within the administrative areas. The average number of passengers getting on and off the subway was used as an indicator of the numbers involved in the floating population, and this measurement allowed us to assess the various types of land use and activities occurring around the subway station.

As an indicator of industrial and economic activities, the number of employees per establishment, which could be used to identify the total number of establishments and the size of the workplace, could be used as a multi-faceted variable. The business start-up rate was also configured as an independent variable. Using the start-up rate, which is a measure of the degree of activation of the local economy, the relationship between the region where start-ups are active and the location of opening and closure of stores related with fashion and beauty was investigated. We considered that the consumption of food, beverages, and goods would occur together in one place, so the number of restaurants as a similar industry type was also taken as an explanatory variable. With “the 52-h limit” total weekly working rule (an amendment to the Labor Standards Act to improve the long-term work problem in Korean society, which was implemented in July 2018 as a system that reduced the legal working hours per week from 68 to 52 h (legal working 40 h + extended 12 h) implemented, “saladents” (a compound word for salaryman and student) have increased and 20–30 s millennials who value “wolabal” (a compound word for work and life balance) are increasing their spending on education for their hobbies and self-development (Korea’s lifetime learning participation rate for adults was 40.0% in 2020 (41.7% in 2019). Except for formal education (1.4%), the participation rate of non-formal education (learning activities other than formal education) was 39.3% in 2020, and, in particular, the participation rate of job-related non-typical education was 20.1% (2020). Of the non-formal education institutions that are separately counted, there were 4,897 lifelong vocational education and training institutes for adults in 2020, of which 2,175 were located in Seoul [74]). Private tutoring institutes that teach these people are densely distributed around in downtown and sub-centers where fashion and beauty-related stores are concentrated [75]. Thus, although it is a heterogeneous industry, the number of vocational education and training institutes for adults was added as an indicator of non-economic activities because of the possibility of using a nearby fashion and beauty-related retail store while using private tutoring
facilities after work or on the weekend. By examining these explanatory variables that reflected the attributes of consumption strength according to the distribution of residence and workplace, we could identify the effects of location on the opening and closure of fashion and beauty-related retail stores.

We calculated the average shortest distance to the subway station for each fashion and beauty-related retail store as a transport factor to understand the physical accessibility of a store visit. The average shortest distance to arterial roads was also calculated for each store. The number of parking spaces was also taken as a variable to indicate accessibility. Through these means, we sought to check how the degree of physical proximity affected the distribution of newly opened and closed fashion and beauty-related stores. The distribution of population, industrial and economic activities, and the physical proximity of stores could be directly or indirectly affect the value of the land on which the stores were located. Thus, officially assessed land prices were also configured as a variable.

4.3.2. Descriptive Statistics and Spatial Autocorrelation Tests

The descriptive statistics of the explanatory variables are presented in Table 6. Before the regression analysis, correlations were first analyzed for all variables, and variables with very high correlations were removed beforehand. Only variables with a coefficient of variance expansion (VIF) of 10 less, which is a diagnostic tool used in relation to multicollinearity, were further confirmed that the explanatory variable input for OLS regression using the GeoDa software satisfied the multi-collinearity condition index of having fewer than 30.

The explanatory variables were configured according to the temporal range of the dependent variable. If some spatial data were not available for acquisition, the data at the most recent time were used. Considering the data units, all variables were set as standardized values.

To review the model for spatial regression analysis, we applied the statistics of Jarque–Bera, Breusch–Pagan, Koenker–Bassett, and White to test the irregularity, spatial heterogeneity, and spatial dependence of the error terms for the variables. The differences were found to be statistically significant. The Lagrange multiplier (LM) statistic was used to determine whether there was a spatial autocorrelation between the dependent variable and the error term. If the null hypothesis was rejected according to the test value, the optimal regression model was selected by SLM and SEM estimations and comparing the result values. The selection of the SLM and SEM was based on the selection criteria proposed by Anselin [76].

After applying LM statistics, the most statistically significant SEM was selected from the LM (error) statistics concerning newly opened “hair, nails, skin care—health” stores and for closed “wearing apparel—clothing”, “cosmetics”, and “hair, nails, and skin care—health” stores. To verify the accuracy of the regression model, the determination coefficient ($R^2$), Akaike information criterion (AIC), log-likelihood, and Schwarz criterion (SC) were also used to compare the results of the three regression models. These four indicators represent the relative measures of statistical fit. A better regression model has higher r-squared and log-likelihood values but lower AIC and SC values.

Some regression models describing the distribution of newly opened and closed retail stores improved the performance of OLS modeling by incorporating spatial dependence using the SLM and SEM in each of the four groups. Some results from these spatial regression models showed that the SEM was better than the SLM, so the estimation results from the SEM were used for our analysis. Thus, we interpreted the analysis results of local geographic factors affecting the spatial distribution of newly opened “hair, nails, and skin care—health” stores and of closed “wearing apparel—clothing”, “cosmetics”, and “hair, nails, and skin care—health” by using SEM results.
### Table 6. Descriptive statistics of variables.

| Variables | Min.   | Max.   | Mean   | S.D.   | VIF  |
|-----------|--------|--------|--------|--------|------|
| POP       |        |        |        |        |      |
| Resident population (person) | 268    | 57,761 | 2299   | 9448   | 3.9  |
| Average of daytime population (person) | 35,633 | 919,903| 254,147| 124,232| 6.4  |
| Monthly average Passengers in subway station (n) | 0      | 367,882| 27,319 | 44,733 | 1.9  |
| Industrial establishments (n) | 19     | 15,787 | 1942   | 1917.8 | 4.2  |
| workers per establishment (person) | 2.1    | 19.7   | 5.6    | 3.2    | 2.0  |
| Food and beverage stores (n) | 0      | 20,718 | 308    | 290.5  | 6.8  |
| start-up rate (%) | 3.1    | 25.9   | 11.0   | 2.8    | 1.4  |
| IEA       |        |        |        |        |      |
| Life-long vocational education and training institutes (n) | 0      | 181    | 4.7    | 13     | 2.6  |
| ACC       |        |        |        |        |      |
| Average nearest distance to main road (m) |        |        |        |        |      |
| opening   | WAC    | 0      | 1504.0 | 158.4  | 173.3 | 4.2  |
|           | FLA    | 0      | 1679.5 | 148.8  | 207.1 | 4.1  |
|           | COS    | 0      | 1566.2 | 134.5  | 177.2 | 4.2  |
|           | HNSH   | 0      | 1622.3 | 180.8  | 165.8 | 7.3  |
| closure   | WAC    | 0      | 918.2  | 141.9  | 93.6  | 1.1  |
|           | FLA    | 0      | 803.1  | 129.0  | 93.7  | 1.5  |
|           | COS    | 0      | 1422.3 | 156.7  | 163.6 | 3.0  |
|           | HNSH   | 0      | 546.3  | 162.4  | 76.9  | 1.2  |
| Parking spaces (n) | 388    | 53,414 | 10,025.2 | 6670.5 | 5.0  |
| LV        |        |        |        |        |      |
| Officially assessed individual land price (thousand won) | 742,238 | 22,528 | 3852  | 2438  | 1.7  |

Note: POP (population), IEA (industrial economic activities), ACC (accessibility), LV (land price), WAC (wearing apparel—clothing), FLA (footwear, luggage, and accessories), COS (cosmetics), and HNSH (hair, nails, and skin care—health).

4.3.3. OLS and SEM Results

The general linear regression model and spatial regression model estimation results of the distribution factors concerning newly opened and closed retail stores related to fashion and beauty in Seoul are shown in Tables 7–9 below.

First of all, it was found that the location of newly opened fashion and beauty-related stores had a significant relationship with areas where there were many industrial establishments or food and beverage stores in adjacent areas. It was also found that the distribution of the regionally active population during the daytime had a more positive influence on the location of newly opened fashion and beauty-related stores than the distribution of the resident population. Land prices, which represent absolute and relative values of land use, were also found to be closely related to the location of newly opened stores.

Conversely, the distribution of food and beverage stores in similar business types in nearby regions had a significant influence on the closure of fashion and beauty-related stores. Land prices also showed a strong relationship with the location of closed retail stores. These findings can be explained as due to varying and contrasting effects on the opening and closing of retail stores according to location. Many retail stores were found...
to have newly opened in regions with a large consumption population, strong economic activity, and high land values, but these regional characteristics also influenced the closure of many retail stores, indicating that the same local geographic variables may have positive or negative effects.

Table 7. The OLS results of newly opened retail stores related with fashion and beauty.

| Independent | Dependent | WAC | FLA | COS | HNSH |
|------------|-----------|-----|-----|-----|------|
| CONSTANT   |           | −42.738 *** (−2.749) | −1.602 (−0.596) | −2.448 (−1.081) | −29.008 *** (−4.527) |
| POP        |           | −0.002 *** (−3.062) | −0.000 *** (−4.702) | −0.000 *** (−3.923) | 0.001 *** (2.833) |
| ADP (person) |         | 0.0003 *** (4.810) | 4.856 *** (5.254) | 3.248 *** (−3.923) | 3.676 * (1.856) |
| MAPS S (n) |           | 5.264 (0.066) | −3.262 (−0.233) | 1.921 * (1.713) | −4.326 (−1.451) |
| IE (n)     |           | 0.036 *** (13.006) | 0.003 *** (5.212) | −0.001 ** (−2.450) | −0.003 *** (−3.205) |
| WPE (person) |         | −0.974 (−0.864) | −0.544 *** (−2.731) | −0.216 (−1.360) | −2.028 *** (−4.768) |
| FBS (n)    |           | −0.128 *** (−5.534) | −0.002 (−0.518) | 0.008 ** (2.375) | 0.048 *** (5.424) |
| SR (%)     |           | 3.613 *** (3.351) | 0.235 (1.232) | 0.165 (1.909) | 2.524 *** (6.158) |
| PTIA (n)   |           | −0.449 (−1.419) | −0.031 (−0.549) | 0.260 *** (5.815) | 1.372 *** (11.419) |
| PS (n)     |           | −0.004 *** (−4.302) | −0.000 (−1.409) | 0.000 * (1.945) | 0.001 ** (2.368) |
| LV         | OAILP (W) | 3.789 *** (2.787) | 1.022 *** (4.258) | 7.738 *** (4.012) | 2.266 *** (4.396) |

Goodness of fit

|            | R-squared | 0.451 | 0.429 | 0.598 | 0.763 |
|            | Log-likelihood | −2285.4 | −155.74 | −1451.91 | −1873.18 |
|            | AIC | 4596.8 | 3127.48 | 2935.81 | 3772.37 |
|            | SC | 4649.44 | 3180.13 | 2988.46 | 3825.01 |

Normality

| Jarque–Bera test | 137,513.245 *** | 21,151.661 *** | 3888.313 *** | 2796.664 *** |
| Breusch–Pagan test | 5969.289 *** | 951.028 *** | 1470.77 *** | 787.508 *** |
| Koenker–Bassett test | 133.652 *** | 53.469 *** | 180.727 *** | 108.387 *** |
| White test | 414.866 *** | 289.771 *** | 350.66 *** | 348.789 *** |

Spatial autocorrelation

| Lagrange multiplier (lag) | 0.395 | 0.673 | 0.648 | 19.213 *** |
| Robust LM (lag) | 0.605 | 0.015 | 4.791 | 3.320 * |
| Lagrange multiplier (error) | 0.034 | 0.839 | 1.053 | 27.716 *** |
| Robust LM (error) | 0.244 | 0.180 | 5.196 | 11.823 *** |
| Lagrange multiplier (SARMA) | 0.639 | 0.853 | 5.844 | 31.036 *** |

Multi-collinearity (MCC-Number) | 23.549 | 23.285 | 23.924 | 24.836 |

WAC (wearing apparel—clothing), FLA (footwear, luggage, and accessories), COS (cosmetics), HNSH (hair, nails, and skin care—health), POP (population), IEA (industrial economic activities), ACC (accessibility), LV (land values), RP (resident population), ADP (average of the daytime population), MAPSS (monthly average passengers in a subway station), IE (industrial establishments), WPE (workers per establishment), FBS (food and beverage stores), SR (start-up rate), PTIA (private tutoring institutes for adults), ANDM (average nearest distance to the main road), ANSS (average nearest distance to a subway station), PS (parking spaces), and OAILP (officially assessed individual land price); p-value: *** < 0.01, ** < 0.05, * < 0.1; β is standardized values, and the parenthesis values mean t-stat. The local geographic factors determining the distribution of fashion and beauty-related retail stores also showed slight differences. Among the variables, it was found that food and beverage stores and private tutoring institutes for adults had a positive and significant relationship with the location of newly opened beauty-related stores but not with newly opened fashion-related stores. The new central business district, a big hotspot for beauty-related stores, has not only the characteristics of the business cluster as the original central business district but also that of its location as a residential cluster. Thus, it was interpreted that the high dense distribution of food and beverage stores (similar industries) for office workers and residents, as well as private tutoring institutes (heterogeneous industries)
for vocational and hobby activities, affect the opening locations of beauty-related stores. As with the analysis of Lee and Pace [76], our results showed that the importance of the physical distance could be underestimated. In particular, fashion-related stores with the largest number of online transactions were found to have many openings even in places with a low relationship with transportation accessibility, which has traditionally played an important role in the survival of stores (the statistical significance level was not satisfied, but a positive correlation was found). Rather, in terms of parking space availability, it was found that a lack of parking spaces significantly affected the closure of fashion-related retail stores.

Table 8. The OLS results of closed retail stores related with fashion and beauty.

| Independent | WAC | FLA | COS | HNSH |
|-------------|-----|-----|-----|------|
| CONSTANT    | -66.582 *** (-3.647) | -0.117 (-0.029) | -9.763 *** (-3.321) | -12.329 ** (-2.484) |
| POP         | \[0.000 (-0.349)\] | \[0.000 *** (-2.997)\] | 1.066 (0.118) | 0.003 *** (4.102) |
| IEA         | IE (n) | 0.027 *** (8.512) | 0.016 *** (8.455) | 0.000 (0.452) | -0.001 (-1.387) |
| IEA         | WPE (person) | -2.588 ** (-2.030) | -0.687 ** (-2.365) | -0.003 (-0.016) | -0.978 ** (-3.0) |
| IEA         | FBS (n) | 0.043 (1.629) | 0.000 (0.084) | 0.015 *** (3.826) | 0.032 *** (4.781) |
| IEA         | SR (%) | 1.678 (1.380) | -0.050 (-0.181) | 0.048 (0.257) | 0.750 ** (2.405) |
| ACC         | PTIA (n) | -0.491 (-1.364) | -0.270 *** (-3.301) | 0.062 (1.148) | 0.586 *** (6.360) |
| ACC         | ANDM(m) | 0.072 ** (2.241) | -0.003 (-0.399) | 0.004 (1.334) | 0.003 (0.305) |
| ACC         | ANSS(m) | 0.028 * (1.664) | -0.001 (-0.191) | -2.063 (-0.007) | -0.002 (-0.670) |
| ACC         | PS (n) | -0.002 ** (-2.201) | -0.001 ** (-2.253) | 2.944 (0.2) | 0.000 (0.422) |
| LV          | OAILP (W) | 1.398 *** (9.113) | 2.384 *** (6.825) | 2.312 *** (10.043) | 2.984 *** (7.554) |

The location of beauty-related stores that directly consume places based on face-to-face services that cannot be easily replaced by online transactions alone showed the spatial dependence. In particular, the spatial ripple effect in terms of the location of retail stores affected closures more than openings. The closure of “hair, nails, and skin care—health”
stores was found to have stronger spatial relationships with similar stores located in nearby areas than other stores.

Table 9. The SEM results of newly opened and closed retail stores related with fashion and beauty.

| Independent | Opening Dependent | Closure Dependent |
|-------------|-------------------|-------------------|
|             | HNSH | WAC | COS | HNSH |
| CONSTANT   | -23.780** (-3.756) | -64.073** (-3.517) | -10.063** (-3.475) | -9.493** (-1.995) |
| POP RP (person) | 0.001** (2.987) | -0.000 (-0.430) | -2.438 (-0.283) | 0.001** (4.340) |
| ADP (person) | 3.166* (1.661) | 0.000*** (2.743) | 2.539** (3.005) | 2.488 (0.175) |
| MAPSS (n) | -4.065 (-1.489) | 3.389 (0.396) | 3.439** (2.823) | -9.061 (-0.438) |
| IE (n) | -0.003*** (-3.152) | 0.027*** (8.456) | -1.267 (-0.003) | -0.001 (-1.287) |
| WPE (person) | -1.601*** (-3.874) | 0.027*** (8.456) | 0.197 (1.062) | -0.444 (-1.432) |
| FBS (n) | 0.054*** (6.287) | 0.042 (1.620) | 0.018*** (4.644) | 0.037*** (5.783) |
| SR (%) | 2.218*** (3.674) | 1.478 (1.239) | 0.006 (0.316) | 0.457 (1.576) |
| PTIA (n) | 1.316*** (11.291) | -0.446 (-1.255) | 0.050 (0.969) | 0.522*** (5.950) |
| ANDM (m) | 0.003 (0.422) | 0.062** (1.981) | 0.005 (1.641) | -0.002 (-0.196) |
| ANSS (m) | 0.004 (0.637) | 0.024 (1.482) | -0.001 (-0.221) | -0.002 (-0.855) |
| PS (n) | 0.000 (1.584) | -0.002** (-2.465) | -9.594 (-0.686) | -0.000 (-0.555) |
| LV OAILP (W) | 2.127*** (3.760) | 1.389*** (8.538) | 2.464*** (9.623) | 2.805*** (6.346) |

Goodness of fit:
- R-squared: 0.781, 0.661, 0.683, 0.675
- Log-likelihood: -1860.933, -2334.068, -1519.417, -1741.723
- AIC: 3747.87, 4694.14, 3064.83, 3509.45
- SC: 3800.51, 4746.78, 3117.48, 3562.09

Spatial effects:
- Spatial error coeff. (λ): 0.275***, 0.164***, 0.308***, 0.345***

5. Conclusions
5.1. Summary of Findings

This study analyzed the relationship between the survival and location characteristics of offline retail stores according to changes in the commercial environment, such as an increase in online transactions. To do this, we identified changes in the spatial distribution of fashion and beauty-related retail stores, which account for a large proportion of online shopping transactions in Korea. In addition, by considering the characteristics of the products handled by these stores, we divided the stores into four subgroups to determine local geographic factors that affected the opening and closure patterns for each subgroup.

First, we found that while the online consumption of fashion and beauty-related products had sharply increased over the past two decades, the distribution of offline retail stores in Seoul still showed an increasing trend. However, among fashion and beauty-related products and services, retail stores involved with “wearing apparel—clothing”, “footwear, luggage, and accessories”, and “cosmetics” showed a decreasing trend of distribution, with only “hair, nails, and skin care—health” retail stores showing a noticeably increasing distribution trend.

Second, we formed spatial points by geocoding based on address data, and performed location analysis for “wearing apparel clothing”, “footwear, luggage, and accessories”, “cosmetics”, and “hair, nails, and skin care—health” stores. Through the visualization of the kernel analysis results, clustering patterns were identified for each retail store subgroup,
and the statistical significance of the kernel density values was confirmed using the NNR index. We found a statistically significant clustering tendency involving large and small hotspots for all four subgroups, with all of them showing a strong clustering around the original central business district and more new downtown areas. “Hair, nails, and skin care—health” stores, in particular, showed a high-density distribution in commercial areas, as well as in residential areas where large apartment complexes were concentrated throughout Seoul.

We also identified local geographic factors affecting the distribution of fashion and beauty-related retail stores that were newly opened and closed in 2019 compared to the situation in 2015. A spatial regression analysis showed that many stores were newly opened in places that also had many closed stores. This finding indicated that the same local geographic variables may have positive and negative effects in terms of store openings or closures. Both newly opened and closed retail stores were distributed in areas with large populations, strong economic activity, and high land values. The distribution of industrial establishments and food and beverage stores was also shown to have a significant effect on the location of both newly opened and closed retail stores. The distributions of food and beverage stores, private tutoring institutes for adults, and parking spaces showed differing effects on fashion-related stores compared to beauty-related stores. The distribution of the daytime and resident population also had differing effects on the retail store subgroups depending on their products and services.

5.2. Spatial Implications

In this study, we divided fashion and beauty stores into four subgroups according to the characteristics of products and services. However, our analysis showed different results depended on whether sale products are easily replaced by online retail or whether products and services could be experienced and consumed in an offline place. Even in the four subgroups, the “hair, nails, skin care—health” retail store group showed different spatial distribution characteristics from the other three subgroups, and it also showed a significant difference in the spatial regression analysis results.

With a significant shift in the purchase path from offline to online, the focus of place consumption is shifting from purchasing products to purchasing experiences and services [77,78]. In the shift from brick-and-mortar retail to online retail, Our findings provide new evidence for the importance of spatial interdependence in retail locations for retailers to survive, including changes in offline retail spaces. All four fashion and beauty stores were concentrated and distributed around a specific space, but beauty-related stores, which also had characteristics of experiencing and consuming products and services, showed a relatively strong spatial dependence. In particular, “hair, nails, and skin care—health” retail stores, which provided both online transactions and face-to-face services, showed the greatest spatial correlation between similar offline stores. The number of them with the characteristics of consuming experiences and services in places had continued to increase during over the past four years, when online transactions have soared, and even during the COVID-19 outbreak.

Fashion-related stores, which could be easily replaced by online retailing, had many newly opened locations, even in places with low physical accessibility factors that have traditionally played an important role in the survival location of stores. Nevertheless, there were also many places where a low physical accessibility was found to be a factor influencing the closure of fashion-related stores. In other words, it was found that the spatial effect of the closure of retail stores in some regions on the closure of neighboring retail stores was greater than the spatial ripple effect arising from the opening of stores in neighboring regions. The closure of one retail store had a significant spatial effect on surrounding chains of retail stores in terms of further possible closures. The concentration of a particular industry affects the same or similar industries that are connected. The location of newly opened and closed fashion and beauty stores was also found to be associated with the location of the same, similar, and heterogeneous industries. If the
continuous closure of retail stores is due to the absence of appropriate policies and not competition, then the problem will be more serious and the negative impact will be longer.

The survival and closure of retail stores can affect structural changes in local commercial and economic spaces in the long run. Therefore, it is necessary to prepare place-based measures at the local level to prevent a series of closures by prioritizing areas with a relatively high risk of survival (a higher closure rate). We can compare the economic and geographic characteristics of neighboring retail stores in areas with higher opening rates and areas with higher closure rates to explore how to improve the retail environment. In that regard, our findings also provide basic reference data for identifying relevant local commercial information, including start-ups related to fashion and beauty. In particular, spatial analysis using a geographic information system will be able to further maximize the effect of local-level place-based policies because it is possible to grasp the spatial ripple effect of the policy through pre-simulation before implementation.

This study had some limitations. By using spatial regression models, we tried to identify the relationship between online search volume and the offline distribution of products such as clothing, shoes, and cosmetics. However, no clear pattern could be found, and these items were removed as independent variables in the end. We consider that this outcome was due to consumers searching in terms of a shopping mall name or company name rather than simply searching for clothes or shoes when entering a search word. We hope to clarify this matter with more targeted research in the future studies.

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