Ph.D. Dissertation of Engineering

Evaluation and Application of Built Environmental Components for Healthy City: Focused on the Cases of Seoul

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계획 방향에 관한 연구
: 서울시 사례를 중심으로

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Evaluation and Application of Built Environmental Components for Healthy City: Focused on the Cases of Seoul

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Publications

Please note that Chapter 1-2 of this dissertation proposal were written as standalone papers (see below), and therefore there is some repetition in the methods and results.

Chapter 1

Choi, Y., Yoon, H., & Jung, E. (2018). Do Silver Zones reduce auto-related elderly pedestrian collisions? Based on a case in Seoul, South Korea. *Accident Analysis & Prevention*, *119*, 104-113.

Chapter 2

Choi, Y., Yoon, H., & Kim, D. (2019). Where do people spend their leisure time on dusty days? Application of spatiotemporal behavioral responses to particulate matter pollution. *The Annals of Regional Science*, *63*(2), 317-339.

Abstract

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Local governments of South Korea have been following the Healthy Cities Movement, and they are making continuous efforts in creating healthy cities and communities. The local governments treat the design and planning of cities with much importance, because an integration of activities in urban settings has been identified as an important factor in creating healthy cities. However, anecdotal evidence has raised questions about the effectiveness of those designs and planning projects based on Healthy Cities approaches. In addition to questions about past projects, citizens and the media are looking for new systems and amenities to solve emerging social and environmental

problems to which most people are new. This increase in questions and demands from citizens not only leads to dissatisfaction with local governments and their communities, but also hinders the proper use of government budgets. Therefore, studies that seek to evaluate past projects and to explore possible projects for healthy cities are becoming important in the field of sustainable development.

Among the factors for creating a healthy city, there is a growing interest in promoting people's active lifestyles through provision of public safety. This safety is emphasized in various areas such as pedestrian safety, crime prevention, air pollution prevention, and drinking water contamination prevention. Various Healthy City projects have been conducted to solve these problems, but due to the lack of data and evaluation tools, the systems and amenities have not been properly evaluated in these projects. Also, for the same reason, there is currently a lack of projects focused on emerging problems.

This two-part research thesis develops a methodology and framework for finding weaknesses of existing Healthy City projects in Seoul. The thesis also identifies new environmental issues to address, in order to provide a healthier environment for citizens. To evaluate the performance of existing projects related to road safety, the first part of this study investigates Silver Zones in Seoul, which are constantly questioned in terms of effectiveness. To explore new environmental issues related to air pollution prevention, the second part of this study analyzes changes in citizens' behavior regarding recreational site selection based on the air pollution severity.

This study seeks to develop useful decision support tools for design and planning for Healthy Cities approaches, by providing an empirical

methodology for evaluation of existing projects and for the exploration of new environmental issues. The evaluation process and results of each chapter will be beneficial in the future for larger communities as they can be used to update design and planning guidelines and explore new issues that may affect citizens' health.

Keywords: Healthy City, Silver Zone, Road Safety, Air Pollution, Particulate Matter

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I. Introduction

In this rapidly urbanizing world, various social and environmental problems become intertwined, which, in turn, affect the health of citizens. Considering this phenomenon, much effort is needed to protect the health of people through the structure and dynamics of the city. The Healthy City Movement, an approach initiated by the World Health Organization (WHO) in 2003, encourages city operators to work together to improve social, economic, and physical environments to promote the health and quality of life of individuals. A healthy city as defined by WHO is not a city that targets a particular rank or status, but rather, one which continuously creates and improves its physical and social environments, supporting individuals to be healthy and to reach their full potential (Zhao, 2011).

As of 2019, more than 3,000 cities of the WHO member countries, including ninety-four cities of South Korea, have joined the Healthy City Movement. The Alliance for Healthy Cities, the international network that recommends policies and planning strategies for Healthy Cities, argues that the integration of activities in an urban setting is an important feature of healthy cities. There are many planning topics and strategies that require attention, to encourage citizens to be active both physically and socially. WHO-led research shows that there are twelve topics and goals of the Healthy City in planning aspects: health, exercise, social cohesion, housing, work, accessibility, food, safety, air quality, water, earth, and climate (Tran, 2016). All these topics are interrelated and important for citizens to have an active lifestyle.

In order to continuously develop and improve each city into a healthy

city, it is essential to evaluate the performance of past projects and to identify new environmental issues. However, not all cities regularly revisit past projects to evaluate their current status. This process can be beneficial for larger communities as the evaluation can be useful for updating design and planning guidelines, and for raising new issues that can affect citizens' health. Therefore, this two-part thesis study aims to evaluate already-established projects and current environmental issues in relation to the topic of healthy cities in Seoul. We chose two environmental settings that are related to the active lifestyles of citizens: (1) the effects of Silver Zones and (2) the effects of air pollution on leisure patterns.

The first part of this thesis evaluates the effect of Silver Zones in South Korea, namely the condition of cities with regard to road safety. Road safety is an important condition for making the city healthy for citizens. In order to improve pedestrian safety, especially for elderly pedestrians, the South Korean government established the Silver Zone system in 2007. The system designates areas as safety zones, and warns drivers of elderly pedestrians through the use of various speed-limit measures. However, questions have been raised about the effectiveness of reducing auto-related elderly pedestrian collisions since the development and implementation of the Silver Zones. Some analytical studies have shown that the Silver Zones are ineffective (Park and Oh, 2011; Lee, 2012), with the media suggesting that reasons for this failure might include ineffective designs, or the lack of advertising and awareness. However, the lack of relevant data accumulated has obstructed a full evaluation of its performance. Therefore, the first part of this paper aims to study the effects of the Silver Zone using valid data, and recommends better designs as part of a system for healthy cities.

The second part of the paper examines how air pollution influences people's leisure patterns, especially with regard to recreational site selection. Particulate matter-based air quality deterioration has become a shared environmental issue in the East Asia Pacific region (Karagulian et al. 2015). Korea also suffers from the harmful effects of PM and has been rated as one of the worse among OECD member countries in 2018 (OECD 2018). Anecdotal evidence suggests that behavior of Koreans has changed due to bad air quality, in that more people are trying to avoid outdoor activities if possible and follow precautions such as wearing masks and using personal air purifiers (Lee 2019). These air quality problems, which affect the condition of healthy cities, cannot be easily changed once they have spread; therefore, constant efforts that strive to avoid air pollution are needed, such as using green energy or increasing air purification systems. Furthermore, paying attention to reactions of citizens is essential to the leaders of cities, so ecological problems do not harm the health of citizens or expand into socioeconomic problems. Therefore, in order to examine the expansion of air quality problems into current social problems and to further prepare design and planning guidelines for healthy cities with respect to air quality issues, the second part of this paper addresses the following questions: (1) Does the increase in PM 2.5 affect the number of visitors to the three categories of recreational places (open spaces, commercial spaces, and indoor sports facilities) at different times of day and week? (2) If so, does the change in the number of visitors differ by the sub-category of those recreational places (i.e., hills, small parks, waterfront parks, multi-complex shopping malls, department stores, and large supermarkets)?

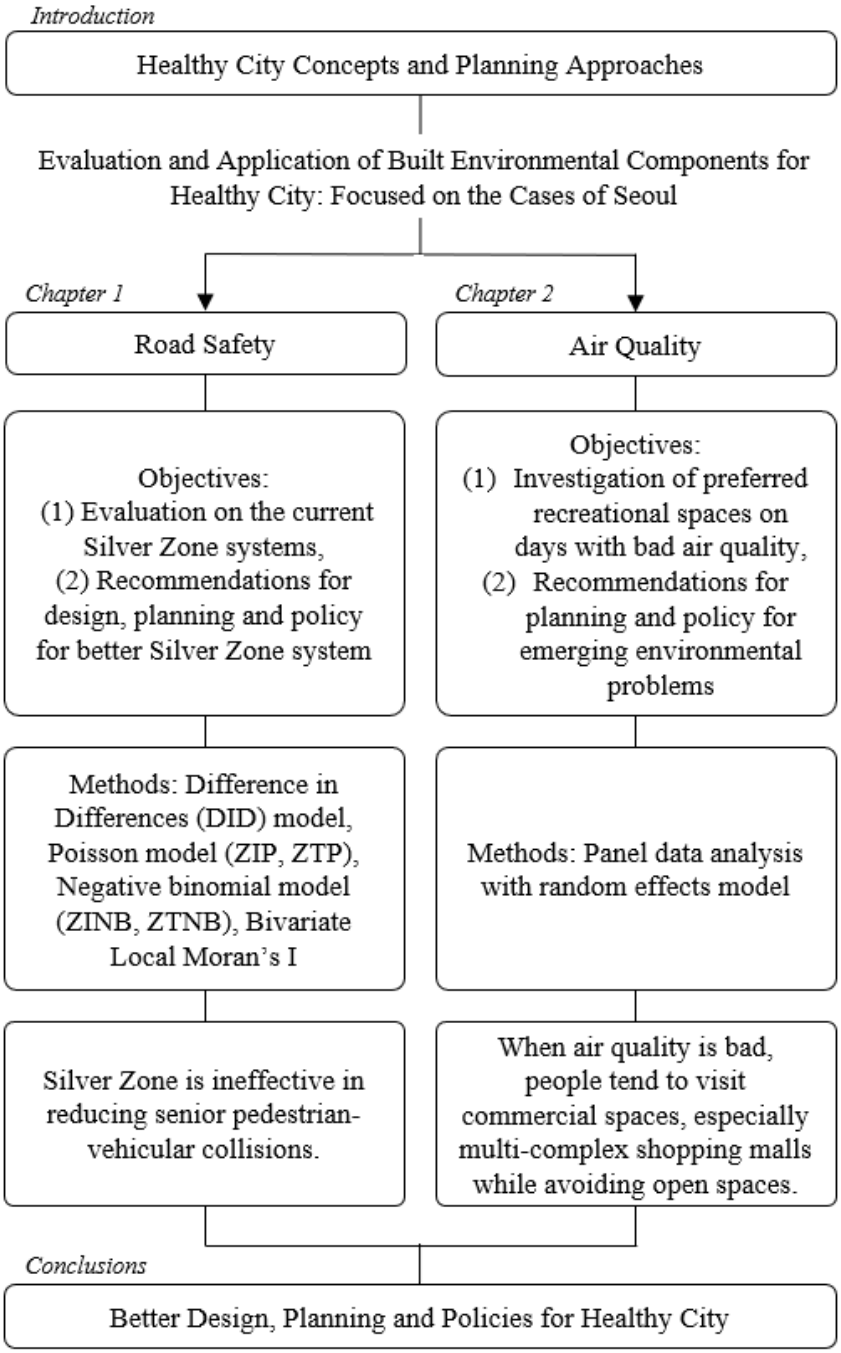

Fig. 1. Outline of the study

II. Chapter 1: Do Silver Zones reduce auto-related elderly pedestrian collisions? Based on a case in Seoul, South Korea

2.1. Introduction

As the world's population rapidly ages, with the ratio of the elderly[1] growing from the current 11% to 22% of the population by 2050 (United Nations, 2015), many societies have made efforts to create healthier and safer environments for senior citizens (Zhao, 2014; Li and Zhao, 2015). Improving neighbourhood walkability, as an integral part of daily life, is one strategy towards this goal (Hahm et al., 2017; Kim et al., 2014). Walking is both a means of exercise and transportation for the elderly. As they experience physical and cognitive losses, they forgo driving and taking public transit to avoid collisions, while maintaining physical activity (Piatkowski et al., 2015; Burbidge and Goulias, 2009).

Elderly pedestrian-vehicular collisions, however, are a serious problem (Rosenbloom et al., 2016; Cœugnet et al., 2017). While pedestrian deaths account for 22% of all vehicle-related casualties, approximately 40% of those involve the elderly[2] (OECD, 2014). This number has been increasing along with the aging population in many member countries of the Organization for Economic Co-operation and Development (OECD). Especially, increase of the traffic volume in high-density cities in the East Asia is a threat to elderly

[1] Age group of 60+
[2] Age group of 65+

pedestrian safety (Zhao et al., 2014). South Korea is no exception. Currently, elderly pedestrian collisions account for 40% of all vehicle-related casualties (OECD, 2014; Whi, 2015).

In order to protect elderly pedestrians from collisions, the South Korean government established the Silver Zone system in 2007. The system mandates areas as safety zones where speed-limit measures, such as traffic signage and road surface markings, caution drivers about the presence of elderly pedestrians. The similar systems in other countries are Silver Zone[3] and Green Man Plus system[4] in Singapore and Safe Routes for Seniors program[5] in the U.S.A. (Fwa, 2016; Tan, 2008; Transportation Alternatives, 2009).

Since the inception and spreading implementation of the Silver Zone, however, questions have been raised about its effectiveness in reducing collisions. Although some analytical research has pointed to the ineffectiveness of these approaches (Park and Oh, 2011; Lee, 2012), and the media has speculated about possible reasons for its failures, the lack of relevant data has prevented a full assessment of its performance. The accumulated number of Silver Zones in Seoul reached 80 in early 2016, but it was not until 2010 that the database on the pedestrian collisions became available by the Korea Road Traffic Authority.

In this study, we empirically investigate the effectiveness of the Silver Zone in two respects: first, whether the establishment of Silver Zones has

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[3] Singapore's National project to enhance road safety for seniors, since 2014.
[4] Technology to help the elderly cross the road more comfortably without adversely affecting the traffic flow by giving more green light time.
[5] City-wide project to improve pedestrian infrastructure for seniors in the U.S.A.

lowered the number of elderly pedestrian-vehicular collisions, and second, whether Silver Zones were established in the appropriate areas, that is, those with the highest frequency of such collisions. To better evaluate Silver Zone program, we not only focused on the effect of Silver Zone, but also the effect of ten other physical elements in the zone, which may have effects on the frequency of collisions. With the analytical results, we further explore ways to improve the performance of Silver Zones.

For the first question, we use generalised linear modelling: Zero Inflated Poisson (ZIP), Zero Inflated Negative Binomial (ZINB), Zero Truncated Poisson (ZTP) and Zero Truncated Negative Binomial (ZTNB) in Difference-in-Difference, one of the quasi-experimental specifications. To answer the second question, we use spatial statistical analyses, namely, the Kernel Density estimation and Bivariate Local Moran's I.

The present study is the first attempt to investigate the environmental components of the Silver Zones that explain the elderly pedestrian-vehicular collisions, and the spatial alignment of the zones and the collision locations. Our multi-pronged evaluation will provide a more comprehensive understanding of the performance of Silver Zones, and thereby be a useful reference for municipalities wanting to improve the current system.

The structure of this study is as follows. In the next section, we briefly review the literature on Silver Zones in South Korea, followed by a description of our analytical methods. After presenting our analytical design, we describe the results, including an overview of the actual effects of Silver Zones as well as the other environmental factors on pedestrian collisions, and the degree of spatial alignment between the designated Silver Zones and senior pedestrian-

vehicular collision spots. The final section discusses the implications of our findings and future research direction.

2.2. Background

2.2.1. Pedestrian Safety

Safety zones are purposed to protect pedestrians from vehicles, adopting a number of safety measures and techniques. School Zone and Silver Zone are some of those examples, made for protecting children and the elderly, respectively, and are established in areas where a large volume of such populations gather. School Zones are commonly located around schools and day-care facilities to help children's commuting safer. Silver Zone is relatively newer than the School Zone system, conceived in response to the increasing concern on the aging society. Japan is a pioneer of Silver Zone since 1986, and South Korea and Singapore have adopted the system recently (Ibrahim, 2003; Fwa, 2016; KoRoad, 2012).

Safety Zones adopt traffic calming measures and techniques, to limit the speed of vehicles. In most of the safety zones, cars are not allowed to drive faster than 20mph (30km/h). To inform drivers about the condition, speed signs are installed in the entrance and the exit of the zone. Within the zones, speed humps, smaller corner radii, pavement treatment, and chicane are deployed to physically and visually deter drivers from speeding. Also, more frequent and brighter lighting and fences are installed to help pedestrians walk with caution. Occasionally, surveillance cameras are operated to warn the drivers and detect the violation (Lee et al., 2013).

2.2.2. Silver Zone

In South Korea, to address the increasing elderly pedestrian-vehicular collisions, the Ministry of Government Administration and Home Affairs (MOGAHA) established the legal framework for the Silver Zone system, with the passage of the Road Traffic Act in May 2007. Since then, as of September 2016, a total of 746 zones have been created in South Korea, of which 80 are located in Seoul (MOGAHA, 2016; Kim, 2015).

The Silver Zone designation is initiated by the requests from the heads of public or private facilities for seniors, such as senior welfare centres, medical institutions, sports centres and parks. Where the request is granted, a safety zone is created with special treatment to vehicular roads within a 300- to 500-metre radius outward from the facility (Ministry of Public Administration and Security, 2012). The borough, the city government and the police department coordinate efforts to manage the Silver Zones thereafter.

In the Silver Zones, the speed is limited to below 30 km/h, and the zone-designation and speed-limit signage is installed. Road surface is marked with colouring in red-brown and lettering the phrase “Silver Zone”. Occasionally, extra measures are added, such as fences, speed bumps, elevated crosswalks, reduced crosswalk slope, realignment to one-way traffic, widened pedestrian pathways, and speed and signal cameras (Ministry of Public Administration and Security, 2012).

However, previous studies, using Before-After evaluation methods, suggested that Silver Zones have no or only a slight effect in reducing collisions (Lee, 2012; Park and Oh., 2011). Lee (2012) analysed the effects of Silver Zone by types of senior care facility, shapes of Silver Zone boundary (rectangular, T,

Y, L, and I shape), and the locations of Silver Zone (at the corner or along the straight road). In Lee (2012), Silver Zone was partially effective in reducing collisions at some locations. Park et al. (2011) found that Silver Zone is effective in reducing the severity of collision by 9.5% but showed only a slight effect, 1.6%, in reducing the number of collision. Anecdotal evidence points to the impracticality of the speed reduction measures the system currently adopts, and pressing the necessity of more vigorous enforcements such as speed and signal cameras, speed bumps and radar speed signs (Kim, 2017). Some editorials also argue that the lack of consideration on the previous collision records leads to failure in prioritizing Silver Zones in the collision-prone spots (Choi, 2015; Yoon, 2013; Lim, 2015; Lee, 2015). Silver Zones are established only when the requests are made, thus locations with high collision rates could have been left untreated if such request was not made (Busan Ilbo, 2016; Park, 2016).

2.2.3. Analytical Methodology

2.2.3.1. Poisson, Negative Binomial, ZIP, ZINB, ZTP and ZTNB in Difference-in-Difference approach

The Difference-in-Difference (DID) approach is one of the quasi-experimental analyses frequently used to evaluate the impact of policy interventions, since it is useful for inferring near-causality in observational studies (Li et al., 2012; Chabé-Ferret, 2015; Dempsey and Plantinga, 2013; Wang and Shi, 2012; Pope and Pope, 2015). DID estimates the effects of interests by comparing the outcome from the treatment and control groups in two different time periods: usually before and after the treatment. While the

treatment group is exposed to the intervention only in the after period, the control group does not receive treatment during either period or receives treatment during both periods. By deducting the difference in the outcomes between the two groups with and without the treatment, in the periods before and after the treatment, we can understand the remaining "difference-in-difference" as a pure impact of the treatment, controlling for all other factors that simultaneously affect both groups, in the before and after periods (Pope et al., 2015).

Data of collisions have special characteristics: The number of collisions per street segment during a certain time period is discrete and generally small or zero. Since collisions are rare events, the count of segments with zero collisions tends to be high. Poisson and Negative Binomial, and their zero-truncated and zero-inflated options are such distribution explaining collision data. The Poisson distribution illustrates the probability of observing discrete numbers of events in a given time (Bradshaw et al., 2009), and thus, has been adopted in many transportation studies (Pérez et al., 2007; Dong et al., 2014; Lord et al, 2005): The distribution, however, assumes the mean and variance to be identical, and for that to be the case, the probability of an event occurrence is identical and independent throughout the entire time period (Chang et al., 2014; Hardin and Hilbe, 2012). The strict assumption of this single-parameter model is often inappropriate to apply to real-life data. The Negative Binomial distribution relaxes this assumption, and has been used for accommodating the condition of overdispersion (Wooldridge, 2012; Hardin et al., 2012).

In case of excessive or non-zero counts in data, zero-inflated and zero-truncated specifications of the Poisson or Negative Binomial modelling are

adopted. These specifications identify the probability of the outcome value zero, then separate or exclude it, respectively, from the distribution of the rest of the outcome values. In zero-inflated approaches, the model is divided into two parts: first, the binary part to determine whether observations fall in a condition of taking only zero value, and second, the Poisson or Negative Binomial part to predict the rest of the counts. In zero-truncated models, the probability of the outcome value zero is taken out by adjustment on their original–Poisson or Negative Binomial–distribution (Nelson, 1977; Keeley et al., 1978; Hardin et al., 2012).

Transportation and crime research have used these models conventionally. Tipakornkiat (2014) used both the Poisson and negative binomial models to find the positive impact of safety rest areas for drivers in reducing the number of road accidents. Because of the overdispersion, the negative binomial model turned out to fit the data better. Schneider et al. (2010) also compared the Poisson and negative binomial models in assessing the association between the characteristics of roadway intersections and the risk of pedestrian collisions in Alameda County, California. For the same reason stated above, the negative binomial model outperformed the Poisson model. Ayati and Abbasi (2011) also selected the negative binomial over the Poisson model to find the impact of traffic volume in collisions on urban highways.

These two models are often compared with their zero-inflated versions. For example, Mouatassim and Ezzahid (2012) compared Poisson and zero-inflated Poisson (ZIP) to model the number of claims from Moroccan private health insurance. As a substantial portion of policyholders had not filed insurance claims during the study period, the ZIP regression performed better.

Kim et al. (2015), using the ZINB model, suggested that drivers' demographic characteristics and the record of past traffic violations predict the number of collisions in South Korea. Since the data included a large portion of drivers who had never been involved with collisions, the zero-inflated model was a better choice for the dataset. The zero-truncated version of the Poisson and negative binomial models are used when the data do not contain any zero values. For example, Heijden et al. (2003) used ZTP to estimate the size of the criminal population. The crime report, the main dataset of the analysis, listed individuals who had been apprehended at least one time, thus the data did not include a zero value.

2.2.3.2. Spatial Analysis: Kernel Density and Bivariate Local Moran's I

Kernel Density Estimation is a non-parametric statistical method used to visualise point patterns of data. By using moving windows focused on data points, so-called kernels, with a specific radius this analytical method generates density surfaces that show where the points are concentrated (Bailey and Gatrell, 1995). Bivariate Local Moran's I is an analytical tool that examines whether two characteristics are spatially correlated. With bivariate local Moran's I, we can identify the degree of such a correlation in the four categories: first, High–High where both values of the variables are high; second, Low–Low where both are low; and Low–High and High–Low where only one is high, while the other is low. Moran's I index of 1 and -1 represents the perfect positive and negative correlation between the two variables, respectively, with values close to zero implying weak correlations. The absolute value of .3 or higher is considered a fairly strong correlation (Yoon and Srinivasan, 2015).

2.3. Analytical Design

2.3.1. Study Site

Our study site consists of 80 Silver Zones in Seoul, South Korea. Assuming that the effect of the Silver Zone may extend beyond this immediate area, we include 300-metre buffers around the zones themselves, which implies an average of a 5-minute walking distance (Azmi et al., 2012). For the DID analysis, we analysed 58 zones established either from 2007 to 2009 or from 2011 and 2014. For the DID analysis with the environmental factors, we excluded zones that had no collision incidence and analysed the rest 27 zones. For the spatial analyses, 32 zones established from 2011 to 2015 were considered. Figure 2 describes our study area.

2.3.2. Dataset and Samples

The two primary datasets were Silver Zone data collected by the Seoul Metropolitan Government from 2007 to 2014 and Elderly Pedestrian Vehicular Collision data from the Korea Road Traffic Authority (KoRoad) from 2010 to 2015. The Silver Zone data include locations, configurations and installation dates of each Silver Zone, and the name and type of facilities that it centres on. The Elderly Pedestrian Vehicular Collision dataset provides detailed information on collisions, including locations, dates, times, the age and gender of the injured party and driver, seriousness of the injury/damages, road types and the weather at the time of the incident. The number of elderly pedestrians injured in vehicular collisions totals 3009, with 478 occurring in 2010, 390 in 2011, 549 in 2012, 564 in 2013, 711 in 2014 and 668 in 2015.

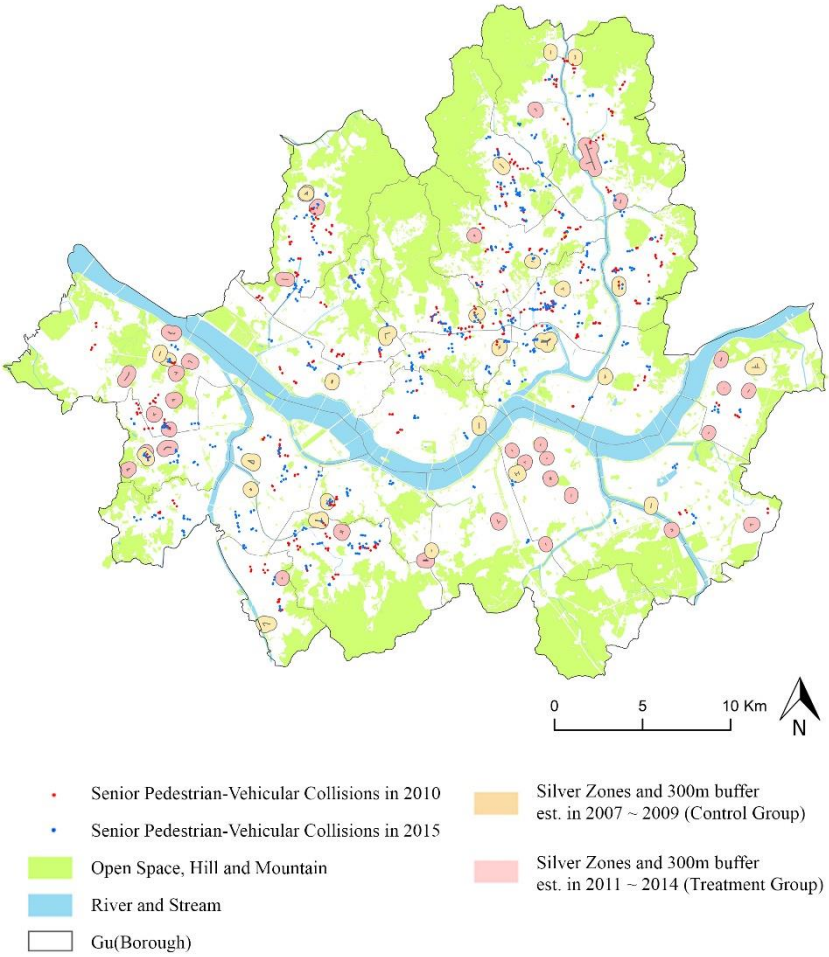

Fig. 2: Study Site: Seoul, South Korea

For the supplementary information about the physical environments of the zones, we used Daum, a web portal that provides eye-level maps, satellite imageries and street views. We included nine different characteristics: distance from the centre of Silver Zone, percentage of coloured road surface in the entire Silver Zone, the number of lanes, distance from a collision to the nearest

crosswalk, speed bump and traffic light, presence and location of fencing, no-sidewalk road signage and land use (e.g., residential and commercial). The descriptive statistics is in Appendix I.

2.4. Analytical Plan

2.4.1. Difference-in-Difference with Poisson, negative binomial, ZIP, ZINB, ZTP and ZTNB models

With DID approach, we compare the count of collisions in the treatment and control groups before and after their designation as Silver Zones. Our treatment group comprises collisions that occurred in the areas designated as Silver Zones and the 300-metre buffer area in 2011, 2012, 2013 or 2014. Our control group is the collision count in the areas that were designated as Silver Zones and the 300-metre buffer areas in 2007, 2008 or 2009. Control group is supposed to be a group of samples that are closely matched with treatment group, whereby the only difference is whether the treatment was imposed or not. Therefore, the areas designated as a Silver Zone in the earlier years can be a more appropriate control group for the areas designated as such in the later years, than the randomly selected, non-Silver Zone areas. To allow for a 1-year stabilisation period, and to measure the full-year effects of those Silver Zones, the collisions were counted in the year 2010 for the before condition and during 2015 for the after condition.

If the Silver Zone designation improved pedestrian safety, the number of collisions would go down more or show less of an increase from 2010 to 2015 in the treatment group, compared with the number counted in the control group. Since new Silver Zones are advertised to be safer and easier to walk, it

has potential to attract more pedestrians. If this were the case, pedestrian collisions would have impacted by the increased exposure. To rule out this possibility, we conducted two sets of t-tests to verify whether the changes of the pedestrian volume differ or not in the two groups (control and treatment groups), in the two points of the collision measurement. Due to data availability, we used data of 2009 and 2015. We could conclude that the treatment and control groups have maintained the same level of senior pedestrians in both years, and the level of change between those two years in those two groups are identical. This implies that the exposure of the senior pedestrians to collisions have changed in a similar way in both of the groups. The result of the t-test is available from the authors upon request.

The full DID model is shown below:

$$g(E(Num\_Collision_i)) = \beta_0 + \beta_1 Treatment_i + \beta_2 After_i + \beta_3 (Treatment_i\_After_i) + \boldsymbol{\beta X_i}$$

Function (1) Difference in Differences (DID) model

Our dependent variable, $Num\_Collision$, is the number of collisions occurred in the each Silver Zone in the aforementioned years (mean: 0.83); *Treatment* is a binary variable indicating whether the collision occurred within the treatment group or the control group (*Treatment* = 1 if established in 2011, 2012, 2013 and 2014 or *Treatment* = 0 if established in 2007, 2008 and 2009). *After* is a binary variable indicating whether the collision occurred in 2015 or

in 2010 (*After* = 1 if occurred in 2015 or *After* = 0 if occurred in 2010). By including the interaction term, *Treatment_After*, as a product of the group and time indicator, we allow differential changes from the before and after periods in the number of pedestrian-vehicular collisions between those two groups. $\boldsymbol{\beta X_i}$ is a vector of the aforementioned environmental characteristics of the Silver Zone. The detailed explanation of the variables is in Appendix I.

We fit the ZIP, ZINB, ZTP and ZTNB models: first, ZIP and ZINB with the three aforementioned variables directly relevant to the DID inference, and then ZTP and ZTNB with all other additional variables representing environmental characteristics of the Silver Zone. In the first analysis, all Silver Zone samples are included, and many of them have not accommodated any collision in either 2010 or 2015. Due to the high frequency of zero value, ZIP and ZINB are utilized to handle the data. In the second analysis, on the other hand, the data is zero truncated because the Silver Zones with collision records are included in the sample. ZTP and ZTNB are utilized to address the zero truncated characteristic of the data.

g(.) is a link function that relates the expected dependent variable to the linear predictors (Fox, 2015). For the Poisson and negative binomial family, a canonical link function–natural log is used. Consequently, the relationship between the dependent and independent variables in Poisson, negative binomial models are shown below:

$$ln(E(Num\_Collision_i)) = \beta_0 + \beta_1 Treatment_i + \beta_2 After_i + \beta_3(Treatment_i\_After_i) + \boldsymbol{\beta X_i}$$

Function (2) Poisson model

For the negative binomial model, as its variance is allowed to differ from the mean, a latent heterogeneity term ε_i is introduced in the conditional mean of the model, where $\exp(\varepsilon_i)$ follows gamma distribution (Shankar et al., 1995):

$$ln(E(Num\_Collision_i)) = \beta_0 + \beta_1 Treatment_i + \beta_2 After_i + \beta_3(Treatment_i\_After_i) + \boldsymbol{\beta X_i} + \varepsilon_i$$

Function (3) Negative binomial model

2.4.2. Spatial Analysis: Kernel Density and Bivariate Local Moran's I

We use two spatial analyses, Kernel Density Estimation (KDE) and Bivariate Local Moran's I, to further investigate the geographical relationship between Silver Zones and sites with a high occurrence of senior pedestrian car-related collisions, and to determine whether the collision points and Silver Zone

locations overlap.

First, we plotted a series of KDE maps to visualise the locations of the new Silver Zones established in each year from 2011 to 2015, and the locations of frequent senior pedestrian car-related collisions in the prior year. If the Silver Zones were established close to the previous year's sites of highest-frequency collisions, the maps should show a geographical match between them.

To achieve a more rigorous assessment of the degree of spatial match than a visual comparison can provide, we used the Bivariate Local Moran's I analysis. We created the two variables aggregated at the level of the census tract[6] to measure their correlation in this fashion: first, the cumulative number of senior pedestrian-vehicular collisions from 2010 to 2014, aggregated by census tract, and second, the total number of Silver Zones in the same census tract as of 2015. The bivariate Local Moran's I function is presented below in Function (4):

$$I_i = A_i \times \sum_{j=1}^{n} \omega S_i$$

Function (4) Bivariate Local Moran's I

A_i is the number of such collisions in the census tract i (up to n), S_i is the number of Silver Zones in the same census tract and ω is a spatial weight

[6] In South Korea, the census unit is equivalent to the census tract in the U.S. It is called *Jigyegu*, and contains approximately 500 residents.

matrix. We chose a distance-based weight matrix over contiguity-based ones, since the analytical units vary in size and configuration, thus could not be consistent in defining neighbouring units. We used a threshold distance of 300 metres because it represents an average 5-minute walking distance for elderly and could be considered a maximum distance seniors are willing to walk as part of their daily routine.

2.5. Findings

2.5.1. Result 1: DID with ZIP, ZINB, ZTP and ZTNB

In Table 1, we present the analytical results of the ZIP, ZINB, ZTP and ZTNB regression.

For the first DID analysis, in order to select the best model for testing the effects of Silver Zone, we conducted two steps of tests; first, we tested zero-inflation with Vuong test to select a model between standard Poisson and ZIP models, and second, we tested overdispersion with a likelihood ratio test to select a model between ZIP and ZINB model (Desmarais and Harden, 2013; Zuur et al., 2009). The Vuong test statistics were significantly positive ($z = 6.64$, $Pr > z = 0.00$), led us to ZIP over the standard Poisson model. The likelihood ratio test indicates overdispersion, led us to ZIP over ZINB model. Therefore, we selected ZIP as the final model. Also, smaller AIC for ZIP reaffirmed our decision.

For the second DID analysis, since we excluded all Silver Zones that had no collision history in 2010 or 2015, the data became zero-truncated. To select between ZTP and ZTNB model, we again used the likelihood ratio test

and confirmed that our data is not overdispersed, consequently, we selected ZTP as our final model.

Table 1: Parameter estimates, standard errors and approximate p-values from the ZIP, ZINB, ZTP and ZTNB models, describing the DID relationships between the number of collisions in treatment and control groups in the before and after period, along with other selected predictors.

	Effects of Silver Zone				**Effects of Silver Zone and Physical Elements associated with Senior Pedestrian Collisions**	
	Zero Inflated Poisson Model		**Zero Inflated Negative Binomial Model**		**Zero Truncated Poisson Model**	**Zero Truncated Negative Binomial Model**
Variables	ZIP with DID	inflate	ZINB with DID	inflate	ZTP with DID and Physical Variables	ZTNB with DID and Physical Variables
After	0.265 (0.292)	-0.287 (0.607)	0.265 (0.292)	-0.287 (0.607)	0.202 (0.390)	0.202 (0.390)
Treatment	0.233 (0.368)	1.200* (0.698)	0.233 (0.368)	1.200* (0.698)	0.241 (0.615)	0.241 (0.615)
After_Treatment	0.032 (0.461)	0.055 (0.947)	0.032 (0.461)	0.055 (0.947)	0.082 (0.472)	0.082 (0.472)
Loc_range	-	-	-	-	1.923** (0.757)	1.923** (0.757)
Percent_colour	-	-	-	-	0.611 (0.685)	0.611 (0.685)
Number_lane	-	-	-	-	0.371 (0.236)	0.371 (0.236)

Dist_crosswalk	-	-	-	-	-0.117** (0.054)	-0.117** (0.054)
Dist_light	-	-	-	-	0.094*** (0.032)	0.094*** (0.032)
Fence	-	-	-	-	-0.658 (0.479)	-0.658 (0.479)
Dist_intersection	-	-	-	-	-0.028** (0.0133)	-0.028** (0.0133)
Speedlimit Signage	-	-	-	-	-0.0675 (0.335)	-0.0675 (0.335)
No_sidewalk	-	-	-	-	0.404 (0.896)	0.404 (0.896)
Residential	-	-	-	-	-0.709 (0.786)	-0.709 (0.786)
Commercial	-	-	-	-	0.248 (0.427)	0.248 (0.427)
Constant	0.985*** (0.233)	0.706 (0.445)	0.985*** (0.233)	0.706 (0.445)	-0.050 (0.952)	-0.050 (0.952)
N	116	116	116	116	27	27
-2LL	-0.0264		-0.0264		-0.2345	-0.8303
df	8		9		15	15
AIC	230.4553		232.455		117.868	117.868
BIC	252.484		257.238		137.306	137.306
Prob > chi2	0.4160		0.4160		0.0404	0.6987

Robust standard errors in parentheses

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

From both the ZIP and ZINB models, we learned that the Silver Zone is ineffective in reducing collisions. All variables directly relevant to DID - *After, Treatment* and their interaction, *After_Treatment* - explain that the change in the number of collisions in the treatment and control groups from the before and after period is not different at 5% significance level.

Among other environmental factors, the *Locational range*–a binary variable indicating whether a collision happened in the Silver Zone, *Distance to traffic lights, Distance to crosswalk* and *Distance to intersections* are demonstrated to be a predictor of senior pedestrian collisions.

First, we found that senior pedestrian collisions are more likely to occur in the Silver Zone compared to their 300-m buffer. The expected number of collisions in the Silver zone is 684% (=exp(1.923)) of that of the 300-m buffered area. The Silver Zone is established in front of senior care facilities where senior pedestrians tend to concentrate, and the chance of collision involving them would increase. In addition, the variable *Distance to traffic lights* suggests that more collisions would occur in locations farther from vehicle traffic lights. When moving 10 metres away from the vehicle traffic light, the expected number of collisions is increased by 109.86% (=exp(0.094)) of that of otherwise cases. Longer distance of traffic intervals may encourage drivers to drive faster and also encourage pedestrians to jaywalk.

Distance to crosswalks is also a factor related to the number of senior pedestrian-vehicular collisions. When moving 10 metres away from crosswalks, the expected number of collisions is reduced to 88% (= exp(-0.117)) of that of the otherwise cases, holding all other variables constant. This means that collisions have occurred more frequently near crosswalks. This result may

imply that the areas near crosswalks are relatively unsafe for senior pedestrians due to drivers' frequent violation of traffic signals or their tendency to make sudden stops. However, it could also be true that simply a higher density of pedestrians is exposed to collisions near crosswalks. The variable *Distance to intersections* can be understood in a similar manner: intersections are also collision-prone spots (Lee and Abdel-Aty, 2015; Lee, et al., 2017; Miranda-Moreno et al., 2011). When moving 10 metres away from intersections, the expected number of collisions is reduced to 97% (= exp(-0.028)) of that of the otherwise cases. In intersections with vehicles coming from many different directions, the chance of collisions naturally increases: where cars make multi-directional turns simultaneously, drivers tend to pay less attention to pedestrians. As mentioned above, it is also possible that increased exposure of the pedestrians in the intersections or crosswalks could have impacted on change in the number of collisions.

2.5.2. Result 2: Spatial Analysis with Kernel Density and Bivariate Local Moran's I

From the Kernel Density maps, we found no apparent relationship between the locations of higher numbers of senior pedestrian collisions in a given year and the locations of newly established Silver Zones in the next year. In general, no spatial match is visible except for some small areas. For example, the northwestern area in Figure 3 (a), and the south western parts in Figures 3 (c), (d), (e) whereby Silver Zones seem to have been inaugurated at sites of higher collision frequency in the previous years.

From the Bivariate Local Moran's I analysis, we found a similar result as above. The bivariate local Moran's I value of -0.006 (p=0.05) implies very little negative or no correlation between the density of senior pedestrian-vehicular collisions and Silver Zone locations (Figure 4). If Silver Zones had been established where such collisions were the most prevalent, then the areas marked as High–High and Low–Low should be dominant in the map. In our analysis, only 50 are marked as High–High and 524 are marked as Low–Low out of a total of 16,230 census tracts in Seoul. Indeed, there is a higher occurrence of spatial mismatch: 1,230 are marked as High–Low, meaning Silver Zones were not established at sites that coincided with a higher number of collisions; and 858 were marked as Low–High, meaning the opposite, that Silver Zones were implemented in areas with low rates of elderly pedestrian-vehicular collisions.

We should note that there is a chance of misreading this result as the real effects of the system. If Silver Zones actually reduce the number of collisions, then the census tracts with a higher number of Silver Zones would have fewer collisions, and thus be categorised as Low–High. Therefore, the large number of census tracts in this category presented in our bivariate local Moran's I result could be read as supporting the effectiveness of the Silver Zone system. However, through our carefully designed quasi-experiment, the Difference-in-Difference analysis and the Kernel Density map, we previously demonstrated the ineffectiveness of the Silver Zone system and therefore eliminate the other interpretation of this analytical result.

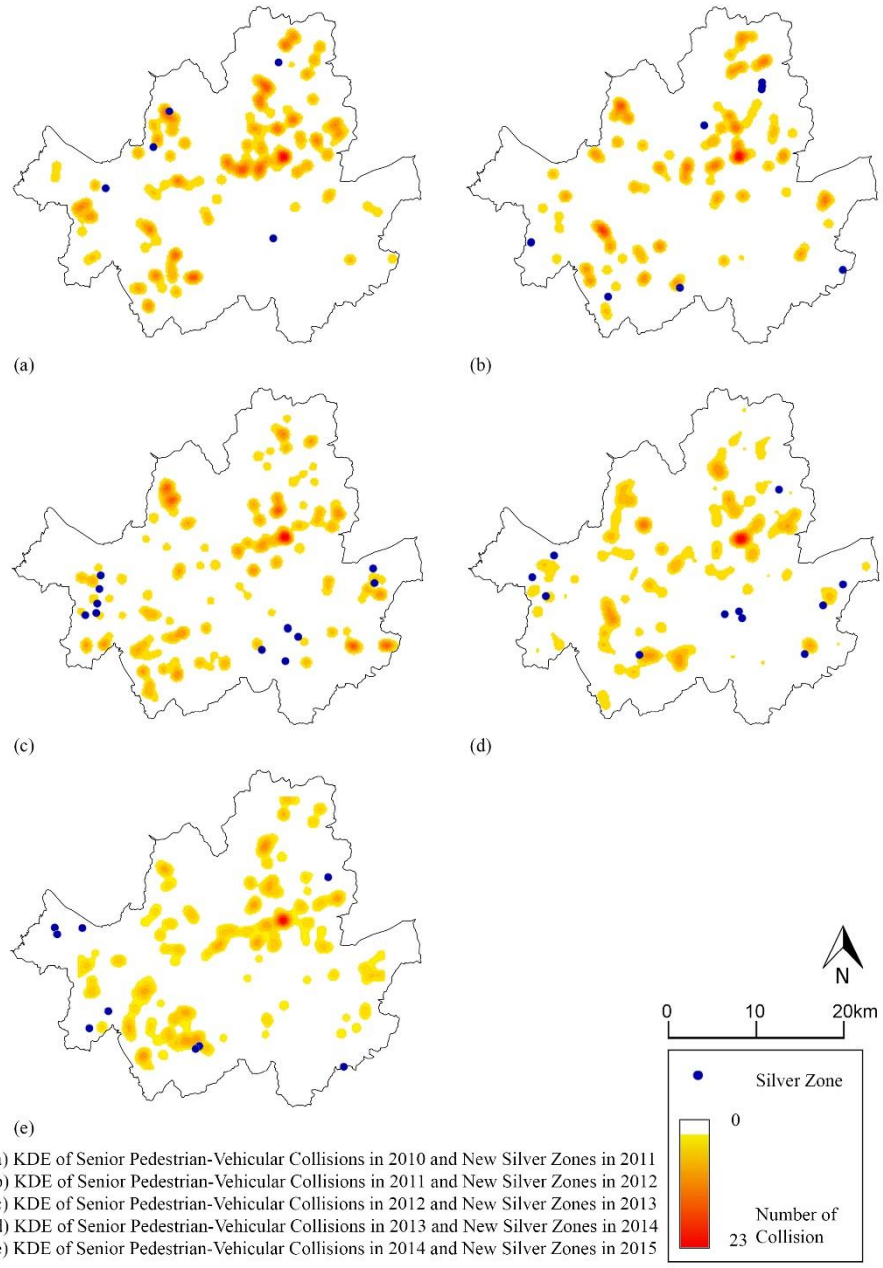

Fig. 3: Kernel Density Estimation of Senior Pedestrian-Vehicular Collisions and New Silver Zones

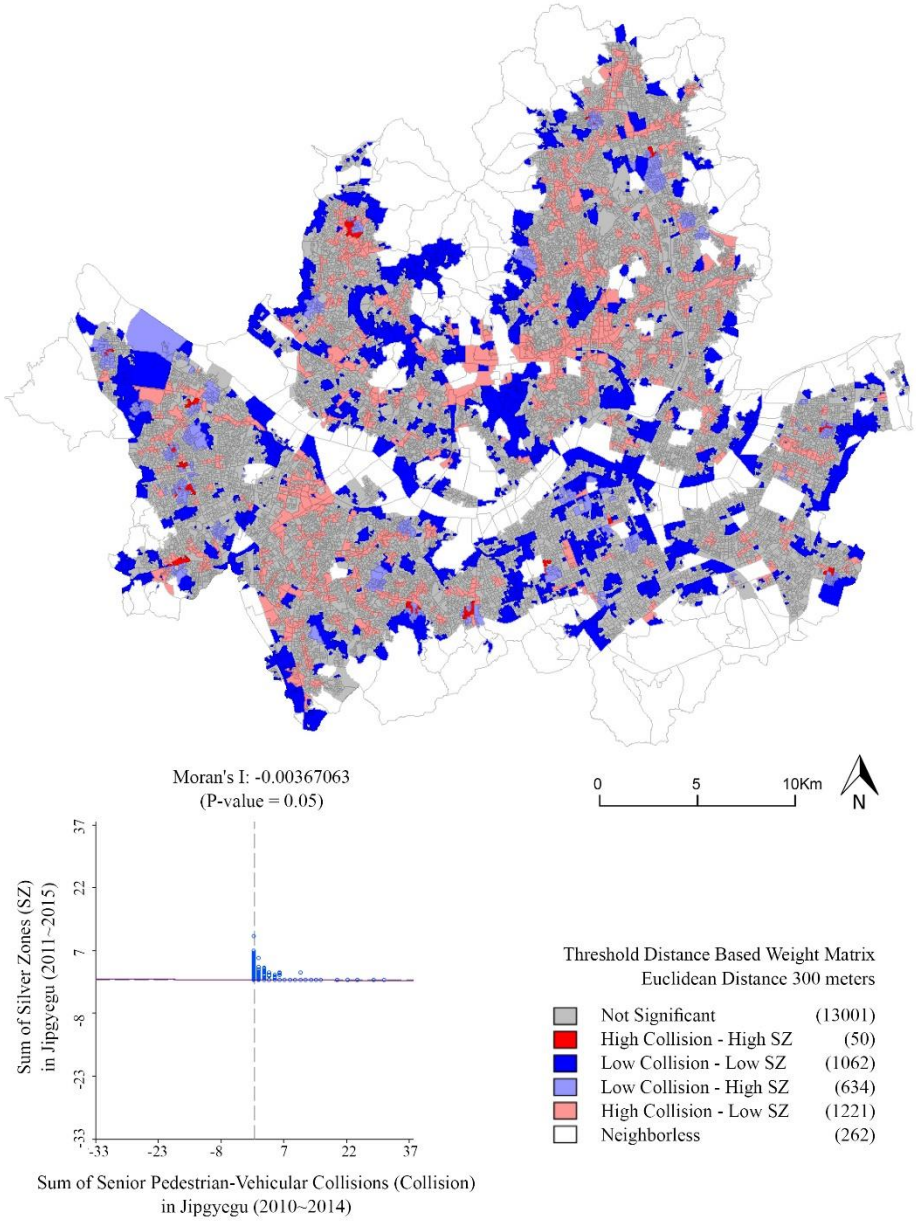

Fig. 4: Bivariate Local Moran's I Cluster Map (Threshold 300)

2.6. Conclusion

In this study, we investigate the effectiveness of the Silver Zone in two respects. First, we assess the changes in the number of elderly pedestrian-vehicular collisions in the two groups through the DID approach, and second, we assess the appropriateness of their locations to address highly collision-prone spots through spatial modelling.

As discussed above, our statistical analyses demonstrate that the Silver Zone, as currently implemented, is an ineffective measure in reducing senior pedestrian-vehicular collisions. The number of collisions increased from 2010 to 2015 without statistical difference in both treatment and control areas; in other words, the Difference-in-Difference was not supported at a statistically significant level. The analysis also highlights which types of physical characteristics contribute to senior pedestrian collisions. Areas bounded as a Silver Zone have more collisions than their 300-metre buffers. In addition, areas farther away from traffic lights and areas closer to crosswalks or intersections invite more of such collisions.

Our analytical results also suggest that current Silver Zone locations do not spatially coincide with areas of higher senior pedestrian-vehicular collisions. The Kernel Density Estimation of senior pedestrian collision density shows that yearly records of such collisions are not closely reflected in new Silver Zone designations the following year. The Bivariate Local Moran's I analysis provides similar results in that the cumulative number of collisions do not overlap with designated Silver Zones. As mentioned in the background of this study, Silver Zones are initiated at the request of individual operators of senior

facilities, without a city-level master planning process incorporating collision pattern studies (Ministry of Public Administration and Security, 2012). The current process creates several problems. On the one hand, the city government could easily overlook areas with high rates of elderly pedestrian-vehicular collisions were it not for the request of Silver Zone by the head of senior citizen facilities. Without a more comprehensive system, the city is not able to coordinate individually requested zone designations with other dangerous sites beyond the vicinity of senior facilities, such as the dangers of long distance of traffic intervals, identified above.

Although the system was originally conceived for seniors, Silver Zones could be used for greater pedestrian safety for all age groups. However, for this system to function effectively, a more comprehensive approach is needed, both for locating these special zones and designing their safety measures. Instead of leaving it to civil petition, the city government should take responsibility for inventorying pedestrian collisions, including locations, through periodic surveys. Based on this information they should prioritise the most critical sites for Silver Zone designation. Moreover, in addition to the signage and road marking that currently comprises the system, other design features and measures could be integrated into the system, such as longer green lights for slow pedestrians, fences to prevent jaywalking, high friction pavement, speed cameras, in-roadway warning flashing light (IRWL) systems to slow the speed of vehicles and part-time pedestrianization (Park et al., 2010; Abdelrahman et al., 2011; Zhang and Ma, 2014; Castillo-Manzano et al., 2014).

III. Chapter 2: Where do people spend their leisure time on dusty days? Application of spatiotemporal behavioral responses to particulate matter pollution

3.1. Introduction

According to the Organization for Economic Cooperation and Development (OECD), air pollution accounts for more than 3 million excess mortalities around the world annually (OECD, 2014). In particular, high concentrations of fine particulate matter (PM 2.5) are detrimental to health, as particles of ultramicroscopic size can easily enter, circulate through, and stay in our bodies (Kim, Kabir and Kabir, 2015; World Health Organization, 2018).

PM-driven deterioration of air quality has become a transboundary environmental problem in the countries of the East Asia Pacific region. During the process of intensive urbanization and industrialization, the sources of PM emission have increased drastically (Karagulian et al., 2015). Korea also has been suffering from the harmful effects of PM. OECD reported that the air quality of Korea was the 5th worst among OECD member countries in 2018 (OECD, 2018), and for more than four months in that same year, the level of PM 2.5 was higher than the World Health Organization (WHO)'s standards. Moreover, the OECD reported that the projected percentage change from 2010 to 2060 in Korea's annual Gross Domestic Product (GDP) will drop about 0.63%,—fourth among OECD members—due to the reduced productivity, additional cost in the health care, and lower farm output caused by air pollution, if Korea does not cope with air pollution properly (Bremer, 2016; Na, 2019).

With the worsening of air quality, from 2013 various media began to report and forecast the level of major air pollutants, including PM, to better inform the people (Ministry of Environment, 2016). Consequently, checking the level of PM has become a new routine for Koreans who are to going outside (Jeon, 2019). Anecdotal evidence points to behavioral changes of people due to bad air quality; more people try to avoid outdoor activities, if possible, and follow precautions such as wearing masks and using air-purifiers (Lee, 2019).

A large vein of studies has focused on the health effects of PM (Song et al., 2016; Wu et al., 2016). However, the effects of PM on human behaviors have not been sufficiently studied. Those involving outdoor activities, in particular, have not been studied on a large spatial scale but only illuminated by case studies of individual recreational places (Chen, Lin and Hsu, 2017; Ban, Zhou, Zhang, Anderson and Li, 2017). One of the main reasons may be the lack of relevant data (Ailshire, Karraker, and Clarke, 2017). Pedestrian volume data is often manually acquired by surveyors' fieldwork. A yearly estimate is calculated on the basis of data recorded over a few days. Due to labor-intensive survey methods and uncertain data quality, accurate pedestrian volume data covering large areas with finer time resolutions have been rare.

To fill the gap in the literature, this study investigates the effects of PM 2.5 on recreational activities in an urban context, with a specific focus on the site selection. The following research questions will be answered: (1) Does the increase in PM 2.5 affect the number of visitors to the three categories of recreational places (open spaces, commercial spaces, and indoor sports facilities) at different times of day and week? (2) If so, does the change in the number of visitors differ by the sub-category of those recreational places? The

study site was Seoul, South Korea, and the study period was March 1 to June 30, 2017. We used pedestrian volume data provided by SKT Geovision, which estimated pedestrian volume using the cell phone signals from SK Telecom's base stations. Compared to traditional pedestrian volume data collected by surveyors or cameras onsite, these data are less prone to measurement errors and cover a much larger area for a longer period of time (Kang, 2016; Yoo, Kim and Ryu, 2014). We categorized recreational spaces into three categories: open spaces, commercial spaces, and indoor sports facilities. We first divided the time into the weekday and weekend, then subdivided the weekday into daytime (from 10 AM to 5 PM) and nighttime (from 7 PM to 10 PM). The panel structure of the data led us to use panel analysis.

3.2. Background

3.2.1. PM and Public Health

Numerous studies in the fields of environment, planning, economics, and epidemiologic and public health have been conducted to examine the relationship between exposure to air pollution and health impacts. Most of them have suggested evidence that exposure to air pollution negatively affects human health, causing respiratory and cardiovascular diseases and lung cancer (Nyhan, et al., 2014; Pope and Dockery, 2006; Liao, et al., 2004; Brunekreef and Holgate, 2002). They have pointed out that PM is more harmful than other types of air pollutants. Brook et al. (2010) provided evidence that exposure to PM increased cardiovascular morbidity and mortality.

The PM problem is not limited to specific cities or countries but is becoming a worldwide issue. Various empirical studies conducted across the

world have demonstrated these negative impacts of PM on personal health outcomes. For example, Ostro et al. (2006) showed that a 10 $\mu g/m^3$ change in 2-day average PM 2.5 concentration is associated with a 0.6% increase in all-cause mortality in nine California counties. Simpson et al. (2005) found that a 10 $\mu g/m^3$ increase in PM 2.5 concentrations leads to an increase of 0.9% in the daily total number of deaths in four Australian cities. Lee et al. (2000) suggested that an increase in air pollution level, especially TSP (Total Suspended Particulates), leads to increases in mortality rates in Korea. Omori et al. (2003) demonstrated that the risk ratio for an increase of 10 $\mu g/m^3$ in suspended particulate matter (SPM) is 1.0077 for all causes of mortality among residents of Japan aged 65 years or older.

3.2.2. Air Pollution Data

Traditionally, personal sampling methods could allow researchers to obtain a better assessment of the negative effects of air pollution exposure. However, scholars have argued that such methods are cost-prohibitive and thus infeasible (Dadvand, et al., 2012; Ye et al., 2018). For this reason, the most commonly used methods have been to employ ambient pollutant concentrations at the locations of surveyees' home addresses. Another approach has been to use census information. However, census data are aggregated, thus does not contain information on the within-unit variance in the characteristics of the residents, and are only available every 5 or 10 years. This approach is unable to account for the spatiotemporal movement of people, so that there may be misclassification errors in the effects of air pollution exposure (Steinle, et al., 2013; Reis, 2018; Chen et al., 2018).

Recently, with an increasing availability of spatiotemporal micro data obtained by air pollution sensors and mobile devices, scholars began to assess the relationship between air pollution and human mobility patterns. They have argued that the level of air pollution was heterogeneous not only spatially but also temporally (Park and Kwan, 2017). It has been emphasized that a spatiotemporal approach that accounts for the temporal and spatial variations in air pollution and human mobility at a fine scale is necessary because they change on a scale of hours or even minutes. In reality, monthly or yearly average air pollution levels do not directly affect human health and mobility, rather, some extraordinarily high levels of pollution on specific days do. Thus, it is clear that spatiotemporal data at a finer scale would improve our understanding of the relationship between air pollution and health and behavioral outcomes (Yu et al., 2018; Park and Kwan, 2017; Nyhan, et al., 2014).

Several studies have utilized newly available mobility data. Yu et al. (2018) examined whether the micro spatiotemporal data obtained from cell phones is better than traditional home-address-based data in estimating air pollution exposure. They found that the former provides more detailed and more accurate location information in linking to the location of air pollutants, reducing misclassification errors. Reis et al. (2018) attempted to examine how the population movements affects the level of pollutants, found that different atmospheric processes had different effects on the spatiotemporal distributions of pollutants. Therefore, they argued that there are variations of individual-level exposure to air pollution. Fallah-Shorshani et al. (2018) argued that the exposures to air pollution for residents and mobility-based population are uneven across cities and by types of pollutants.

Although some studies suggested advantages of using mobile big data rather than conventional census data, only a few studies have adopted that approach due to the lack of available data even in the recent past. With the growing significance of air quality issues, and to yield more precise analytical results for policy implications, spatiotemporal variations of air pollution should be considered in empirical studies. In particular, pollution-influenced behavioral changes represent one research agenda that is important for implementation of practical and realizable environmental policies. Although we are aware that severe pollution levels restrict mobility, our understanding of the degree of that influence and the spatial distribution of the patterns is still limited.

3.3. Analytical Design

3.3.1. Study site

Our study site consists of 1,073 public spaces with recreational purposes in Seoul, South Korea. We divided the sites into the three categories: open spaces, commercial spaces, and indoor sports facilities. All of the open spaces are open air, and they consist of 7 palaces, 11 hills, 722 small parks (≤10,000 m^2), 123 large parks (>10,000 m^2), and 21 waterfront parks, totaling 884. Commercial spaces are either indoor or outdoor, including 9 specialty stores, 34 traditional markets, 13 business buildings, 15 multi-complex shopping malls, 16 department stores, and 86 large supermarkets, totaling 173. We also included 10 indoor sports facilities among the study sites (Table 2, Fig. 5).

Table 2. Study sites

Category	Sub-category	Location	Numbers		Percent	
Open spaces			884		82.95	
	Palaces	outdoor		7		0.65
	Hills	outdoor		11		1.03
	Small parks (≤10,000 m^2)	outdoor		722		67.29
	Large parks (>10,000 m^2)	outdoor		123		12.02
	Waterfront parks	outdoor		21		1.96
Commercial spaces			173		16.12	
	Traditional markets	outdoor		34		3.17
	Specialty stores	indoor		9		0.84
	Business buildings	indoor		13		1.21
	Multi-complex shopping malls	indoor		15		1.40
	Department stores	indoor		16		1.49
	Large supermarkets	indoor		86		8.01
Indoor sports facilities			10		0.93	
	Indoor sports facilities	indoor		10		0.93
Total			1073	1073	100	100

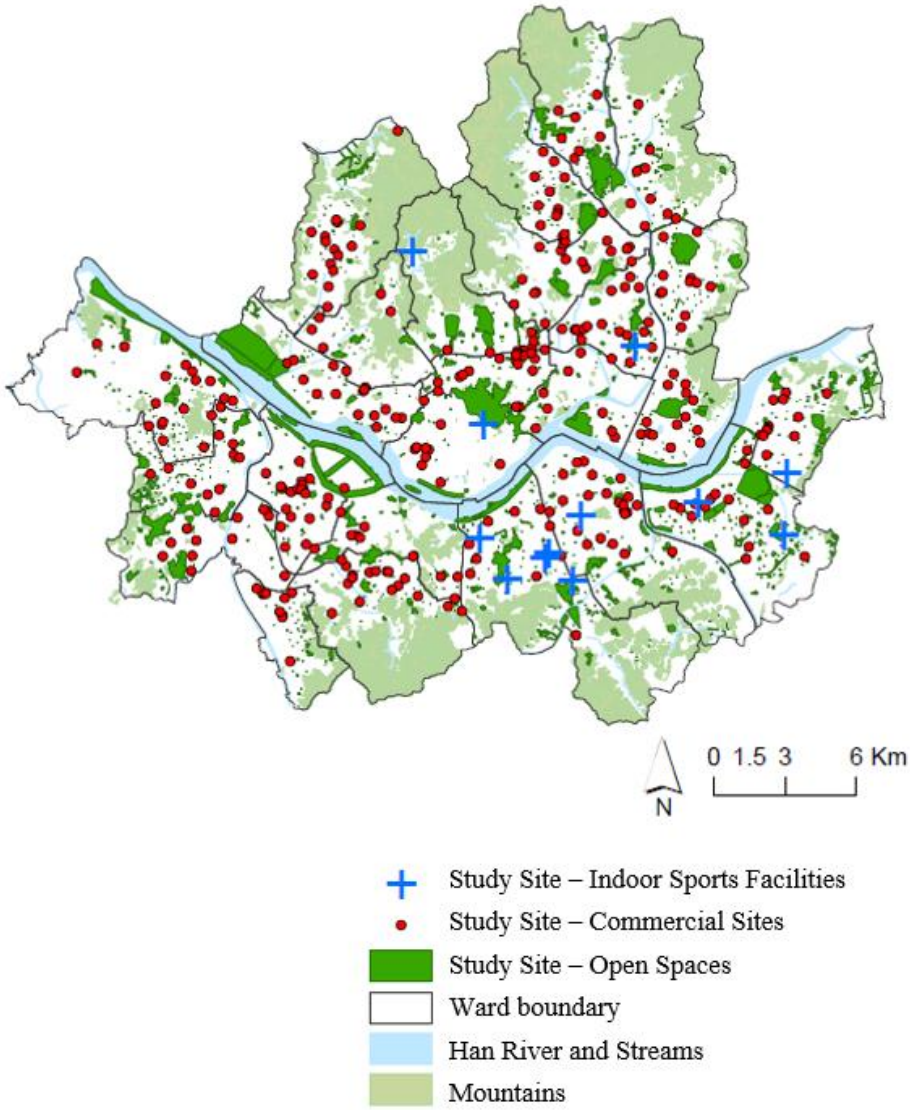

Fig. 5. Study Site: Seoul, South Korea

3.3.2. Data and Sample

The study period was from March 1 to June 30, 2017. As shown in Table 3, we divided all data into three different time groups: time group 1, daytime on weekdays (10 AM to 5 PM); time group 2, nighttime on weekdays (7 PM to 10 PM); time group 3, weekends (10 AM to 10 PM). We chose time groups to include times when most leisure activities are done but that did not overlap with commuting hours. On weekends, we included 5 PM to 7 PM in the time group. The days when large-scale street protests were held (2 days in time groups 1 and 2; 5 days in time group 3) and the days with no records of air pollutant levels (10 days in time groups 1 and 2) were excluded from the study period.

Table 3. Time groups

Time group	Days	Time
Time group 1	Weekday	10 AM to 5 PM
Time group 2	Weekday	7 PM to 10 PM
Time group 3	Weekend	10 AM to 10 PM

The main data used in this study are hourly pedestrian volume measured at a 50-meter grid called pCell, provided by SKT Geovision. SKT Geovision is a division of Korea's largest telecommunication company, SK Telecom. Pedestrian volume was estimated using the cell phone signals from SK Telecom's base stations (Kang, 2016; Yoo, Kim and Ryu, 2014). We extracted the hourly pedestrian volume data for Seoul and aggregated to the time-group scale (Table 3). Then we spatially joined the data with 1,073 study-site locations in GIS. The air pollution data is sourced from Air Korea (Air Korea, n.d.). The

air quality is measured in real time from 39 locations, one or two stations in the 25 wards of the city (Air Korea, nd): the levels of air pollutants—fine particulate matter (PM 2.5), particulate matter (PM 10), carbon monoxide (CO), ozone (O3), nitrogen dioxide (NO2), sulfur dioxide (SO2). Air Korea provides historical data as hourly data. The weather conditions are measured in real time from 29 Automatic Weather System (AWS) stations of Korea Meteorological Administration, one or two stations in the 25 wards of the city (Korea Meteorological Administration, n.d.): temperature, wind speed and precipitation. Korea Meteorological Administration provides the data on a minute basis, hourly, daily and monthly to public. These sets of data are used for smartphone application and the official websites reporting the air quality, thus it is safe to assume that the most people react to the level of PM 2.5 and alter their behaviors based on such information (Yoon, 2019). We extracted the hourly data of air pollution and weather condition for Seoul and aggregated to the time-group scale (Table 3). Then we spatially joined the data with 1,073 study-site locations in GIS. Social environment data—monthly unemployment rate and monthly consumer price index—were obtained from Statistics Korea. Built environmental information on the study sites and their surroundings—area of the study sites, land use, locations of bus stops and subway stations—were obtained from the digital map provided by the National Geographic Information Institute of South Korea.

3.4. Analytical Plan

In order to estimate the effects of PM on the number of visitors to the sites, we employed a random effects panel. Our model is described as follows:

$$M_{it} = \alpha + \beta_{it}P_{it} + \gamma_i S_i + \delta_{it}(P_{it} \times S_i) + \theta_{it}Z_{it} + \kappa_{it}W_{it} + \lambda_i L_i + u_{it} + e_{it}$$

Function (5)

where M_{it} denotes pedestrian volume measured as the number of visitors in location *i* and time *t*; P_{it} denotes the level of PM 2.5 in location i and time t. S_i denotes the type of study site as dummy variable; $P_{it} \times S_i$ denotes the interaction terms of the mean level of PM 2.5 and the type of study site. Z_{it} denotes the level of other pollutants for controlling purposes in location i and time t; W_{it} denotes the weather conditions and unemployment rates for location i and time t; L_i consists of location-specific characteristics that affect pedestrian volume, such as distance to subway stations, the number of bus stops, and land use types (Function 5).

The dependent variable is the sum of visitors to each site during the time group (*Visitors*). The main question variables are the average level of PM 2.5 of the time groups at each study site (*Pm25mean*) and the indication of the three main study sites: open spaces (*Openspace*), commercial spaces (*Commercial*), and indoor sports facilities (*Indoor_sport*). To decipher varying effects of PM 2.5 by the type of recreational space, we also specified the interaction terms of the mean level of PM 2.5 and study sites, including open spaces (*Pm25mean_OS),* commercial spaces (*Pm25mean_CM),* and indoor sports facilities (*Pm25mean_IS)*.

As the sub-categories of the open spaces, we also specified five different kinds of open spaces: hills and mountains (*Os_hills*), palaces (*Os_palace*), large parks (*Os_largepark*), small parks (*Os_smallpark*), and waterfront parks

(*Os_waterfront*). We categorized commercial spaces into six different sub-categories: specialty stores (*Com_specialty*), traditional markets (*Com_tradimarket*), business buildings (*Com_building*), multi-complex shopping malls (*Com_complex*), department stores (*Com_department*), and large supermarkets (*Com_ supermarket*). For the same reason described above, we again made five interactions of the mean level of PM 2.5 and sub-categories of open spaces (*Pm25mean_OS_HL*, *Pm25mean_OS_PC*, *Pm25mean_OS_LP*, *Pm25mean_OS_SP, Pm25mean_OS_WP*) and six interactions of the mean level of PM 2.5 and commercial space (*Pm25mean_CM_SP*, *Pm25mean_CM_TM*, *Pm25mean_CM_BD*, *Pm25mean_CM_MC*, *Pm25mean_CM_DP, Pm25mean_CM_SM*).

We considered five other types of air pollutants besides PM 2.5; an average of PM 10 (*Pm10mean*), an average of O3 (*O3mean*), an average of CO (*Comean*), an average of NO2 (*No2mean*), and an average of SO2 (*So2mean*). We excluded PM 10 (*Pm10mean*) and SO2 (*So2mean*) based on correlations with other pollutants from all models, (1) through (13).

For the purpose of controlling, we specified several categories of variables. The weather is known to substantially affect outdoor leisure activities (Chen, Lin and Hsu, 2017), so we specified average temperature (*Temp_mean*), maximum wind speed (*Windsp_max*), and total precipitation (*Rain_sum*). We also specified the unemployment rate for the month, as it affects the incidence of leisure (*Unemployment*) (Colman and Dave, 2013). Some other variables indicating the built environmental characteristics and the surroundings of the site (*Area, Cnt_bus, Dist_subway, LU_residential, LU_commercial, LU_mixed, LU_public, LU_openspace, LU_water*) were also specified for the purpose of

controlling. The size of site and the accessibility via public transportation determines the total number of visitors. In addition, because there may be a population who are likely to visit the study sites from nearby area, controlling the types of surrounding land use are important. Descriptive statistics are available upon request from the authors.

As discussed above, the intention of this study was to assess the effects of PM 2.5 on recreational activities, which may vary over very small time intervals as well as by different locations. Generally, panel data analysis consists of a cross-section of individual subjects that are repetitively measured over time (Gujarati and Porter, 2009; Yoon, 2017). Two types of panel models are widely used: fixed-effects and random-effects panel models. Fixed-effects panel models treat panel-specific characteristics as fixed parameters; by contrast, random-effects panel models treat panel-specific characteristics as random error (Croissant and Millo 2008). The latter are used when the sample is large and randomly selected from a population. Under this condition, the subject-specific characteristics can be regarded as a random variable and can be treated as normally distributed error.

With the Hausman test, we can discern which option is better. It tests against the null hypothesis that the subject-specific error is not correlated with regressors in the model (Hausman, 1978). If we fail to reject the null hypothesis, the random effect model can be chosen due to its superiority in measuring the effect of time-invariant variables and its efficiency by virtue of having fewer parameters (Greene, 2003). In this study, we employed a random effects panel analysis based on the Hausman test (daytime on weekdays: Prob>chi2 = 0.9021; nighttime on weekdays: Prob>chi2 = 0.3633; weekends: Prob>chi2 = 0.0828).

3.5. Findings

For the first research question—(1) Does the increase in PM 2.5 affect the number of visitors to the three categories of recreational places (open spaces, commercial spaces, and indoor sports facilities) at different times of day and week?—we found that there was a statistically significant relationship between the PM 2.5 level and the number of visitors to a particular type of study site in daytime on weekdays and weekends. In both time groups, the number of visitors to open spaces decreased and the number of visitors to commercial spaces increased with increasing PM 2.5 level. These results confirmed the anecdotal evidence that people tend to avoid outdoor activities and prefer to stay in indoor facilities in reaction to bad air quality. But, the number of visitors to the indoor sports facilities did not show any significant changes with the level of PM 2.5. Interestingly, these relationships were much stronger on weekends than on weekdays. From the second research question—(2) Does the change in the number of visitors differ by the sub-category of those recreational places?—we found levels of pedestrian volume change that differed by the sub-categories of open and commercial spaces. Among the five sub-categories of open spaces listed above, visitors to waterfront parks declined the most; while the commercial spaces, the multi-complex shopping mall invited the largest increase in the number of visitors along with higher PM 2.5. Contrary to the above findings, during the nighttime on weekdays, none of the sites showed significant differences in the number of visitors with an increase in PM 2.5. Below, we report detailed analytical results organized by time group.

3.5.1. Time group 1 – daytime on weekdays

In Table 4, we present the analytical results for time group 1.

Table 4. Panel regression analysis results of weekday time group 1 (10 AM to 5 PM). Parameter estimates, standard errors, and approximate p-values from the panel data analysis models, describing the relationships between the number of visitors in open spaces, commercial spaces, and indoor sports facilities, along with other selected predictors.

Variables	**Weekday time group 1**				
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**
	Open space	**Commercial**	**Indoor sport facilities**	**Open spaces (sub-category)**	**Commercial (sub-category)**
Study site					
Openspace	-709.50*** (164.75)				
Os_hill				-4,155.83*** (471.08)	
Os_palace				-806.47 (533.90)	
Os_largepark				-1.28 (145.80)	
Os_waterfront				3,342.18*** (423.51)	
Commercial		742.43*** (168.93)			
Com_specialty					-49.59 (670.94)
Com_tradimarket					-325.94 (502.02)

Com_complex					-1,567.25*** (604.83)
Com_department					-92.98 (571.68)
Com_supermarket					-170.05 (452.46)
Indoor_sport			57.74 (615.86)		
Aerosol pollutant					
Pm25mean	4.26 (3.08)	-5.56*** (1.89)	-4.00** (1.83)	-0.65 (1.85)	0.27 (15.38)
O3mean	19.33*** (1.71)	19.33*** (1.71)	19.35*** (1.71)	16.04*** (1.66)	37.53*** (6.34)
Comean	-109.75*** (25.89)	-109.97*** (25.89)	-109.22*** (25.89)	-85.20*** (25.31)	-256.78*** (91.86)
No2mean	18.71*** (2.69)	18.72*** (2.69)	18.73*** (2.69)	14.46*** (2.63)	42.44*** (9.71)
Interactions					
Pm25mean_OS	-9.84*** (2.96)				
Pm25mean_OS_HL				-22.27** (9.98)	
Pm25mean_OS_PC				-10.69 (11.76)	
Pm25mean_OS_LP				-10.12*** (3.04)	
Pm25mean_OS_WP				-88.12*** (6.85)	
Pm25mean_CM		10.25*** (3.02)			

Pm25mean_CM_SP					45.86* (23.93)
Pm25mean_CM_TM					-10.01 (17.23)
Pm25mean_CM_MC					50.58** (20.11)
Pm25mean_CM_DP					-10.00 (19.90)
Pm25mean_CM_SM					-7.48 (15.49)
Pm25mean_IS			0.78 (11.61)		
Weather					
Temp_mean	2.95*** (0.47)	2.95*** (0.47)	2.95*** (0.47)	3.26*** (0.46)	1.34 (1.70)
Windsp_max	-2.63 (1.99)	-2.63 (1.99)	-2.66 (1.99)	-2.72 (1.97)	-2.13 (6.81)
Rain_sum	-2.25** (0.88)	-2.25** (0.88)	-2.26** (0.88)	-1.85** (0.86)	-4.33 (3.16)
Social environment					
Unemployment	7,093.52*** (665.86)	7,093.35*** (665.86)	7,098.03*** (665.89)	7,293.48*** (646.89)	6,222.46** (2,438.22)
Built environment					
Area	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.37*** (0.01)
Cnt_bus	8.79 (6.15)	8.59 (6.15)	9.08 (6.23)	10.31** (4.80)	-18.64 (16.71)
Near_sub_dis	-0.50*** (0.16)	-0.49*** (0.16)	-0.55*** (0.16)	-0.45*** (0.12)	-0.14 (0.45)
LU_residential	-1,522.21***	-1,480.32***	-1,568.74***	-1,022.83**	1,126.02

	(536.17)	(536.12)	(543.21)	(432.05)	(971.55)
LU_commercial	271.93 (740.43)	312.56 (739.27)	538.33 (747.66)	-40.38 (615.47)	1,236.00 (1,232.67)
LU_mixed	-1,339.93*** (485.98)	-1,312.73*** (486.04)	-1,460.58*** (491.15)	-990.84** (386.06)	1,162.75 (942.32)
LU_public	-2,750.10** (1,141.46)	-2,705.23** (1,141.74)	-3,390.75*** (1,145.58)	-1,303.88 (870.49)	-2,875.42 (2,671.98)
LU_openspace	-386.89 (603.60)	-345.67 (604.28)	-735.17 (605.84)	-314.62 (454.25)	-2,303.76 (2,612.19)
LU_water	2,634.44*** (766.10)	2,655.91*** (765.99)	2,316.62*** (771.63)	-566.47 (694.55)	4,431.67* (2,681.85)
Constant	1,402.16*** (415.33)	663.18 (406.13)	948.56** (406.21)	446.38 (319.13)	-1,022.36 (933.39)
N	71,494	71,494	71,494	59,289	11,540
Adj-R2	0.41	0.41	0.40	0.62	0.81

Standard errors in parentheses

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

From models (1) to (3), we can learn that commercial spaces attract the most visitors in general, compared to open spaces and indoor sports facilities. Commercial spaces had approximately 742 more visitors (*Commercial Coeff.* = 742.43) compared to the average visitors to open spaces and indoor sports facilities (reference groups), as shown in model (2), while open spaces had approximately 710 fewer visitors (*Openspace Coeff.* = -709.50) compared to the average visitors to the commercial spaces and indoor sports facilities (reference groups).

The level of PM 2.5, however, differentially influences this choice of

leisure place. From models (1) and (2), it is suggested that the number of visitors to open spaces decreased by 9.84 people per $10\mu g/m^3$ incremental increase of PM 2.5, while that of commercial spaces increased by 10.25 people under the same condition (*Pm25mean_OS Coeff.* = -9.84; *Pm25mean_CM Coeff.* = 10.25).

From the same analyses with sub-categories of open spaces and commercial spaces, variations in the PM effects are revealed. First, among the open spaces, waterfront parks lost the most visitors when there was a higher level of PM 2.5; approximately 88 fewer people visited the waterfront per $10\mu g/m^3$ increase of PM 2.5 (*Pm25mean_OS_WP Coeff.* = -88.12). Most of the waterfront parks in Seoul are flanked by highways, and the air quality may be relatively poor due to the vehicle emissions; people may worry that the poor air quality would be exacerbated when the PM level is high. Visitors to large parks declined the least; approximately 10 fewer people visit those places per $10\mu g/m^3$ increase of PM 2.5 (*Pm25mean_OS_LP Coeff.* = -10.12). This may be due to the belief that urban green spaces can lower the airborne pollutant level, since it has been evident that trees can intercept and contain atmospheric particles in their leaf structure (Beckett, Freer-Smith and Taylor, 2000). People may feel that negative effects of PM would be mitigated when they are outdoors with trees.

As presented in model (5), among the different sub-categories of commercial spaces, the number of visitors to multi-complex shopping malls is positively associated with an increase of PM 2.5 by the largest magnitude. When PM 2.5 increased by $10\mu g/m^3$, approximately 50 more people visited multi-complexes (*Pm25mean_CM_MC Coeff.* = 50.58). In Seoul, multi-

complex shopping malls (i.e., Coex, Lotte World Tower) provide facilities for various types of activities such as shops, restaurants, arcades, movie theatres, aquariums, special events venues, playgrounds, and so forth, and thus it is an especially convenient place when people wish to stay indoors for a long time to avoid bad air.

Other pollutants also matter. An average level of CO is negatively associated with the number of visitors (*Comean Coeff.* = -256.78 ~ -85.20). CO is a precursor for PM 2.5, so its negative association with the number of visitors is as expected. An average level of O3 and an average level of NO2 (*O3mean Coeff.* = 16.04 ~ 37.53; *No2mean Coeff.* = 14.46 ~ 42.44) are positively associated with the visitors across all models of time group 1. Since O3 is related to strong UV radiation (Jasaitis, Vasiliauskienė, Chadyšienė, and Pečiulienė, 2016), a day with a higher ozone level is likely to be a bright sunny day and more people might go out for activities. NO2 is a precursor for O3 (Vaida, 2005), thus its relationship with pedestrian volume may align with that of the ozone level.

Socioeconomic conditions and built environments also affect pedestrian volume. The impact of monthly unemployment rate on the number of visitors was significant and strongly positive (*Unemployment Coeff.* = 6,222.46 ~ 7,293.48). With a 1% increase in the unemployment rate, approximately 6,200 to 7,200 more people spent their time outside their homes. Some of the built environmental characteristic of the study site and their surroundings also exerted significant impact on the number of visitors to the sites. Distance to the nearest subway was negatively (*Dist_subway Coeff.* = -0.49 ~ -0.45) associated with the number of visitors across all models. Some types of land use within

400 meters showed statistically significant impact as well (*LU_residential Coeff.* = -1,489.87 ~ -1,022.83; *LU_mixed Coeff.* = -1,317.52 ~ -990.84; *LU_public Coeff.* = -2,706.94 ~ -2,706.50; *LU_water Coeff.* = 2,655.02 ~ 2,655.23).

3.5.2. Time group 2 – nighttime on weekdays

In table 5, we present the analytical results of panel regression models for time group 2 (from 7 PM to 10 PM).

Table 5. Panel regression analysis results of weekday time group 2 (7PM to 10 PM). Parameter estimates, standard errors, and approximate p-values from the panel data analysis models, describing the relationships between the number of visitors in open spaces, commercial spaces, and indoor sports facilities on weekends, along with other selected predictors.

Variables	**Weekday time group 2**		
	Model (6)	**Model (7)**	**Model (8)**
	Open space	**Commercial**	**Indoor sport facilities**
Study site			
Openspace	-185.37*** (53.02)		
Os_hill			
Os_palace			
Os_largepark			

Os_waterfront			
Commercial		192.99*** (54.37)	
Com_specialty			
Com_tradimarket			
Com_complex			
Com_department			
Com_supermarket			
Indoor_sport			27.53 (197.25)
Aerosol pollutant			
Pm25mean	-1.06 (0.96)	-2.87*** (0.56)	-2.57*** (0.54)
O3mean	4.57*** (0.75)	4.57*** (0.75)	4.57*** (0.75)
Comean	4.32 (9.18)	4.26 (9.18)	4.41 (9.18)
No2mean	7.92*** (0.94)	7.93*** (0.94)	7.92*** (0.94)
Interactions			
Pm25mean_OS	-1.81* (0.95)		

Pm25mean_OS_HL			
Pm25mean_OS_PC			
Pm25mean_OS_LP			
Pm25mean_OS_WP			
Pm25mean_CM		1.88* (0.98)	
Pm25mean_CM_SP			
Pm25mean_CM_TM			
Pm25mean_CM_MC			
Pm25mean_CM_DP			
Pm25mean_CM_SM			
Pm25mean_IS			0.27 (3.61)
Weather			
Temp_mean	2.38*** (0.16)	2.38*** (0.16)	2.38*** (0.16)
Windsp_max	0.43 (0.78)	0.43 (0.78)	0.44 (0.78)
Rain_sum	-0.60 (0.47)	-0.60 (0.47)	-0.60 (0.47)

Social environment			
Unemployment	1,216.16*** (271.21)	1,216.50*** (271.21)	1,214.31*** (271.21)
Built environment			
Area	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
Cnt_bus	4.27** (1.98)	4.22** (1.98)	4.35** (1.99)
Near_sub_dis	-0.20*** (0.05)	-0.19*** (0.05)	-0.21*** (0.05)
LU_residential	-472.81*** (172.52)	-462.09*** (172.54)	-485.34*** (173.97)
LU_commercial	-125.08 (238.25)	-114.27 (237.92)	-56.69 (239.45)
LU_mixed	-407.19*** (156.37)	-400.35** (156.42)	-438.67*** (157.30)
LU_public	-947.96*** (367.29)	-937.23** (367.45)	-1,114.15*** (366.89)
LU_openspace	-113.94 (194.22)	-103.79 (194.48)	-204.43 (194.03)
LU_water	989.29*** (246.51)	994.40*** (246.52)	906.97*** (247.13)
Constant	439.21*** (133.87)	246.56* (130.94)	320.70** (130.34)
N	70,603	70,603	70,603
Adj-R2	0.43	0. 43	0.42

Standard errors in parentheses

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

In the nighttime on weekdays, a similar pedestrian distributional pattern was observed but with smaller magnitude than that of daytime. Commercial spaces attracted the most visitors in general (Model (7)), approximately 192.99 more visitors compared to that of open spaces and indoor sports facilities (*Commercial Coeff.* = 192.99). Open spaces did the opposite by attracting 185.37 fewer people than reference sites (*Openspace Coeff.* = -185.37) (Model (6). These patterns are not changed by the level of PM 2.5.

Most of the meteorological variables, socioeconomic conditions, and built environment characteristics affected pedestrian volumes in a similar way, with smaller magnitudes than those for the daytime on weekdays (time group 1).

3.5.3. Time group 3 – weekends

In table 6, we present the analytical results for the weekend time period (time group 3).

Table 6. Panel regression analysis results of weekend time group 3 (10 AM to 10 PM). Parameter estimates, standard errors, and approximate p-values from the panel data analysis models, describing the relationships between the number of visitors in open spaces, commercial spaces, and indoor sports facilities on weekends, along with other selected predictors..

	Weekend time group 3				
	Model (9)	**Model (10)**	**Model (11)**	**Model (12)**	**Model (13)**

Variables	**Open space**	**Commercial**	**Indoor sport facilities**	**Open spaces (sub-category)**	**Commercial (sub-category)**
Study site					
Openspace	-1,665.61*** (381.73)				
Os_hill				-9,968.91*** (1,097.17)	
Os_palace				-2,971.66** (1,242.53)	
Os_largepark				-29.73 (339.19)	
Os_waterfront				8,112.55*** (982.73)	
Commercial		1,751.66*** (391.41)			
Com_specialty					-662.54 (1,539.13)
Com_tradimarket					-1,025.29 (1,151.54)
Com_complex					-3,236.42** (1,386.83)
Com_department					-196.88 (1,311.78)
Com_supermarket					-476.88 (1,038.03)
Indoor_sport			20.07 (1,427.58)		

Aerosol pollutant					
Pm25mean	-34.67** (16.97)	-65.18*** (12.31)	-60.16*** (12.11)	-45.70*** (13.18)	-38.72 (63.49)
O3mean	53.39*** (9.47)	53.38*** (9.47)	53.27*** (9.47)	47.47*** (10.04)	82.50*** (27.61)
Comean	-942.66*** (176.07)	-944.59*** (176.07)	-944.07*** (176.09)	-734.87*** (187.41)	-1,984.35*** (500.64)
No2mean	156.18*** (15.57)	156.34*** (15.57)	156.11*** (15.57)	125.22*** (16.50)	327.47*** (45.52)
Interactions					
Pm25mean_OS	-30.75** (14.35)				
Pm25mean_OS_HL				-67.29 (56.08)	
Pm25mean_OS_PC				-17.46 (60.07)	
Pm25mean_OS_LP				-70.32*** (16.06)	
Pm25mean_OS_WP				-279.02*** (37.24)	
Pm25mean_CM		31.47** (14.70)			
Pm25mean_CM_SP					79.16 (91.30)
Pm25mean_CM_TM					-32.98 (65.84)
Pm25mean_CM_MC					65.31 (77.67)
Pm25mean_CM_DP					-56.32

					(76.25)
Pm25mean_CM_SM					-11.82 (59.30)
Pm25mean_IS			10.81 (54.54)		
Weather					
Temp_mean	7.63*** (2.94)	7.64*** (2.94)	7.66*** (2.94)	7.80** (3.12)	7.36 (8.52)
Windsp_max	17.02* (10.10)	17.03* (10.10)	17.10* (10.10)	9.34 (10.82)	54.00* (28.20)
Rain_sum	-8.15*** (2.76)	-8.14*** (2.76)	-8.20*** (2.75)	-8.28*** (3.05)	-7.40 (6.74)
Social environment					
Unemployment	41,361.16*** (3,718.55)	41,382.77*** (3,718.58)	41,367.79*** (3,718.71)	38,864.94*** (3,954.66)	54,538.69*** (10,759.05)
Built environment					
Area	0.02*** (0.00)	0.02*** (0.00)	0.02*** (0.00)	0.02*** (0.00)	0.85*** (0.03)
Cnt_bus	-0.42 (14.20)	-0.91 (14.20)	0.24 (14.38)	2.45 (11.08)	-37.71 (38.02)
Near_sub_dis	-0.92** (0.36)	-0.90** (0.36)	-1.04*** (0.37)	-0.85*** (0.27)	0.15 (1.03)
LU_residential	-2,909.52** (1,237.21)	-2,809.04** (1,237.08)	-3,014.38** (1,254.04)	-1,778.83* (998.17)	3,344.41 (2,209.33)
LU_commercial	401.22 (1,708.51)	495.70 (1,705.82)	1,042.30 (1,726.01)	-217.04 (1,421.86)	2,810.36 (2,803.09)
LU_mixed	-2,593.19** (1,121.38)	-2,527.16** (1,121.52)	-2,876.65** (1,133.86)	-1,730.33* (891.89)	3,142.98 (2,142.92)

LU_public	-5,708.54** (2,633.91)	-5,595.48** (2,634.55)	-7,229.67*** (2,644.67)	-2,031.25 (2,011.05)	-6,025.67 (6,077.10)
LU_openspace	-1,180.02 (1,392.83)	-1,078.39 (1,394.40)	-2,004.43 (1,398.68)	-890.17 (1,049.49)	-5,079.86 (5,940.51)
LU_water	5,584.24*** (1,767.75)	5,638.39*** (1,767.50)	4,829.65*** (1,781.34)	-2,026.68 (1,604.57)	12,606.68** (6,100.68)
Constant	1,919.82** (975.47)	179.93 (953.95)	857.57 (954.65)	-170.84 (762.11)	-5,196.95** (2,183.62)
N	36,338	36,338	36,338	30,136	5,864
Adj-R2	0.38	0.38	0.37	0.57	0.65

Standard errors in parentheses

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

In this time group, the pedestrian distributional pattern is similar to that of the two other time groups, but the magnitudes are the largest. Commercial spaces attracted the most visitors and open spaces attracted the fewest visitors in general by a large margin (*Commercial Coeff.* = 1751.66; *Openspace Coeff.* = -709.50) compared to the difference observed on weekdays.

The effects of PM 2.5 also correspond to the results for weekdays. On weekends, the number of visitors to open spaces and commercial spaces decreased by approximately 31 people and increased by 31 people, respectively, with 10 $\mu g/m^3$ increment of PM 2.5 (*Pm25mean_OS Coeff.* = -30.74. *Pm25mean_CM Coeff.* = 31.47) (model (9), (10)). As presented in model (12), among the different sub-categories of open spaces, the number of visitors to waterfront parks was negatively associated with increased PM 2.5 by the largest magnitude. When PM 2.5 increased by $10\mu g/m^3$, approximately 279 fewer

people visited waterfront parks (*Pm25mean_OS_WP Coeff.* = -279.02). Visitors to large parks diminished the least; approximately 70 fewer people visited those places per 10$\mu g/m^3$ increase of PM 2.5 (*Pm25mean_OS_LP Coeff.* = -70.32).

On weekends (time group 3), most of the meteorological variables, socioeconomic conditions, and built environment characteristics affected the pedestrian volumes in a similar way with much larger magnitudes than that of the daytime on weekdays (time group 1).

3.6. Conclusion

In this study, we investigated the relationship between the level of PM 2.5 and the number of visitors in recreational places in Seoul, South Korea. In particular, we examined the PM 2.5 effects on pedestrian volume in different time groups (weekday daytime vs. weekday nighttime vs. weekend) and in different categories of places (open spaces, commercial spaces, and indoor sport facilities). We used panel data models to account for the time and spatial variations of population volume and air pollution at a recreational-site level. Our results confirm the anecdotal evidence that people avoid open spaces and prefer to stay in indoor facilities as PM increases. That is evidence of behavioral change induced by air quality.

The main findings are summarized as follows. When the level of PM increases, pedestrian volume decreases in open spaces during the daytime on weekdays as well as weekends. During the nighttime period of weekdays, the equivalent PM effects are not observed at any types of recreational sites. First, the number of visitors to mountains and hills, large parks, and waterfront parks

decrease much more than the numbers of visitors to small parks when the PM 2.5 level increases. The number of visitors decreases the most for waterfront parks with an increase of PM 2.5. Unlike open spaces, commercial spaces (and specifically multi-complex shopping malls) attract more visitors with an increasing level of PM 2.5. The number of visitors to indoor sports facilities was unaffected by the level of PM 2.5 throughout the week.

Behavioral changes triggered by PM levels and intended to minimize exposure to pollution could create negative economic and social consequences. First, reduced outdoor activities would inevitably result in reduced revenues for recreation and tourism industries and local businesses in the networks (Giles et al., 2011). Second, staying indoors for a long time may cause other health problems induced by lack of physical activity. A recent report highlights that, as awareness of the health issues surrounding PM grows in Korea, schools often cancel outdoor physical education classes, and some schools replace the class with a virtual reality version to keep students in a classroom (Han, 2019). These changes in behavior can result in lack of exercise and consequent adolescent obesity and cardiovascular disease (Oh, 2019; Frank, Sallis, Conway, Chapman, Saelens and Bachman, 2006).

As an early empirical study of the impact of PM on human behaviors, this study helps evaluate existing environmental policies and supports establishment of guidelines for new policies. Reducing the level of PM is obviously important; however, it is not an easy task since the main sources of PM are closely associated with urban infrastructures that support urban life. Coal-based power plants, factories, construction sites, and transportation facilities are some examples: ceasing operation is infeasible despite the

threatening levels of PM generated (Lü, Liang, Feng, Li and Liu, 2015). Adaptation policies, therefore, should be implemented simultaneously until technological advancement helps to drastically decrease PM emissions.

The findings of this study provide an understanding of the human response to PM for policy development. People tend to cluster in indoor spaces in reaction to high PM levels. The indoor air quality of large-scale public assembly facilities is neither publicly monitored nor announced. However, it is frequently reported that indoor air quality might not be good either. Large amounts of carbon dioxide from a crowd, fine particulate matter from clothing shops, and formaldehyde and VOC from the interior materials concentrated in indoor spaces are also detrimental to human health (Hu and Li, 2015; Amodio et al., 2014; Chao and Chan, 2001; Salonen et al., 2009). To address this issue, governments can raise public awareness about this and provide financial aid for air purification systems to improve indoor air quality, if necessary.

Planners and policy makers also need to be sensitive to the locational and/or distributional pattern of PM. Our findings show a quite distinctive spatial and temporal variation of pedestrian density as well as of PM level even within a single city. Although it is not directly revealed in this study, such variations in pedestrian volumes are observed within a single commercial district, and the micro-environments also differ (Hahm, Yoon and Choi, 2019; Hahm, Yoon, Jung and Kwon, 2017). This implies that an equal level of reduction goal may not meet the requirements necessary for a healthy living environment. To be more practical, different strategies, guidelines, and policies should be developed taking into account locations and times. For example, the PM level of a roadside area is usually worse than elsewhere, and workers near it or

pedestrians on it are exposed to more severe levels of air pollution (Rakowska et al, 2014; Chan, Kwok, Lee, and Chan, 2001; Chan, Kwok, and Chan, 2000). Stricter rules should be imposed for roadside areas, while appropriate regulatory or financial support should be supplied.

This study has some limitations. First, we adopted one season of the year—spring 2017 —as the study period based on the availability of data. Including all four seasons in the analysis, however, could have permitted valuable comparisons. Second, we studied Seoul, the capital city of South Korea. People in smaller cities or rural areas may react differently than those we observed in Seoul. Expanding the study site might yield some complementary results.

IV. Conclusions

As a member of the Healthy Cities Movement, the local government of Seoul is continuously working to create new systems, amenities, and policies to make Seoul a healthy city. However, while new systems are continuously built, a lack of understanding of the performance of existing systems and amenities or a lack of understanding of new environmental issues leads to deficiency of necessary systems and amenities. To address these weaknesses, this two-part study proposes methods for evaluating existing projects for healthy cities, and methods for exploration of the emerging environmental issues that need attention in order to maintain healthy cities.

In chapter 1, the existing Healthy Cities project was evaluated using the Silver Zone of Seoul as an example. However, the study found that Silver Zones were ineffective in reducing auto-related senior pedestrian collisions. The spatial analysis revealed that the Silver Zones were not built in the places where many senior pedestrian collisions occurred, but only where the senior care facilities requested. These findings pointed out that the inefficiency of Silver Zones is not caused by the design of them, but by lack of prior efforts from the local government's management system. The evaluation in this chapter also identified and recommended several safety measures, other than Silver Zones, such as such as extending the length of green lights for slow-moving pedestrians, fences to prevent jaywalking and speed cameras, that have demonstrated their effectiveness in reducing auto-related pedestrian collisions.

In Chapter 2, the study examined the impact of new environmental problems such as air pollution, and argued that bad air quality affected the

recreational site selection of citizens. The analysis revealed that when the quality of air is bad, many people avoid outdoor activities and rather visit indoor facilities. People especially prefer to visit the multi-complex malls where they can enjoy various kinds of activities. This phenomenon shows that local governments need to increase their effort toward improving outdoor air quality through the promotion of green energy and the implementation of air purifying systems in public spaces, but while doing so, they also need to make indoor facilities safe for people by providing good indoor air quality and diversifying the programs. The analysis also recommended that people should be prepared for socioeconomic problems that may arise as the use of outdoor facilities decreases.

This study has explored ways of strengthening our understanding and strategies for Healthy City approaches focused on Seoul. It suggested the importance of reviewing and evaluating past projects and investigating new environmental and social issues. This evaluation process allows the government to develop a healthier city. In addition, the empirical methodologies and results of each chapter will be beneficial in the future when governments decide on further initiatives for maintaining a healthy city.

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Appendices

Appendix I. Description of Variables

Variables	Description	Obs.	Mean	Std. Dev.	Min.	Max.	Type of Variable
Num_Collision	Number of collisions	116	0.828	1.675	0	7	Discrete variable
After	Collisions occurred in 2015 (*After* = 1 if occurred in 2015 or *After* = 0 if occurred in 2010)	116	0.5	0.502	0	1	Dummy variable
Treatment	Silver Zones established in 2011,2012,2013 and 2014 (*Treatment* = 1 if established in 2011, 2012, 2013 and 2014 or	116	0.552	0.499	0	1	Dummy variable

	Treatment = 0 if established in 2007,2008 and 2009)						
After_Treatment	Interaction of *After* and *Treatment*	116	0.276	0.449	0	1	Continuous variables
Location_Range	Location of collision (within Silver Zone or its 300m buffer) (*Location_Range* = 1 if location of collision is within Silver Zone or *Location_Range* = 0 otherwise)	27	0.082	0.17	0	.667	Dummy variable
Percent_colour	Percentage of coloured road surface marking in the Silver Zone area	116	0.27	0.21	0	0.86	Continuous variables

Number_lane	Number of lanes at the collision location	27	2.11	0.708	1.3	3.5	Discrete variable
Dist_crosswalk	Distance to the nearest crosswalk from the collision location	27	3.388	3.774	0	19.367	Continuous variables
Dist_light	Distance to the nearest vehicle traffic light from the collision location	27	4.814	5.465	0	21.567	Continuous variables
Fence	Fence installed at the collision location (*Fence* = 1 if fence is installed at the collision location or *Fence* = 0 otherwise)	27	0.185	0.284	0	1	Dummy variable
Dist_intersection	Distance to the nearest	27	6.553	8.702	0	32.933	Continuous

	intersection from the collision location						variables
Speedlimit Signage	Speed-limit signage installed at the collision location (*Speedlimit Signage* = 1 if Speedlimit Signage is installed at the collision location or *Speedlimit Signage* = 0 otherwise)	27	0.526	0.413	0	1	Dummy variable
No_sidewalk	Roadway without sidewalk at the collision location (*No_sidewalk* = 1 if collision occurred on a road with no pedestrian pathway or	27	0.290	0.328	0	1	Dummy variable

	No_sidewalk = 0 otherwise)						
Residential	Residential land use in the collision location (*Residential* = 1 if collision occurred in residential area or *Residential* = 0 otherwise)	27	0.22	0.299	0	1	Dummy variable
Commercial	Commercial land use of the collision location (*Commercial* = 1 if collision occurred in Commercial area or *Commercial* = 0 otherwise)	27	0.515	0.383	0	1	Dummy variable

국문 초록

건강도시계획 요소의 평가 분석과 계획 방향에 관한 연구 : 서울시 사례를 중심으로

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최근 우리나라의 여러 지방자치 단체들은 세계건강보건기구(WHO)에서 제시하는 건강도시 개념을 바탕으로 건강도시의 구현을 위해 지속적인 노력을 하고 있다. 건강도시 개념에 따르면 여러가지 건강도시적 요소 중 시민들이 여러가지 신체 활동을 할 수 있는 도시환경을 만드는 것이 매우 중요하다. 이에 따라 우리나라의 여러 지방자치 단체들도 건강도시 접근법을 사용하여 도시환경의 계획 및 설계 관련 사업을 지속적으로 수행하고 지역의 보건을 증진시키는 노력을 해왔다.

하지만 정부가 설립한 여러 건강도시 사업들의 효용성에 대해서는 꾸준히 의문이 제기되어왔다. 또한 국민들은 새로운 사회

및 환경 문제 해결을 위한 건강도시적 시스템과 편의시설 사업의 부족함을 문제삼고 이에 대한 해결 방안을 해당 지방정부에 직접 요구하기도 한다. 국민들의 이러한 불만과 요구가 전략적으로 해결되지 않을 경우, 정부에 대한 국민들의 불신을 야기할 수 있는 것은 물론, 건강도시 구현이라는 궁극적 목적에 부합하지 않는 예산 사용을 초래할 수 있다. 따라서, 과거에 설립된 건강도시 사업을 주기적으로 재평가하여 지속적으로 개선해 나아가고, 급부상 중인 사회적, 환경적 문제를 능동적으로 파악하여 우리사회에 새롭게 필요한 건강도시 사업을 제안하는 연구가 중요시되고 있다.

건강도시 개념에는 건강도시 구현을 위한 여러 요소가 있으며 그 중에서도 안전한 환경은 중요한 요소이다. 이에 따라, 도시 내에서 사람들이 더욱 활동적으로 생활할 수 있도록 하는 안전한 도시환경을 조성하는 것에 대한 관심이 지속적으로 증가하고 있다. ‘안전’에는 보행자 보호, 범죄 예방, 대기 오염 또는 식수 오염 방지 등과 같은 다양한 세부요소가 있으며, 국내에서도 이러한 안전과 예방에 목적을 둔 다수의 건강도시 사업이 수행되어 왔다. 하지만, 데이터 및 평가방법의 부족으로 인해 기존의 안전 관련 건강도시 사업의 효용성이 제대로 평가되지 못하고 있는 실정이다. 또한, 이러한 데이터와 평가방법의 결여는 우리 사회에서 새롭게 나타나는 사회적, 환경적 문제를 능동적으로 탐색하고 그에 알맞는 건강도시 사업 구상을 어렵게 한다.

본 연구는 건강도시 요소 중 안전과 관련된 서울시의 기존 건강도시 사업의 평가와 새롭게 필요한 건강도시 사업의 탐색에 적합한 방법론과 프레임워크를 제시하는 것을 목적으로 한다. 두개의 챕터로 구성되어 있는 본 연구의 첫번째 챕터에서는 보행자 안전과 관련된 기존 건강 사업의 효용성 평가를 위해 서울시의 노인보호구역 (Silver Zones)를 사례로 들어 평가한 후 개선점을 제시하였다. 두번째 챕터에서는 최근 국내 대기 오염의 심각화로 인해 발생할 수 있는 새로운 사회적, 환경적 문제를 탐색하기 위해 대기오염 수준이 서울시민들의 여가활동 장소 선택에 미치는 영향을 분석하고 이에 대응하는 새로운 건강도시 사업을 제안하였다.

본 연구 과정에서 사용된 평가방법은 향후 건강도시 구현을 위한 도시계획 및 설계 과정에서 평가 및 의사결정지원 도구로 활용 가능할 것으로 예상된다. 또한, 각 챕터의 분석 결과는 건강도시 계획 및 설계 가이드라인에 개선점을 제시하는 데에 근거 자료로 사용될 수 있을 것으로 사료된다.

주요어: 건강도시, 노인보호구역, 교통안전, 대기오염, 미세먼지

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