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Could Smart City Improve Traffic Congestion? A case study of the Smart Columbus Program in Ohio, U.S.*

Kihyun Kwon**

스마트 도시가 교통 혼잡을 개선할 수 있는가? 미국 오하이오주 스마트콜럼버스 프로그램 사례연구

권기현**

Abstract: This study aims to assess the cumulative performance of the Smart Columbus Program, the multiple portfolio projects, focusing on the effect on traffic congestion. Using 'Free Flow Factor (FFF)' data as a traffic speed index published by StreetLight Data, Inc., we employ a quasi-experimental design to evaluate the change between Fall 2018 (pre-intervention period) and Fall 2020 (post-intervention period). Before the difference-in-differences (DID) analysis, we conduct the Propensity Score Matching (PSM) method to identify an equivalent counterfactual control group for the treatment group.

Key finidngs from our empirical analyses are as follows. First, travel delays generally decreased in the study area (Central Ohio) during the Smart Columbus Program period. Second, the effect on traffic congestion varies across the time of day. For instance, a 2.6 percent increase in FFF (decrease in traffic delays) in the study area only during peak evening hours. Third, the Smart Columbus program affects travel delays, but it has mixed results according to the day of the week. For instance, during peak evening hours, while there was a 3.6 percent increase in FFF (decrease in delays) on weekdays, a 2.1 percent decrease in FFF (increase in delays) on weekend days. Our empirical results suggest that the Smart Columbus Program positively impacted traffic congestion reduction despite modest effects.

Key Words: Smart City, Smart Columbus Program, Free Flow Factor (FFF), Propensity Score Matching (PSM), Difference-in-Differences (DID)

키 워 드: 스마트 도시, 스마트 콜럼버스 프로그램, 혼잡도측정지수(FFF), 성향점수매칭 (PSM), 이중차분법 (DID)

1. Introduction

The growing interest in the concept of the Smart City and the need to solve problems associated with urbanization have led to significant attention and funding for technology development and deployment over the last few years (Ahvenniemi et al., 2017). While many smart city projects by public and private investments have been conducted in the world, urban planners and policymakers are faced with the difficult task of measuring the impact of these projects under various investments and policies (Caragliu and Del Bo, 2019; Bjørner,

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2021; Cocks and Johnson, 2021). The purpose of this study is to examine how the Smart City projects focused on mobility of city residents affect traffic congestion. We illustrate it with a case study of the Smart Columbus Program in Ohio. In 2016, the City of Columbus received $40 million from the U.S. Department of Transportation (US DOT) as the winner of the Smart City Challenge (SCC) and $10 million from a private firm (Vulcan, Inc) to launch an initiative including various smart city projects, called Smart Columbus, which aims to improve accessibility and mobility, reduce congestion and carbon emissions, foster sustainability, and enhance the quality of life for Columbus residents and visitors (City of Columbus, 2019).

The traffic congestion problem has been a big issue for planners and policymakers in almost all urban areas because it leads to wasted fuel, vehicle emissions, and additional costs regarding public health (Beaudoin et al., 2015; Cao et al. 2017). To address this, cities have developed and deployed new intelligent technologies such as intelligent transportation systems (ITS) which can be seen in Smart City initiatives, city projects, and public research projects (Ahvenniemi et al., 2017; Bjørner, 2021; Cao et al., 2017; Cocks and Johnson, 2021). Since the concept of Smart City appeared relatively recently, there is not much empirical work investigating these projects' impacts on mobility performance, such as traffic congestion. Therefore, our access to a highly disaggregate, comprehensive transportation database from the Columbus region may provide a great opportunity to evaluate the direct impacts of the Smart Columbus Program projects on traffic congestion.

We employ a quasi-experimental study design to estimate the effects on traffic congestion. Quasi-experimental methods are used in policy analysis to evaluate the impacts of an intervention or policy change on outcomes (Giuliano et al., 2016; Wing et al., 2018; Yu and Zhang, 2019; Lee, 2020). A major issue in implementing a quasi-experimental study design is to select an appropriate counterfactual control group without a systematic difference from the treatment group (Giuliano et al., 2016; Lee, 2020). In this study, the Propensity Score Matching (PSM) method is conducted before difference in differences (DID) models to match an appropriate counterfactual control group with the treatment group. We then analyze changes in Free Flow Factor (FFF) indicating traffic congestion level as a proxy for travel delay and statistically compare the measure pre- and post-intervention, which the objective of assessing how the Smart Columbus Program has affected traffic congestion.

This study is organized as follows. In the next section, we review the literature on the links between traffic congestion and Smart City. In section 3, we provide the background information on the Smart Columbus Program portfolio. Section 3 also explains about data sources, research methodology, and variables used in the models. In section 4, we discuss results from Propensity Score Matching (PSM) and the difference-in-differences (DID) models for the analysis of the impacts on traffic congestion. In section 5, we provide our conclusions and a discussion of the policy implications that may arise from the analysis.

2. Literature Review

Traffic congestion has been a critical issue for urban and transportation planning despite a few decades of effort and billions of dollars of public spending to alleviate congestion (Transportation Research Center, 2007; Beaudoin et al., 2015). This is because traffic congestion results in vehicles moving at lower speeds, thereby increasing travel time and vehicle emissions and constraining the range of travel for a given time budget (Schaller, 2021). To address this, many studies have argued the need for a substantial number of investments in public transportation systems and services. In theory, the diversion of automobile drivers to public transit decreases the number of private vehicles on roads, leading to a reduction in traffic congestion (Cervero and Landis, 1995; Handy, 2002). In addition, new public transit systems may increase transit ridership and induce more dense development in surrounding areas, which decreases automobile usage and air pollution (Stokenberga, 2014; Giuliano et al., 2016; Ingvardson and Nielsen, 2018).

While many cities have made substantial efforts on the provision of public transit services to improve traffic congestion, these efforts have had mixed and inconclusive results (Baum-Snow and Kahn, 2005; Giuliano et al., 2016). For instance, Baum-Snow et al. (2005) examine the effect of rail transit investment on the public transit ridership using 16 rapid rail transit systems located in large U.S. cities. They find that rail transit investment leads to reduced commuting times but does not reduce congestion levels. Giuliano et al. (2016) examine the impact of the Exposition (Expo) light rail line in Los Angeles on transit ridership and freeway traffic. Their empirical models show a net increase in transit ridership, but the effects of roadway traffic are small and localized.

As technologies have been developing, cities developed and deployed new intelligent technologies, which can be seen in Smart City initiatives, projects, and portfolios (Ahvenniemi et al., 2017; Cocks and Johnson, 2021). Smart City represents a rather abstract idea or conceptual urban development model to increase ‘smartness’ in various ways and areas because it refers to unexplored and interdisciplinary fields (Angelidou, 2014; Ahvenniemi et al., 2017; Yigitcanlar and Kamruzzaman, 2018). A common understanding is that Smart City refers to the use of various information technologies to connect and integrate urban systems and services, resulting in innovative transport systems, infrastructures, and efficient energy systems (Lombardi et al., 2012; Angelidou, 2014; Söderström et al., 2014; Caragliu and Del Bo, 2019).

In recent years, Smart City has become a priority policy agenda and essential research topic in many cities (Yigitcanlar, 2017). Many empirical studies have focused on the development of a framework for strategic planning for Smart City development (Stratigea et al., 2015; Ahvenniemi et al., 2017). For instance, Stratigea et al. (2015)'s study develops an ICT-enabled participatory planning framework for guiding policymaking toward the planning of smart cities. Ahvenniemi et al. (2017) identify the relation between the sustainable and smart city concepts and develop respective assessment frameworks.

Part of the existing literature focuses on the impact of Smart City on technical and economic aspects. For instance, Caragliu and Del Bo (2019) investigate the urban innovation impact of Smart City policies using data on Smart City features for 309 European metropolitan areas, Smart City policy intensity, and urban innovation outputs. They find that Smart City policies have a significantly positive impact on urban innovation measured through patenting activity, especially in high-tech classes. In addition, Yu and Zhang (2019) examine the effect of Smart City policies (SCP) on energy efficiency (EE) in China's cities. Their empirical models show a statistically positive impact of SCP on EE.

As a Smart City project, several studies focus on emerging transportation modes and examine the impacts of autonomous vehicles (AVs) and mobility-on-demand services such as car-sharing and ride-hailing on traffic congestion (Fagnant and Kockelman, 2018; Schaller, 2021). However, there is mixed and inconclusive evidence on the effectiveness associated with traffic congestion. For instance, Fragnant and Kockelman (2018) investigate the potential of shared autonomous vehicles (SAVs) in Texas using multiple scenarios. They find each SAV could potentially replace between 10 and 13 private vehicles, and they argue dynamic ride-sharing (DRS) plays an essential role in avoiding congestion problems. Schaller (2021) examines the effect of shared services such as Uber and Lyft in reducing vehicle miles traveled (VMT) in several cities: Boston, Chicago, New York, San Francisco, and suburban California. The model results show that shared services are likely to increase VMT due to the addition of dead-head miles.

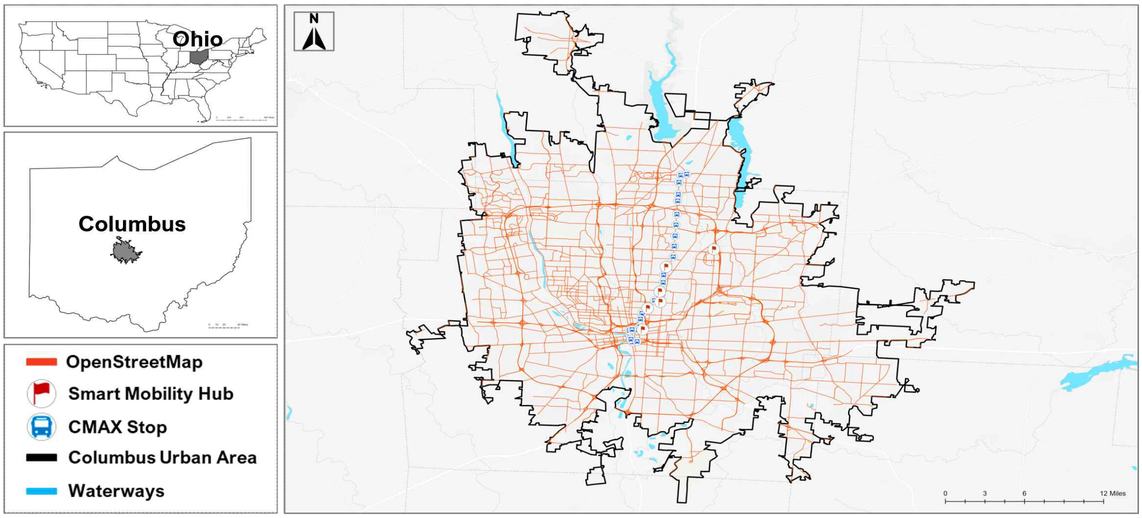

Figure 1. Study Area

This study contributes to the existing literature as follows. First, this study examines Smart City's direct impacts on the program-level mobility outcome. While several studies associated with Smart City have been published, previous studies on impact assessments of Smart City are rather sparse. Moreover, the existing literature presents conflicting evidence when it comes to the relationship between Smart City projects and traffic congestion. Therefore, the findings of this study shed light on the impacts of Smart City projects on traffic congestion. Second, as a methodological contribution, we employ Propensity Score Matching (PSM) before difference-in-differences (DID) models to match an appropriate counterfactual control group with the treatment group. Lastly, our access to a highly disaggregate and comprehensive transportation database may provide a great chance to evaluate the direct impacts of the Smart Columbus Program projects on traffic congestion. Choi and Ewing (2021) argue that only limited studies have been done on segment-level travel delays for some reasons such as data availability. We utilize FFF on road segments as a proxy for travel delay.

3. Data and Methods

Columbus, located in central Ohio, is the state capital of Ohio. With a 2022 population of 921,605, it is the largest city in Ohio and the 14th largest city in the United States (U.S. Census Bureau, 2022). Columbus is a highly car-dependent community. About 88.7% of all workers drive to work, about 3.1% walk or bicycle, and about 2.4% use public transit (American Community Survey (ACS), 2019).

Smart Columbus is the smart city initiative for the Columbus, Ohio, USA region. The Smart Columbus Program including eight projects, which mainly aims to reduce traffic congestion by encouraging individuals to shift from private vehicles to shared-use services and transit through advanced technologies utilizing advancements in Intelligent Transportation System (ITS), Connected Vehicles (CV), Autonomous Vehicles (AV), and Electric Vehicles (EV). There might be a reduction in road travel times, thereby reducing traffic congestion, especially around the regions of Smart Columbus projects (City of Columbus, 2019). Further information can be found in the Smart Columbus website (http://smart.columbus.gov/).

One of the projects associated with mobility technologies is creating a technology infrastructure

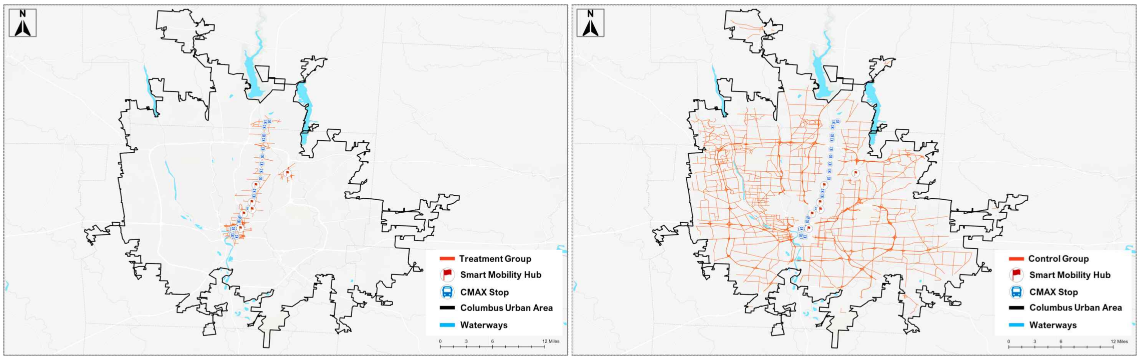

Figure 2 The Treatment Group(left) and the Candidates of the Control Group(right)

for Smart Mobility Hubs (SMHs) along the Central Ohio Transit Authority' s (COTA) BRT line (called CMA), which pair Wi-Fi-equipped touch screen kiosks with various modes of transportation, such as bike-share, scooters, and ride-share pick up and drop off points to improve mobility in the Linden and Easton areas of Columbus. We use OpenStreetMap (OSM) road segments data as a unit of analysis (Figure 1).

We employ a quasi-experimental approach to control many confounding factors that affect travel delays beyond the scope of the Smart Columbus Program. The road segments near the Cleveland Avenue corridor are selected as the treatment group due to their methodological compatibility and the potential to account for geographically localized and generalized impacts of the Smart Columbus Program. The candidates of the control group are road segments outside the treatment road segments. We then remove several road segments from the candidates of the control group to avoid contamination effects by using the 1200-meter elimination zone from treatment road segments, increased road segments with the Ohio State University (OSU) main campus boundary, and three airports (Ohio State University Airport, Rickenbacker International Airport, John Glenn Columbus International Airport). Finally, we identify two groups (576 road segments for treatment and 3,950 road segments for control) for Propensity Score Matching (PSM) (Figure 2).

This study evaluates the change in travel delays on a set of road segments between before and after the Smart Columbus Program projects. In the pre-/post-test to treatment or control groups, study subjects should be randomly assigned to a group that receives the treatment (treatment group) or a group that does not receive the treatment (control group) (Giuliano et al., 2016; Yu and Zhang, 2019). However, in this study, assigning subjects to the treatment and control groups is non-random; thus, evaluators cannot assume equivalence between the two groups. Therefore, the Propensity Score Matching (PSM) technique is conducted before difference in differences (DID) analysis to match an appropriate counterfactual control group with the treatment group

3.1 Propensity Score Matching (PSM)

The Propensity Score Matching (PSM) method quantitatively matches the control group sharing a common trend with the treatment group (Heckman et al., 1998). Propensity scores indicate the conditional probability of assigning a unit to a particular treatment condition, given a set of observed covariates: $(z = i|X)$, where z = treatment, i = treatment condition, and X = covariates. In a quasi-experiment, the probability $(z = i|X)$ is unknown, but it can be estimated from the data using a logistic regression model, where treatment assignment is regressed on the set of observed covariates

(Olmos and Govindasamy, 2015). The propensity score allows matching of individuals in the control and treatment conditions with the same likelihood of receiving treatment. After conditioning on the propensity scores, the treatment and control groups are balanced, and treatment assignment bias can be minimal (Ma et al., 2019; Lee, 2020).

We use a logistic regression model to estimate propensity scores for road segments. Covariates for the propensity scores should be theoretically related to both outcome and treatment (Olmos and Govindasamy, 2015). We include three types of covariates such as land use, socio-economic characteristics, and road segment length. We use the current-parcel-level land use data from Mid-Ohio Regional Planning Commission (MORPC) for land-use variables. Considering a 400-meter buffer zone around the road segment as its catchment area. Many empirical studies examining factors that influence transit ridership at the station level often use the station's catchment area, defined by pedestrian walking distance, to assess land-use and built environment characteristics. Although the catchment area can be defined in different ways based on transportation modes and urban attributes, most studies have used thresholds of 400 meters (a ¼ mile buffer) in either Euclidean or network distance as a pedestrian catchment area because of assumed standard walking distances (Zhao et al., 2013; Jun et al., 2015). We calculate the proportion of each land use type within the 400-meter catchment areas for all road segments (576 road segments for treatment and 3,950 road segments for control).

For socio-economic variables, we use the block-group level American Community Survey (ACS) data based on 2012-2017 5-year estimates from US Census Bureau. We use median household income, unemployment rates, and population density from the data as socio-economic variables. We spatially join the average median household income, unemployment rates, and population density of block groups intersected with each road segment catchment area to calculate the socio-economic variables. After estimating propensity scores, we use the nearest neighbor algorithm to match treatment road segments with control road segments.

3.2 Difference-in-differences (DID)

This study estimates the impact of the Smart Columbus Program on traffic congestion by evaluating the change in travel delays on a set of road segments in the treatment group as compared to those in the control group. The comparable road segments are methodically selected to have characteristics similar to the treatment group in terms of physical attributes, land use, and socio-economic conditions. For the outcome variable, we use FFF, a traffic speed index published by StreetLight Data, Inc., and join them into matched treatment and control road segments.

Streetlight Data is an on-demand mobility analytics platform. They take big data from mobile devices to fuel analyses like origin-destination matrices, travel time and select link studies. Through the platform, we can obtain traffic information such as the volume of trips over different periods of time, differences by day type and day part, and trip time, length, and speed (U.S Department of Transportation, 2018). Further information can be found on the website(https://www.streetlightdata.com/). We obtain travel time and delay indicator from Streetlight Data, which is expressed as FFF. It is a ratio of the average trip speed for the day part to the maximum average trip speed for the segment in any hour during the entire data period. Based on the results of descriptive analysis and the progress of the Smart Columbus Program, Fall 2018 is selected as the pre-intervention period, and Fall 2020 is chosen as the post-intervention period.

Using treatment and matched control road segments through Propensity Score Matching (PSM), we perform the difference-in-differences (DID) models. We estimate the following regression model:

$$\mu = \beta_0 + \beta_1 treat_t + \beta_2 time_t + \beta_3 (treat * time) + \epsilon$$

where μ is the expected mean value of FFF for subject i at time t; $treat$ is a dummy variable for the treatment group and $time$ is a dummy variable for the post-treatment time period (Fall 2020). The interaction term, $treat*time$, is equivalent to a dummy variable equals 1 for observations in the treatment group, in the second period (Fall 2020).

The difference-in-differences (DID) estimates indicate that β_1 is the coefficient of the treatment variable and reflects the baseline differences between treatment and control group pre-intervention. Coefficient β_2 is the change in FFF among the control group. Coefficient β_3 is the main parameter of interest. It is a DID estimator, which estimates the change in the treatment group that is attributable to the Smart Columbus Program and whether the difference between the treatment and control groups is statistically significant (Giuliano et al., 2016).

4. Results and Discussion

4.1 Propensity Score Matching (PSM) results

Table 1 shows the results of a logistic regression model for the Propensity Score Matching (PSM). We include all covariates statistically significant and theoretically known to influence traffic congestion for the matching

Table 1. Logistic Regression Results

	Dependent variable: treatment	
	Coefficient	Std. Err.
Median Housheold Income	-0.000	0.000***
Population Density	-0.000	0.000
Average Unemployment Rate	-0.023	0.012**
Land Use: Agricultural	-0.026	0.017
Land Use: Institution	0.025	0.006***
Land Use: Miscellaneous	-0.027	0.010***
Land Use: Open Space	-0.009	0.005*
Land Use: Commercial	0.014	0.003***
Land Use: Industrial	-0.028	0.006***
Road Segment Length	-0.000	0.000***
Constant	0.253	0.271
Number of observations	4,526	
Log Likelihood	-1526.773	

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

Table 2. Standard Differences (a) Before and (b) After PSM

	Absolute standard differences between treatment and control group (%)	
	(a) Before	(b) After
Median Housheold Income	77.12*	1.22
Population Density	30.43*	2.65
Average Unemployment Rate	20.94	2.10
Land Use: Agricultural	24.10	0.95
Land Use: Institution	22.65	1.07
Land Use: Miscellaneous	27.73*	3.40
Land Use: Open Space	34.33*	0.18
Land Use: Commercial	44.02*	4.29
Land Use: Industrial	21.78	6.47
Road Segment Length	23.22	3.05
Constant	77.12	1.22
Number of observations	4,526	

Note: * indicates variables above the 25% threshold

Table 3. Chi-square Test Results (a) Before and (b) After PSM

	(a) Before	(b) After
X^2 Statistics	321	3.9
Degree of Freedom	10	10
P-value	5.04e-63***	0.952
Number of observations	4,526	1,152

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

process. Most variables are statistically significant.

The propensity scores estimated for road segments through a logistic regression model are input into the nearest neighbor matching. This algorithm selects a subset of 576 road segments from the 3,950-potential control as one-to-one matches with the treatment road segments.

Table 2 shows standard differences of covariates between treatment and control groups before and after Propensity Score Matching (PSM). A standard difference above 25% for a variable suggests an imbalance between treatment and control groups (Olmos and Govindasamy, 2015; Lee, 2020). As can be seen in Table 2, we observe that there is no imbalance after the Propensity Score Matching.

Table 3 presents the results of a Chi-square test. A statistically significant chi-square indicates that at least one of the variables included in the model generates an imbalance between two groups (Olmos and Govindasamy, 2015). As can be seen in Table 3, a statistically significant chi-square value in (a) indicates one or more covariates are resulting in an imbalance between treatment and control groups.

On the contrary, after Propensity Score Matching (PSM), the chi-square statistic is no longer statistically significant, indicating an equivalence between two groups.

The distributions of propensity scores in Figure 3 visually confirm an improved balance and similarity between treatment and control groups after PSM. Parallel histogram in Figure 3 presents substantial dissimilarity in propensity score distributions between control (left) and treatment (right) groups before PSM. As can be seen in Figure 3, Propensity Score Matching (PSM) improves the similarity and balance in propensity score distributions between two groups.

Figure 4 shows the geographic locations of treatment and matched control road segments for DID models.

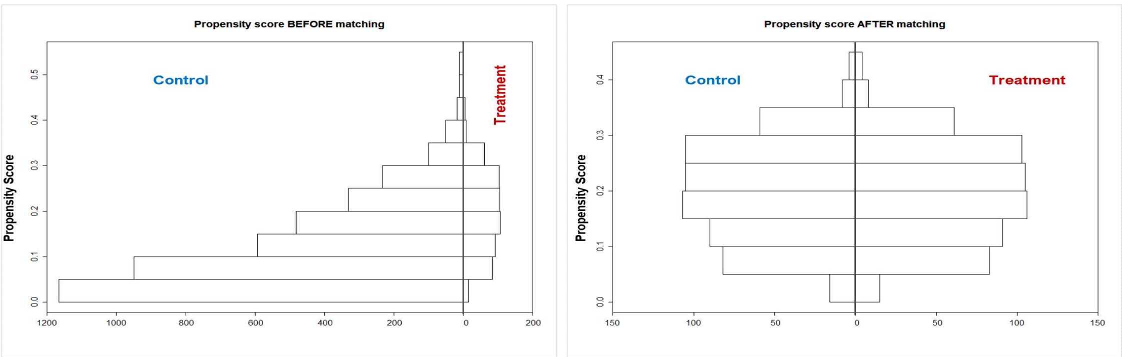

Figure 3. Distributions of Propensity Scores Before (left) and After (right) matching

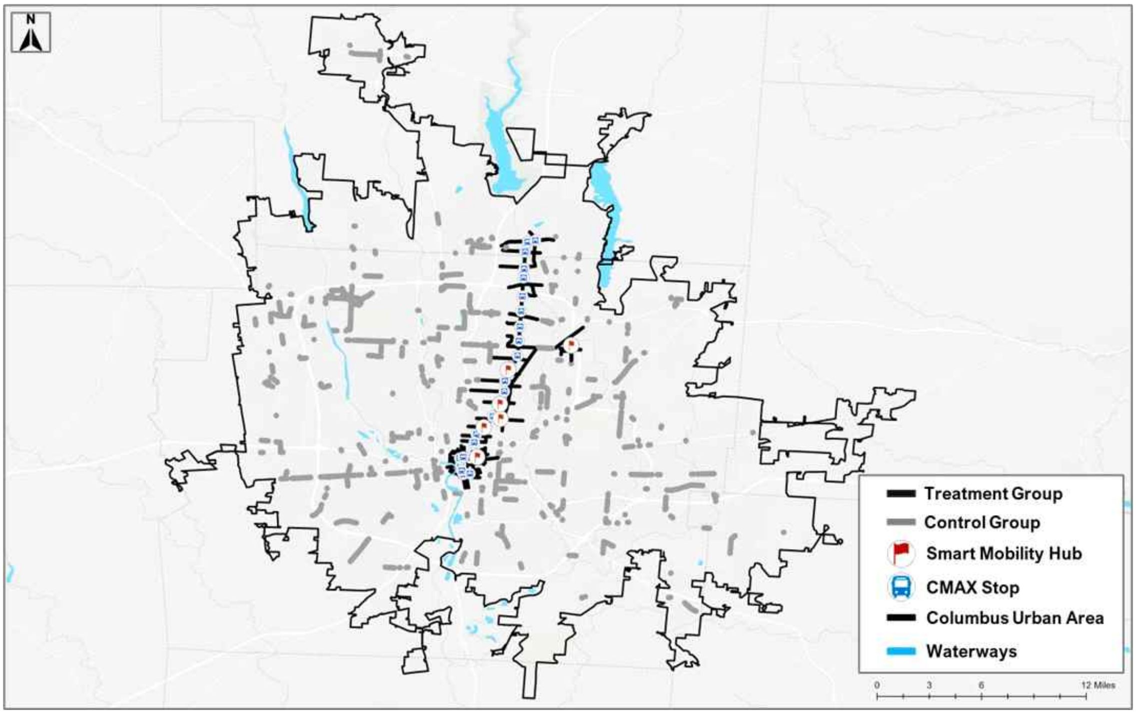

Figure 4. Geographic Locations of Treatment and Matched Control Road Segments

Table 5. Average FFF for the Study Period

	All Days (M-Su)			Weekday (M-Fri)			Weekend (Sa-Su)		
	Fall 2018	Fall 2020	Percent Change	Fall 2018	Fall 2020	Percent Change	Fall 2018	Fall 2020	Percent Change
Control	0.7123	0.7507	5.4	0.7060	0.7488	6.1	0.7417	0.7666	3.4
Treatment	0.6971	0.7454	6.9	0.6852	0.7456	8.8	0.7521	0.7596	1.0

Table 4. Results of DID model for FFF

	All Days (M-Su)			Weekday (M-Fri)			Weekend (Sa-Su)		
	All Day	Peak AM	Peak PM	All Day	Peak AM	Peak PM	All Day	Peak AM	Peak PM
Treatment (β_1)	-0.015* (0.008)	-0.030*** (0.008)	-0.020*** (0.008)	-0.021*** (0.008)	-0.034*** (0.008)	-0.025*** (0.008)	0.010 (0.008)	0.004 (0.009)	0.014 (0.009)
Time (β_2)	0.038*** (0.008)	0.061*** (0.008)	0.049*** (0.008)	0.043*** (0.008)	0.067*** (0.008)	0.057*** (0.008)	0.025*** (0.008)	0.036*** (0.009)	0.020** (0.009)
DID (β_3)	0.010 (0.011)	0.014 (0.012)	0.026** (0.011)	0.018 (0.011)	0.016 (0.012)	0.036*** (0.011)	-0.017 (0.012)	-0.025* (0.013)	-0.021* (0.013)
Intercept (β_0)	0.712*** (0.006)	0.735*** (0.006)	0.675*** (0.006)	0.706*** (0.005)	0.725*** (0.006)	0.663*** (0.005)	0.742*** (0.006)	0.784*** (0.006)	0.727*** (0.006)

Note: **p<0.1, **p<0.05; ***p<0.01. Numbers in parentheses are std. Err.

4.2 Difference-in-differences (DID) results

Based on the matched treatment and control road segments, we estimate the impacts of the Smart Columbus on FFF as a proxy for traffic congestion using difference in differences (DID) model. FFF is an indicator of traffic congestion. The high FFF means little congestion on road segments (low traffic delays).

Table 4 shows FFF and the percent change between fall 2018 (pre-intervention period) and fall 2020 (post-intervention period). For All Days (i.e., combined weekdays and weekends) and Weekdays alone, FFF of the treatment group increased more than that of the control group. On the other hand, FFF of the control group increased more on the weekend as compared to that of the treatment group.

Table 5 presents the difference in differences (DID) regression results for All Days, Weekdays, and Weekend average FFF.

Time ($\beta 2$) indicates that FFF increased among the control group for all cases of interest. For All Days, Weekdays, and Weekend, FFF of the control group increased between pre- and post-intervention with statistically significant ranging from 2.0% (Weekend, Peak PM) to 6.7% (Weekday, Peak AM).

The increases are statistically significant in all cases, indicating traffic congestion improved in control road segments through the Smart Columbus Program.

There are positive values for several cases of interest ($\beta 3$), indicating that FFF for treatment segments increased as a result of the intervention. This suggests that the Smart Columbus Program caused a reduction in congestion during these periods. The results are only statistically significant for two periods, however, namely All Days, Peak PM (2.6% increase in FFF) and Weekdays, Peak PM (3.6% increase in FFF). Conversely, the negative values in this DID suggest that the Smart Columbus Program caused an increase in congestion during these periods, specifically Weekend, Peak AM (2.5% reduction in FFF) and Weekend, Peak PM (2.1% reduction in FFF). While the unfavorable results are significant, they do not reach the same level of significance as the favorable results. Our results suggest that the Smart Columbus Program was responsible for a modest reduction in traffic delays during the peak evening hours in general (all days of the week).

5. Conclusions

This study aims to assess the cumulative performance of the Smart Columbus Program, the multiple portfolio projects, focusing on the effect on traffic congestion. Using 'Free Flow Factor (FFF)' data as a traffic speed index published by StreetLight Data, Inc., we employ a quasi-experimental design to evaluate the change between Fall 2018 (pre-intervention period) and Fall 2020 (post-intervention period). Before the difference-in-differences (DID) analysis, we conduct the Propensity Score Matching (PSM) method to identify an equivalent counterfactual control group for the treatment group.

Key findings from our empirical analysis as follows. First, travel delays generally decreased in the study area (Central Ohio) during the Smart Columbus Program period. Second, the effect on traffic congestion varies across the time of day. For instance, a 2.6 percent increase in FFF (decrease in traffic delays) in the study area only during peak evening hours. Third, the Smart Columbus program affects travel delays, but it has mixed results according to the day of the week. For instance, during peak evening hours, while there was a 3.6 percent increase in FFF (decrease in delays) on weekdays, a 2.1 percent decrease in FFF (increase in delays) on weekend days. Our empirical results suggest that the Smart Columbus Program positively impacted traffic congestion reduction despite modest effects.

While there has been the global growth of smart cities through many technological innovations, the actual adoption of these technologies in U.S. urban areas has been a later trend than in other countries (Cocks and Johnson, 2021). Many projects implemented in the Smart Columbus Program are not yet widely used in US transportation. As such Smart Columbus Program serves as a model for other regions. In addition, while several studies associated with Smart City have been conducted, impact assessments of Smart City are rather limited. Therefore, through a highly disaggregated and comprehensive transportation database, this study contributes to our understanding of how Smart City fosters urban mobility performance by investigating their impact on traffic congestion. Our empirical findings, based on DID models, allow us to conclude that Smart City do have a positive impact on reduction in traffic delays despite modest effects.

As a limitation, we rely on traffic data from StreetLight Data inc. without detailed traffic information. Although they offer average traffic volume and speeds on road segments, we still cannot capture mode effects. In terms of mobility performance assessment, it is crucial to look at the changes by mode such as private automobile, bus, truck, and taxi. Future research could use more detailed data, including traffic information by mode, to better understand how Smart City affects specific modes' traffic volumes and speeds. Future studies could benefit from exploring a wider range of case studies beyond the Ohio example. We recommend incorporating qualitative methods, such as surveys or interviews, to enrich the data.

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탄산화 양생한 플라이애시와 실리카퓸 혼입 시멘트 페이스트의 강도특성

노 건* · 장정국**

Strength characteristic of carbonation-cured cement paste incorporating fly ash and silica fume

Noh, Geon*, Jang, Jeong Gook**

Abstract: This study investigates the effect of carbonation curing on the strength characteristic of cement paste materials mixed with fly ash and silica fume. Carbonation curing was found to enhance mechanical strength by promoting the formation of $CaCO_3$, which densifies the microstructure. However, the incorporation of a large amount of fly ash and silica fume negatively affected strength as their pozzolanic reactions consumed $Ca(OH)_2$, competing with the carbonation reaction. The negative impact on strength was proportional to the replacement ratios of fly ash and silica fume, as higher substitution reduced the availability of $Ca(OH)_2$ for carbonation reactions. These findings suggest that while carbonation curing is effective for strength enhancement, optimizing the substitution ratios of fly ash and silica fume is crucial to minimize adverse effects.

키 워 드: 플라이애시, 실리카퓸, 탄산화 양생, 시멘트, 탄소중립

Key Words: fly ash, silica fume, carbonation curing, cement, carbon neutrality

1. 서 론

기후변화와 지구온난화에 대한 우려가 심화됨에 따라 전 세계적으로 탄소중립을 달성하기 위한 노력이 가속화되고 있다. 산업 전반에서 이산화탄소 배출 저감을 위한 기술 개발이 활발히 이루어지고 있는 가운데, 전 세계 CO_2 배출량의 약 7%를 차지하는 시멘트 산업은 탄소 배출을 줄이기 위한 핵심 산업 중 하나로 주목받고 있다(Benhelal et al., 2013). 시멘트 제조 과정은 석회석의 열 분해로 인한 화학적 탈탄산 반응과 클링커를 고온으로 소성하는 연료 연소 과정에서 대규모 CO_2를 배출하는 구조적 한계를 가지고 있다. 이에 따라, 시멘트 산업의 탈탄소화를 위해 혁신적인 기술 적용과 대체 원료 활용이 절실한 상황이다(Ostovari et al., 2021).

이러한 배경에서 이산화탄소 포집・활용・저장(CCUS; Carbon capture, utilization, and storage) 기술은 시멘트 제조 공정에서 발생하는 CO_2를 포집하고 이를 다양한 방식으로 활용하거나 저장하는 솔루션으로 주목받고 있다. CCUS는 공정 중 발생하는 CO_2를 포집하여 광물 탄산화와 같은 과정을 통해 안정된 광물의 형태로 고정할 수 있다(Markewitz et al., 2019). 광물 탄산화는 CO_2를 알칼리 금속을 지닌 광물과 반응시켜 고정하는 방식으로, 시멘트 및 콘크리트 제품의 물리적 특성을 개선하는 동시에 장기적으로 탄소 배출을 줄이는 데 기여한다. 이는 2050 탄소중립 목표를 달성하기 위한 시멘트 산업의 중요한 기술적 접근법으로 인식되고 있다(Li et al., 2013). 특히, 산업 부산물 및 폐기물을 활용한 탄소 저감 기술은 경제성과 환경적 지속 가능성을 동시에 만족시키는 해결책으로 평가된다. 대표적인 예로 탄산화 양생 기술은 CO_2를 콘크리트의 양생 단계에서 투입하여 재료의 역학적 성능을 향상시키는 동시에 CO_2를 안정적으로 고정하는 과정을 포함한다

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(Jang et al., 2016). 이 기술은 클링커 사용량을 줄이고 공정에서 발생하는 CO_2를 활용함으로써 시멘트 제조의 환경적 영향을 크게 줄일 수 있다(Meng et al., 2019).

더불어, 플라이애시(Fly ash)와 실리카퓸(Silica fume)과 같은 산업 부산물의 활용은 시멘트 산업의 탈탄소화를 촉진하는 중요한 요소로 꼽힌다. 플라이애시는 석탄 화력발전소에서 생성되는 부산물로, 시멘트 콘크리트의 장기강도를 개선시키고 치밀도를 증가시켜 내구성을 향상시킬 수 있다. 또한, 이를 통해 시멘트의 CO_2 사용량을 줄이고, 천연 원료를 대체할 수 있다(Vargas & Halog, 2015). 실리카퓸은 금속 실리콘 및 페로실리콘 제조 과정에서 발생하는 미세한 규소 산화물로, 고농도의 SiO_2 함량을 통해 시멘트 기반 재료의 강도 및 내구성을 크게 개선한다. 또한, 실리카퓸의 높은 반응성은 포졸란 반응을 통해 수화물 구조를 강화하고 CO_2 배출량 감소 효과를 극대화할 수 있다. 본 연구는 CCUS 기술 및 광물 탄산화와 같은 첨단 기술이 시멘트 산업에 적용될 수 있는 가능성을 바탕으로, 탄산화 양생 기술과 플라이애시 및 실리카퓸 활용이 시멘트 기반 재료의 압축강도 특성에 미치는 영향을 조사하였다.

2. 실험방법

본 연구에서는 플라이애시와 실리카퓸을 혼합한 시멘트 페이스트의 역학적 특성과 탄산화 깊이를 측정하기 위해 다양한 배합의 시멘트 페이스트 시험체를 제작하였다. 주 결합재로 탄산화 반응성이 높다고 알려진 벨라이트 시멘트 (BRC; Belite-rich cement)를 사용하였으며 광물조성, 화학조성, 물리적 성질은 Table 1과 같다(Kim et al., 2022).

플라이애시와 실리카퓸의 대체율을 조정하여 각 성분의 영향을 조사하였다. 모든 시험체의 물-결합재 비(W/B)는 0.5로 고정하였으며, 세부 배합비는 Table 2와 같이 설정하였다. 시험체 제작은 ASTM C349에 따라 40 mm × 40 mm × 160 mm 크기의 몰드에 페이스트를 주입하여 이루어졌다. 혼합 과정은 건식 재료(BRC, 플라이애시, 실리카퓸)를 2분 동안 혼합한 후, 물을 천천히 첨가하여 3분간 추가 혼합하는 방식으로 진행되었다. 혼합된 페이스트는 몰드에 주입한 후, 고무망치와 다짐봉을 이용해 다짐하여 공기를 제거하고 표면을 평탄하게 정리하였다. 시험체는 양생방법에 따라 수중양생과 탄산화 양생으로 나누어 관리되었다.

Table 1. Chemical and physical properties of cement used in this study.

Type	Property	Belite-rich cement
Chemical composition (wt%)	CaO	62.5
	SiO_2	25.3
	Al_2O_3	3.1
	Fe_2O_3	3.6
	SO_3	2
	R_2O	0.5
Mineral composition (wt%)	C_3S	31
	C_2S	48
	C_3A	3
	C_4AF	11
Physical property	Density (g/cm3)	3.2
	Blaine (cm2/g)	3400

Table 2. Mix proportion of specimens used in this study

Specimen code	Materials
FA0SF0	BRC(100)
FA10SF0	BRC, Fly ash, Silica fume (90:10:0)
FA20SF0	BRC, Fly ash, Silica fume (80:20:0)
FA30SF0	BRC, Fly ash, Silica fume (70:30:0)
FA40SF0	BRC, Fly ash, Silica fume (60:40:0)
FA0SF10	BRC, Fly ash, Silica fume (90:0:10)
FA10SF10	BRC, Fly ash, Silica fume (80:10:10)
FA20SF10	BRC, Fly ash, Silica fume (70:20:10)
FA30SF10	BRC, Fly ash, Silica fume (60:30:10)
FA40SF10	BRC, Fly ash, Silica fume (50:40:10)

수중양생은 상온의 수중에서 28일 동안 진행하였다. 탄산화 양생은 20℃, 상대습도 60%, CO_2 농도 10%, 상압의 조건을 유지하는 탄산화 챔버에서 28일 동안 수행하였다. 양생이 완료된 시험체는 ASTM C348과 ASTM C349에 따라 역학적 성능과 탄산화 깊이를 측정하였다. 휨강도는 ASTM C348 기준에 따라 28일 양생된 시험체를 대상으로 3점 굽힘 시험을 통해 측정하였다. 각 배합에 대해 3개의 시험체를 시험하고 평균값을 기록하였다. 압축강도는 ASTM C349에 따라 휨강도

시험 후 파괴된 시험체 조각을 사용하여 측정하였다. 강도 시험은 프리캐스트 콘크리트 제조 공정을 고려하여 각 배합에서 3일 및 28일 양생된 시험체를 대상으로 압축강도를 평가하였다. 탄산화 깊이는 탄산화 양생이 완료된 시험체를 대상으로 휨 강도 시험이 완료된 파괴 단면에 페놀프탈레인 용액을 분무하여 비중성화 영역과 중성화 영역을 구분하는 방식으로 측정하였다.

3. 결과 및 고찰

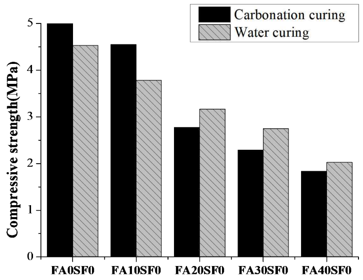
3일 압축강도 측정 결과는 Figure 1과 같다. 수중 양생과 탄산화 양생 조건 모두에서 플라이애시와 실리카퓸의 혼입은 초기 강도 발현에 부정적인 영향을 미쳤다. 수중양생 조건에서는 FA0SF0 시험체가 가장 높은 강도를 나타냈으며, 플라이애시의 함량이 증가할수록 압축강도는 감소하였다. 이는 플라이애시가 낮은 초기 반응성으로 인해 수화 생성물을 형성하지 못했기 때문으로 판단된다.

실리카퓸 혼입 시에도 유사한 이유로 인해 초기강도에 부정적인 영향을 미쳤을 것으로 사료된다(Jena et al., 2019). 탄산화 양생 조건에서는 수중양생에 비해 강도가 전반적으로 더 높게 나타났다. 이는 탄산화 과정에서 $Ca(OH)_2$가 CO_2와 반응하여 생성된 $CaCO_3$가 조직을 치밀하게 형성하면서 강도를 증가시켰기 때문으로 분석된다. 탄산화 반응은 Eq. 1의 화학 반응식으로 설명된다(Rostami et al., 2012).

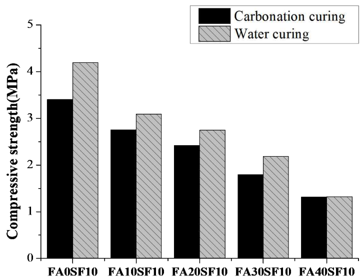
$$Ca(OH)_2 + CO_2 \rightarrow CaCO_3 + H_2O \quad \text{Eq. (1)}$$

플라이애시와 실리카퓸이 혼입된 시험체에서는 탄산화 반응을 통해 일부 강도 증가가 관찰되었으나, 플라이애시와 실리카퓸이 Ca^{2+}을 필요로 하는 반응에 관여함으로써 초기 강도 발현에 제한적인 영향을 미쳤다고 사료된다.

Figure 2와 같이 28일 압축강도는 수중양생과 탄산화 양생 조건 모두에서 플라이애시와 실리카퓸의 혼입량 증가에 따라 감소하는 경향을 보였다. 수중양생 조건에서는 FA0SF0 시험체가 가장 높은 강도를 기록했으며, 플라이애시 함량이 증가할수록 강도가 점차 감소하였다.



(a)



(b)

Figure 1. Test results of 3 days compressive strength (a) without silica fume or (b) with silica fume

이는 플라이애시가 $Ca(OH)_2$를 포함한 수화반응을 통해 Calcium-silicate-hydrate(C-S-H)와 Calcium-alumino-silicate-hydrate(C-A-S-H) 같은 비정질 상(amorphous phase)을 형성하며 강도를 발현하지만, 동시에 $Ca(OH)_2$가 소모되어 탄산화 반응에 필요한 Ca^{2+}의 가용량이 감소했기 때문으로 판단된다(Zhang et al., 2016). 플라이애시의 포졸란 반응은 다음 식과 같이 설명될 수 있다.

$$SiO_2 + Ca(OH)_2 + H_2O \rightarrow C-S-H \quad \text{Eq. (2)}$$

$$Al_2O_3 + Ca(OH)_2 + H_2O \rightarrow C-A-S-H \quad \text{Eq. (3)}$$

플라이애시는 Ca^{2+}을 필요로 하는 이 반응을 통해 비정질 상을 형성하며 강도를 발현하지만, 동시에 Ca^{2+}의 소모로 인해 탄산화 반응에 필요한 $Ca(OH)_2$의 가용량이 감소하게 된다. 실리카퓸

역시 Eq. 2와 같은 반응을 통해 Ca^{2+}을 소모하며 C-S-H 겔을 형성한다(Thomas et al., 1999). 탄산화 양생 조건에서는 $Ca(OH)_2$가 CO_2와 반응하여 $CaCO_3$를 생성함으로써 조직의 치밀화를 촉진하고 강도를 증가시키는 경향을 보였다. $CaCO_3$는 조직 밀도를 향상시키며 강도 발현에 기여한다. 그러나 플라이애시와 실리카퓸의 혼입량이 많을수록 $Ca(OH)_2$가 포졸란 반응에 소모되어 $CaCO_3$ 형성이 제한되고, 이로 인해 탄산화 양생 조건에서도 강도 발현이 상대적으로 낮게 나타났다. 이는 Figure 2에서도 확인할 수 있듯이 플라이애시와 실리카퓸의 혼입량 증가가 압축강도의 저하를 초래했음을 뒷받침한다.

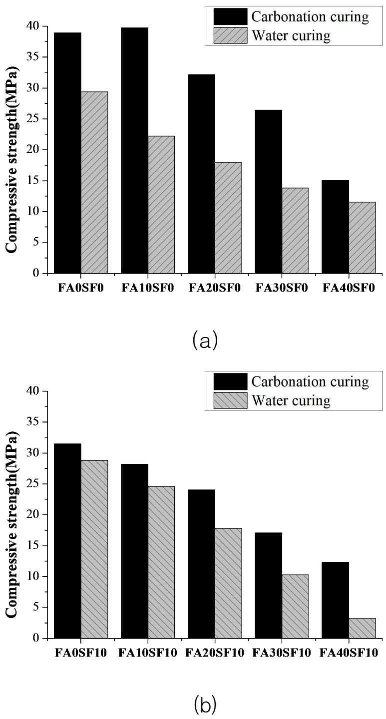


Figure 2. Test results of 28 days compressive strength (a) without silica fume or (b) with silica fume

Figure 3에 보이는 것과 같이 휨강도 실험 결과는 양생 조건과 혼화재의 종류 및 혼입량에 따라 명확한 차이를 나타냈다. 3일 휨강도에서는 수중양생 조건에서 플라이애시를 소량 혼입하면 초기 휨강도가 소폭 증가하는 경향을 보였다. 이는 플라이애시의 구형 입자가 초기 조직의 물리적 충전 효과를 제공하여 강도 발현에 긍정적인 영향을 미쳤기 때문이다. 그러나 플라이애시 함량이 증가함에 따라 반응성이 낮아 조직 강화 효과가 제한되어 휨강도가 점차 감소하였다.

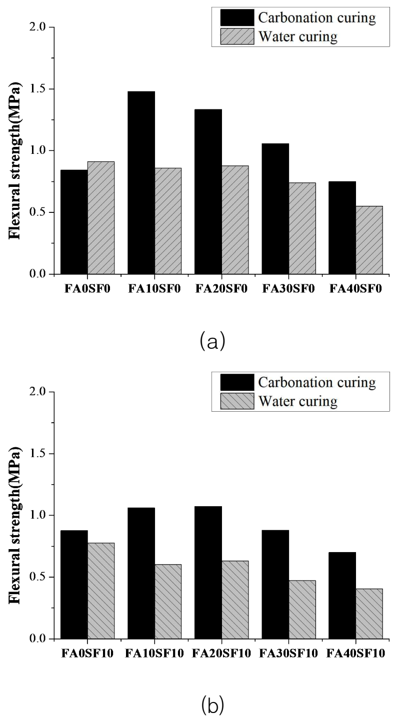
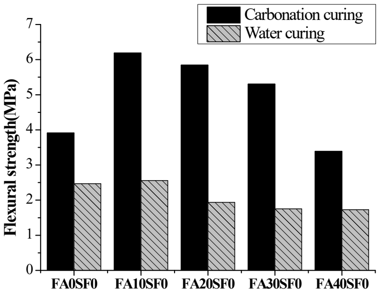


Figure 3. Test results of 3 days tensile flexural strength (a) without silica fume or (b) with silica fume

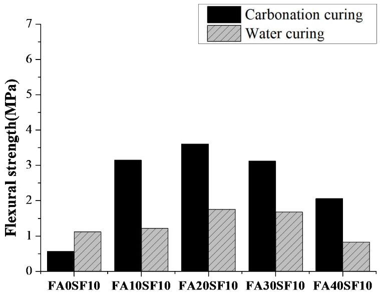
실리카퓸을 혼입한 경우에는 높은 비표면적이 수화 과정에서 물 요구량을 증가시키고, 페이스트 조직의 균질성을 저하시켜 휨강도가 감소하는 결과를 보였다. 탄산화 양생 조건에서는 수중양생 조건에 비해 3일 휨강도가 전반적으로 더 높게 나타났다. 이는 탄산화 과정에서 생성된 $CaCO_3$가 페이스트 조직을 치밀하게 형성하여 휨강도 발현에 기여했기 때문이다. 플라이애시와 실리카퓸을 혼입한 경우에도 탄산화 반응으로 휨강도가 증가하는 경향을 보였으나, 함량이 증가할수록 $Ca(OH)_2$가 포졸란 반응에서 소모되어 $CaCO_3$ 생성량이 감소했고, 이로 인해 조직 치밀화와 강도 발현 효과가 제한되었다.

Figure 4의 28일 휨강도 결과에서도 유사한 경향이 나타났다. 수중양생 조건에서는 플라이애시

함량이 증가할수록 휨강도가 감소하였으며, 실리카퓸 혼입 역시 강도를 저하시켰다. 이는 장기 강도 발현에서도 플라이애시와 실리카퓸이 조직 밀도를 저하시켜 강도 발현을 제한했기 때문으로 판단된다.



(a)



(b)

Figure 4. Test results of 28 days flexural strength (a) without silica fume or (b) with silica fume

탄산화 양생 조건에서는 $CaCO_3$가 장기적으로도 조직을 치밀하게 형성하여 28일 휨강도 발현에 기여했으나, 플라이애시와 실리카퓸의 함량이 증가함에 따라 휨강도는 점차 감소하였다. 이는 플라이애시와 실리카퓸이 $Ca(OH)_2$를 필요로 하는 반응을 통해 조직 밀도를 높이지만, 동시에 $Ca(OH)_2$의 가용량을 감소시켜 탄산화 반응을 제한하기 때문이다. 전반적으로, 탄산화 양생 조건에서 휨강도는 수중양생 조건에 비해 전반적으로 높은 값을 보였으나, 플라이애시와 실리카퓸의 혼입량이 많아질수록 강도 발현이 제한되는 경향이 확인되었다.

탄산화 깊이에 대한 실험 결과는 Figure 5와 같다. 플라이애시와 실리카퓸을 혼입하지 않은 FA0SF0(Plain) 시험체는 탄산화가 덜 진행된 것으로 나타났으며, 절단된 단면에서 붉은 빛을 띠는 비탄산화 영역이 명확히 관찰되었다. 이는 페놀프탈레인 용액이 pH 9 이상에서 붉은색을 띠는 반응 특성과 관련이 있다. Plain 시험체의 경우 pH가 높은 상태로 유지되었기 때문에 비탄산화 영역이 상대적으로 더 넓게 나타난 것으로 분석된다.

반면, 플라이애시와 실리카퓸을 혼입한 시험체에서는 비중성화 영역이 감소하고 탄산화 깊이가 증가하는 경향이 확인되었다. 이러한 결과는 플라이애시가 페이스트 내 pH를 저하시킬 수 있는 영향을 미쳤기 때문으로 판단된다(Khunthongkeaw et al., 2006). 플라이애시의 주요 성분인 SiO_2와 Al_2O_3는 포졸란 반응을 통해 $Ca(OH)_2$를 소비하며 C-S-H 또는 C-A-S-H 구조를 형성한다. 이는 $Ca(OH)_2$의 농도를 감소시켜 페이스트의 pH를 낮춘 것으로 사료된다. 이 과정에서 $Ca(OH)_2$의 농도가 감소하고, 플라이애시에는 소량의 황산염(SO_4^{2-}) 또는 기타 산성 산화물이 포함되어 있어 페이스트의 알칼리도를 추가적으로 저하시킬 가능성이 있다(Okoye et al., 2017). 이는 플라이애시의 혼입으로 인한 특성이며, 실리카퓸에서는 관찰되지 않는다. Plain 시험체에서는 $Ca(OH)_2$가 충분히 존재하여 pH가 높은 상태로 유지되고, 이에 따라 페놀프탈레인 용액을 분사했을 때 붉은 빛을 띠고, 플라이애시 혼입 시험체에서는 $Ca(OH)_2$가 소비되면서 pH가 낮아지고, 결과적으로 탄산화 깊이가 증가하며 비중성화 영역이 축소된 것으로 해석된다.

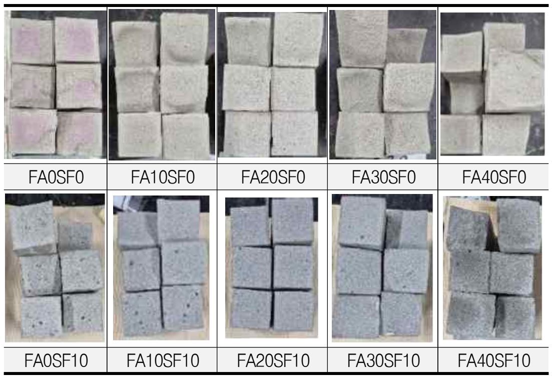


Figure 5. Test results of carbonation depth

4. 결 론

본 연구에서는 플라이애시와 실리카퓸을 혼입한 페이스트의 역학적 성능을 수중양생 및 탄산화 양생 조건에서 평가하고 탄산화 양생 조건에서 탄산화 깊이를 측정하였다. 플라이애시와 실리카퓸의 혼입은 시멘트 페이스트의 물리적 및 화학적 특성에 다양한 영향을 미쳤다.

플라이애시는 초기 수화반응성이 낮아 3일 압축강도와 휨강도 발현에 부정적인 영향을 미쳤으며, 실리카퓸은 높은 비표면적으로 인해 수화 과정에서 물 흡수량을 증가시켜 초기 강도 발현에 악영향을 미쳤다. 탄산화 양생 조건에서는 $CaCO_3$가 조직을 치밀하게 형성하며 강도 발현을 촉진하는 경향을 보였다. 그러나 플라이애시와 실리카퓸 혼입량이 증가할수록 $Ca(OH)_2$가 포졸란 반응에서 소모되어 $CaCO_3$ 생성이 제한되면서 강도 향상 효과는 감소하였다.

28일 압축강도와 휨강도에서도 플라이애시와 실리카퓸 혼입 시험체는 수중양생과 탄산화 양생 모두에서 강도 발현이 감소하였다. 이는 플라이애시와 실리카퓸이 $Ca(OH)_2$를 소모하여 장기 강도 발현에 중요한 C-S-H 및 C-A-S-H와 같은 반응 생성물의 형성을 저해했기 때문으로 판단된다. 또한, 탄산화 깊이 측정 결과, 플라이애시와 실리카퓸은 $Ca(OH)_2$ 감소로 인해 페이스트의 pH를 낮추는 영향을 미쳤으며, 일부 플라이애시 내 산성 산화물이 이러한 pH 저하를 가속화했을 가능성도 확인되었다. 반면, Plain(FA0SF0) 시험체는 $Ca(OH)_2$가 충분히 유지되어 높은 알칼리도를 보였고, 이에 따라 비중성화 영역이 더 넓게 형성되며 가장 우수한 강도를 발현하였다.

결론적으로, 플라이애시와 실리카퓸의 혼입은 포졸란 반응을 통해 조직 밀도를 일부 향상시키는 긍정적인 효과가 있지만, $Ca(OH)_2$의 소비로 인해 초기 및 장기 강도 발현에 제한적인 영향을 미칠 수 있다. 이러한 결과는 플라이애시와 실리카퓸을 혼입한 페이스트의 최적 혼합비를 도출하고, 강도 발현 성능을 향상시키기 위한 추가적인 재료 설계가 필요함을 시사한다. 또한, 산업부산물인 플라이애시와 실리카퓸의 물리화학적 특성 변동에 따른 추가적인 연구가 필요하다.

본 연구는 플라이애시와 실리카퓸 혼입 페이스트의 강도 발현 메커니즘을 종합적으로 분석하였으며, 이를 바탕으로 산업부산물을 활용한 저탄소 시멘트 기반 재료와 이를 활용한 프리캐스트 콘크리트 제품의 제조를 위한 기초자료를 제공할 수 있을 것으로 기대된다.

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Can Bus Rapid Transit (BRT) Improve Regional Economic Activities? Evidence from Business Sales of Intermountain Region, United States

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Abstract: The development of public transportation systems, such as Bus Rapid Transit (BRT), has long been associated with changes in residential patterns and property values. However, less attention has been given to how public transit infrastructure impacts business performance, particularly in terms of sales. This study aims to fill this gap by examining the effect of BRT systems on business sales in the Intermountain region of the United States. Using multilevel modeling (MLM) and a dataset of 130,848 business establishments, the analysis investigates the role of proximity to BRT stations, regional characteristics, and business traits in determining sales outcomes. The results reveal that businesses located closer to BRT stations experience significantly higher sales compared to those farther away, with the proximity effect being particularly strong for businesses within 0-799 meters and 800-1600 meters of a BRT station. Additionally, businesses founded after the 2008 economic recession tend to have lower sales, while older businesses and those in the service sector also exhibit declining sales trends. The study further highlights the importance of public transportation access in driving business performance, especially in urban areas. These findings have important implications for urban planning, business development strategies, and policies aimed at fostering economic growth through improved transportation infrastructure.

키 워 드: 간선급행버스체계, 대중교통, 경제활동, 비즈니스 매출, 위계선형모형

Key Words: Bus Rapid Transit (BRT), Business activity, Business sale, Public transportation, Mulilevel regression modeling

1. Introduction

As urban areas of South Korea increasingly adopt various forms of public transportation, including Great Train eXpress (GTX), Bus Rapid Transit (BRT), Light Rail Transit (LRT), and even autonomous shuttles, it is expected that the residential landscape, particularly for low-income communities, will be influenced by reduced travel costs and improved mobility (Yang and Chang, 2024). Public transit development has been shown to have significant effects not only on residential patterns but also on the surrounding economic environment (Sanchez, 1999). Previous studies have highlighted that the introduction of public transportation can lead to increased property values, often resulting in rent hikes and displacement of low-income populations in proximity to transit hubs (Kim et al., 2021). Research has consistently shown that land price premiums tend to be most pronounced within a 0.5-mile walking distance from public transit stations (D. Rodríguez & C. Mojica, 2009; R. Cervero & C. Kang, 2011). This effect is particularly dominant in central business districts (CBDs), where access to public transit is most advantageous for both residents and businesses (M. Jun, 2012).

While much of the existing literature has focused on the impact of public transportation on

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residential property values, fewer studies have explored the effects of transit development on business outcomes, such as sales and revenue. Businesses located near public transit stations may experience different dynamics, with proximity to transit potentially influencing customer flow, employee access, and overall business performance (Kim et al., 2021). Given the critical role that businesses play in urban economies, it is important to understand how transportation infrastructure like BRT systems affect business sales, particularly in regions with diverse economic conditions.

This research aims to fill this gap by examining the impact of BRT systems on business sales in the Intermountain region of the United States. By exploring the relationship between proximity to BRT stations and business performance, this study seeks to contribute to a broader understanding of how public transportation development can influence economic outcomes for businesses in addition to the residential impacts typically discussed in urban studies.

2. Literature Review

2.1 Land use impact of BRT

Bus Rapid Transit (BRT) systems offer numerous advantages over other urban public transit options. Despite the constraints of integrating BRT into existing roadways and transit networks, BRT remains a practical, cost-effective option with potential to transport high passenger volumes and to be implemented quickly relative to other systems (Deng & Nelson, 2005). Furthermore, BRT' s popularity is bolstered by its broader impacts, particularly on urban land development. Research consistently indicates that BRT can significantly influence land use patterns, potentially fostering urban redevelopment and encouraging more sustainable urban growth (Levinson, Zimmerman, Clinger, Rutherford et al., 2003; Deng & Nelson, 2005; Wright et al., 2007; Cervero & Dai, 2014; Rodriguez et al., 2016).

BRT' s capacity to serve as a catalyst for urban redevelopment is widely recognized, although its effects vary by city and depend on specific local factors. For example, Jun (2012) found that in Seoul, BRT contributed to increased development density within urban centers compared to suburban areas, especially around commercial zones. This growth pattern was associated with a redistribution of non-residential activities—such as retail and employment—in areas surrounding BRT lines, further supporting the trend of businesses relocating from suburban areas into central urban zones.

2.2 Land and Property Values and BRT

The shifts in land use due to BRT influence property values, particularly for commercial and retail spaces. Research by Cervero and Kang (2011) highlights that land prices for non-residential uses within 150 meters of BRT stops were 2.5 times higher than residential values within 300 meters of BRT stops, with these premiums particularly pronounced in central business districts (CBDs). Jun (2012) similarly observed that land price premiums tended to be more significant near BRT lines within urban cores than in outer zones.

The value impact of BRT on properties is often spatially sensitive, particularly within walking distance from BRT lines. Rodriguez and Mojica (2009) found that properties within a 0.5-mile walking distance of BRT stations experienced notable increases in value, with the most significant impacts observed within a 0.25-mile band. Nelson et al. (2013) also identified this concentrated influence, noting that closer proximity to BRT stations correlated with higher property value premiums. Studies by Wang et al. (2015) and Perk et al. (2017) further support that properties near BRT stops tend to appreciate due to increased accessibility, a phenomenon seen across various public transit systems (Xu et al., 2016; Cohen & Brown, 2017; Yu et al., 2018; Seo et al., 2019).

Despite the strong association between property value and distance to BRT systems, some researchers argue that dedicated BRT lines—a key characteristic distinguishing BRT from other transit modes—are underexplored in current literature. Understanding the unique impact of dedicated lines could enable more effective, sustainable urban planning around BRT corridors. Moreover, while property value changes are well-documented, limited research focuses on how these shifts influence business attraction and clustering near BRT lines, which may offer further insights into urban economic dynamics around transit systems.

3. Methods

3.1 Study areas

The study area for this analysis is focused on four states in the Intermountain region of the United States that have implemented Bus Rapid Transit (BRT) systems: Arizona, Colorado, Nevada, and Utah. In total, this region has 11 BRT systems, which vary in scope, ridership, and service design. These states have actively adopted BRT systems as part of public transportation strategies, making them key examples for understanding the policy and planning decisions driving BRT adoption in mid-sized to large cities in the U.S. However, at the same time, by focusing on a geographically cohesive region with multiple systems, the study allows for meaningful comparisons while controlling for macro-level regional factors, such as climate, culture, lifestyle, and land use patterns.

Arizona has the most BRT systems among these states, operating six: SR-51 Rapid, I-17 Rapid, South Mountain West Rapid, South Mountain East Rapid, I-10 West Rapid, and I-10 East Rapid. Each of these routes is designed to address high commuter demand by providing efficient transit options along major corridors and highways.

Colorado is represented by the Fort Collins MAX BRT, which serves as the main BRT system in the region. The Fort Collins MAX BRT focuses on providing high-frequency service through the central corridor of Fort Collins, promoting connectivity and access to key locations within the city.

Nevada operates two BRT lines in Las Vegas: the Metropolitan Area Express (MAX) and the Strip & Downtown Express (SDX). The MAX serves major residential and commercial areas, while the SDX connects the high-traffic tourist areas along the Las Vegas Strip to the downtown core.

Utah has two BRT systems: the 3500 South MAX and the Utah Valley Express. However, for this study, we exclude the Utah Valley Express, as it was recently constructed and has limited available data for analysis. The 3500 South MAX line, which serves the western part of Salt Lake County, will be the focus within Utah, providing insight into the BRT impact in this metropolitan area.

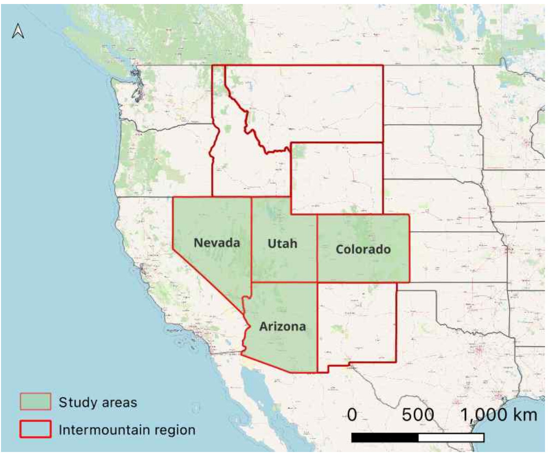

Figure 1. Study areas
(Nevada, Utah, Colorado, and Ar izona States)

This geographic selection provides a diverse sample of BRT services across varying urban environments and transit needs, facilitating analysis of BRT’s impact on land use and property values in different regional contexts.

3.2 Data and Variables

For this study, two primary data criteria were used: business data and regional characteristics. These criteria are necessary to evaluate the relationship between Bus Rapid Transit (BRT) systems and business activity across diverse urban settings in the Intermountain region of the

United States.

Regional Characteristics

To capture differences in urban form across regions, this study uses the Sprawl Index developed by Ewing and Hamidi (2014), a measure that quantifies the compactness of metropolitan areas. Higher values of the Sprawl Index indicate more compact, densely developed urban areas, whereas lower values suggest more sprawling, less dense development. This index allows for comparison of urban form and its potential impact on the effectiveness of BRT systems.

The study focuses on four Metropolitan Statistical Areas (MSAs) in the Intermountain region, each of which has operational BRT systems and varying degrees of urban compactness, as indicated by the Sprawl Index. The selected MSAs and their respective index values are as follows:

- Phoenix-Mesa-Glendale, AZ (Sprawl Index: 78.3)
- Salt Lake City, UT (Sprawl Index: 106.96)
- Las Vegas-Paradise, NV (Sprawl Index: 121.2)
- Fort Collins-Loveland, CO (Sprawl Index: 115.15)

These MSAs were chosen because they each have operational BRT systems with varying urban forms, allowing for a comparative analysis of BRT impact in different urban contexts.

Business Data

Business data were obtained from the Million Dollar Database, which provides detailed information on active and inactive businesses, including data on total sales and business duration. For this study, only active businesses were included to ensure relevance to current economic activity and interactions with BRT systems.

The business data spans a five-year period from 2013 to 2017, but analysis is focused on the most recent data from 2017 to reflect current conditions and business performance trends. This dataset includes the following variables (Table 1).

The dependent variable is the natural logarithm of total sales in 2017. This transformation allows for a normalized analysis of business revenue across different industries and business sizes.

Proximity to BRT Lines: Businesses are classified based on their distance to Bus Rapid Transit (BRT) stations, using two defined buffers: within 0–799 meters and within 800–1600 meters. This categorization facilitates an examination of the impact of BRT accessibility on business performance.

Distance to Central Business District (CBD): This variable measures each business' s proximity to the nearest CBD centroid, enabling analysis of how centrality influences business outcomes relative to BRT station access.

NAICS Code: Each business is identified according to the North American Industry Classification System (NAICS) as either service-oriented or non-service. This classification provides insights into the varying responses of different business sectors to BRT proximity.

Table 1.Variables

Variables		Description	Mean	S.D.
Dependent Variable	ln(Sales)	Natural Log of Sales	9.58	4.56
Regional Characteristics (Level2)	Compactness index		105.41	18.98
Business Characteristics (Level1)	Dist 0~799m	the number of active business fall within each buffer area	0.33	0.47
	Dist 800~1600m			
	Dist_CBD	distance from business to the nearest CBD Block Group Centroid	0.39	0.49
	Established After 2008's Recession	Businesses started after economic recession in 2008	9,200.75	6,653.34
	Business Duration	operating years	0.54	0.50
	NAICS sector	service:1, others: 0		

Post-2008 Establishment: This binary variable indicates whether a business was established post-2008 economic recession, offering a basis to compare the performance of newer establishments with those founded earlier. This distinction may reveal insights into economic resilience and adaptability.

Business Duration: Calculated as the difference between 2017 and the establishment year, this variable reflects business age. It serves as a control for assessing the influence of business maturity on sales performance.

By integrating both regional and business-level variables, this study seeks to understand the impacts of BRT systems on business sales. The use of the Sprawl Index allows for an examination of how different levels of urban compactness might influence BRT effectiveness, while the business data provides insights into how proximity to BRT systems impacts sales, depending on factors such as business type, duration, and centrality within the urban fabric.

Table 2 below summarizes the distribution of businesses in proximity to BRT stations across the four regions analyzed — Arizona, Colorado, Nevada, and Utah.

Using ArcGIS, 1,575,462 businesses were identified across these regions, and proximity analyses were performed to determine the distribution of businesses within 800 meters, 800–1600 meters, and beyond 1600 meters of BRT stations.

Table 2.Number of businesses

State	Total	Out of buffer	800~1600m	0~800m
Arizona	691,391	672,195	10,037	9,159
Colorado	62,575	49,527	4,835	8,213
Nevada	345,073	288,885	33,575	22,613
Utah	476,423	470,101	3,202	3,120

Colorado has the smallest absolute number of businesses (62,575), but it has the largest percentage of businesses within walking distance (0–800 meters) of BRT stations, with 13.2% (8,213 businesses) located within this range. Additionally, 7.72% (4,835 businesses) fall within the 800–1600 meter buffer, indicating a higher concentration of businesses around BRT stations compared to other states.

Arizona and Nevada show an opposite pattern to Colorado. In Arizona, 97.2% of businesses (672,195 out of 691,391) are located beyond 1600 meters from BRT stations, with only 1.32% within the 0–800 meter buffer. Nevada also has a high percentage of businesses (83.7%) located outside the BRT influence buffer, with only 6.5% within the 0–800 meter range.

Utah has a similar pattern to Arizona, with 98.2% of its businesses (470,101 out of 476,423) located beyond the 1600 meter buffer. Only 0.65% (3,120 businesses) are within 0–800 meters, indicating minimal business concentration around BRT lines.

3.3 Methods

This study examines the impact of Bus Rapid Transit (BRT) systems on business sales across four regions (Arizona, Colorado, Nevada, and Utah) in the Intermountain region of United States.

To address regional variations in the impact of BRT proximity on business sales, we use multilevel modeling, also known as hierarchical linear modeling (HLM). This approach is suitable for

Table 3.Multilevel Regression Model Results

Variables		Random effect model (level 1)		Random effect model (level 1 + level 2)	
		coefficient	standard error	coefficient	standard error
Business Characteristics (Level1)	Dist 0~799m	0.188	0.033***	0.188	0.033***
	Dist 800~1600m	0.328	0.030***	0.328	0.030***
	Dist_CBD	0.001	0.000	0.001	0.001
	Established After 2008's Recession	−1.327	0.027***	−1.327	0.027***
	Business Duration	−0.002	0.001***	−0.002	0.001***
	NAICS sector	−1.084	0.042***	−1.084	0.042***
Regional Characteristics (Level2)	Compactness index			−0.011	0.005

Note: ***significance p 〈0.01

data that is nested, as it can separate effects at the business level from effects at the regional level (Yang et al., 2023). In this study, businesses are nested within regions, and each region has unique characteristics that may influence business performance. Multilevel modeling enables us to distinguish between business level (level 1) and regional level effects (level 2).

Level 1 effects (Business-Level) include individual business characteristics, such as proximity to BRT stations, NAICS industry classification, duration since establishment, and total sales. In addition, level 2 effects (Regional-Level) includes regional attributes, including the Sprawl Index.

By specifying both levels in our model, we can control for shared regional characteristics while analyzing how proximity to BRT impacts sales at the business level. This approach also addresses issues of external validity by testing the model across four distinct regions, allowing us to generalize findings across different urban settings within the Intermountain West.

4. Results

In this study, we analyze the factors influencing business sales using a dataset of 130,848 samples, excluding any missing values. The dependent variable, Ln_Sales, represents the natural log of business sales. This transformation was applied due to the high skewness observed in the raw sales data, ensuring a more normal distribution and better model performance. The independent variables include both regional and business attributes, which we discuss in detail below.

In the initial phase of the analysis, we begin by fitting the Null Model (Unconditional Model), which is an intercept-only model with no independent variables. This model helps us understand the variance in the dependent variable, Ln_Sales, and provides insights into the Intraclass Correlation (ICC), which represents the proportion of variance explained by group-level factors (Level 2). The dependent variable, Ln_Sales, is the natural logarithm of business sales, which was log-transformed to address skewness in the raw data.

The Null Model estimates the Level-1 variance (residual variance within business units) as 20.76699, while the Level-2 variance (variance attributed to the regional differences) is estimated at 0.03255. The Tau value of 0.03255 represents the regional-level variance-covariance of residuals, and the correlation between these residuals is 1.000, suggesting that regional variance is perfectly correlated across the units within each region.

The model also provides the Intraclass Correlation (ICC), which is calculated as the ratio of Level-2 variance to the total variance (Level-1 + Level-2 variance). In this case, the ICC is 0.16%, indicating that only a small proportion (16%) of the variance in business sales is attributable to regional differences, with the remaining variance primarily driven by within-business (Level-1) factors.

To estimate fixed effects, we apply Maximum Likelihood (ML) estimation, which is generally more reliable when the number of Level-2 samples is large. However, given that there are only four regions (Level-2 units) in this study, we use Robust Standard Errors to account for the small sample size.

Next, we extend the Null Model by adding Level-1 variables (business level attributes) to examine whether this forms a Random Intercept Model. This step helps determine whether including individual-level variables reduces the within-group variance and increases the explanatory power of the model. After adding the Level-1 variables, we observe a reduction in Level-1 variance from 20.77 to 17.86, indicating that the inclusion of these variables accounts for some of the within-business variability. All Level-1 variables, except for Dist_CBD (distance to the CBD), show highly significant results at the 95% confidence level, indicating that these variables play a substantial role in explaining the variation in business sales. The variables Dist 0~799m, Dist 800~1600m, Founding Year After Recession, Business Duration, and NAICS Sector are all significant predictors of business sales.

For the final step, we introduce both Level-2 variables (regional attributes) and Level-1 variables (station and business characteristics) into a Multilevel Model (MLM). This model allows us to explore the combined effects of regional and individual business characteristics on sales. Importantly, the addition of regional-level variables leads to a 57.4% reduction in Level-2 variance, from 0.065 to 0.027, suggesting that the inclusion of both regional and individual-level factors explains a significant portion of the variance in business sales.

The results from the MLM show that proximity to BRT stations (both Dist 0~799m and Dist 800~1600m) is positively associated with business sales, with coefficients of 0.188 and 0.328, respectively. This indicates that businesses located closer to BRTstations tend to have higher sales. However, Dist_CBD (distance to the CBD) shows a positive but not significant relationship with sales, suggesting that being closer to the CBD may not have a strong impact on sales in this context.

The model also reveals that businesses founded after the 2008 recession experience a significant decline in sales, as indicated by the negative coefficient of -1.327. Similarly, longer business duration is associated with a slight decline in sales, with a coefficient of -0.002. This suggests that older businesses may face challenges in adapting to changing market conditions. Lastly, businesses in the service sector tend to have lower sales compared to other types of businesses, with a significant negative coefficient of -1.084.

5. Discussion and Conclusion

The findings from this study highlights several key factors influencing business sales, with a particular emphasis on the effects of proximity to public transportation infrastructure, the economic context post-2008 recession, business characteristics, and regional differences. By using multilevel modeling, we were able to assess both individual and regional-level variables, providing a nuanced understanding of how these factors interact and contribute to variations in business activities. There are several critical points to discuss.

First, the most consistent and significant finding across all models is the positive relationship between proximity to Bus Rapid Transit (BRT) stations and business sales. Businesses located within 799 meters and between 800 and 1600 meters of a BRT station saw significant increases in sales compared to those located farther away. This supports the growing body of literature suggesting that public transportation accessibility is a crucial determinant of local business success, particularly in urban areas (Kim et al., 2021).

The findings align with previous studies that have shown that transportation infrastructure, especially BRT systems, provides easy access for customers and employees, increasing foot traffic and overall sales for businesses located nearby (Cervero, 2007). Proximity to BRT stations offers convenience for consumers, potentially lowering transportation costs and increasing access to goods and services. Thus, the positive relationship found in this study highlights the importance of considering transportation systems when planning urban development and business location strategies.

Secondly, the negative relationship between business duration and sales further supports the idea that older businesses may face difficulties in maintaining strong growth, which could be attributed to market saturation or challenges in adapting to new business models. Established businesses may struggle to innovate or keep pace with changing consumer preferences, which can lead to stagnant or declining sales over time. These findings are consistent with research showing that business longevity does not always translate to ongoing success, as market conditions, consumer demands, and competition evolve (Davidsson et al., 2003).

Moreover, the study found that businesses in the service sector tend to have lower sales than those in other industries. This could be due to the more volatile nature of service-oriented industries, which are often more sensitive to changes in consumer demand, economic cycles, and ridership levels. Service industries, such as hospitality, food services, and personal services, may be more vulnerable to economic fluctuations, including recessions, changes in commuting patterns, and shifts in consumer behavior. This finding emphasizes the need for businesses in the service sector to adapt more rapidly to changing market conditions, particularly in light of external factors like transportation and macroeconomic shifts.

The findings of this study have several policy implications, particularly for urban planning and transportation development. Policymakers should consider the significant role that public transportation systems, such as BRT, play in promoting local business success. By ensuring that businesses are well-served by public transit, cities can help foster economic growth and enhance the viability of businesses in underserved areas. Investing in transportation infrastructure, particularly in the proximity of key business districts, may stimulate economic activity and improve business outcomes, especially for small businesses and those in the service sector.

6. Limitations

Despite the meaninful findings from the study, several limitations should be acknowledged. First, the analysis relies on data primarily from the intermountain region of the western United States, which may limit the generalizability of findings to other regions. Second, the study primarily utilizes quantitative data. Although this approach offers robust statistical insights, incorporating qualitative data—such as surveys or interviews with BRT users and local business owners—could provide a richer understanding of user experiences and the broader socio-economic impacts of BRT implementation.Third, the study focuses on the service sector's sales performance, limiting its scope regarding sectional variations and externalities. Future research could delve deeper into these variations and address potential externalities, such as congestion or gentrification, to provide a more comprehensive evaluation of BRT impacts. Therefore, future studies could address these gaps to produce more generalizable and nuanced insights into the effects of BRT systems across diverse urban environments.

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SARS-CoV-2 검출을 위한 하수기반역학 분야 최신 동향 연구

조영래* · 이도균**

Wastewater-Based Epidemiology in SARS-CoV-2 Surveillance: Current Methods and Future Directions

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Abstract : The COVID-19 pandemic highlights the significance of wastewater-based epidemiology (WBE) as a public health surveillance tool. WBE facilitates the non-invasive detection of SARS-CoV-2 RNA in wastewater, offering early indications of community outbreaks. This method integrates viral concentration, RNA extraction, and advanced analytical techniques such as ultrafiltration, PEG precipitation, and digital PCR (dPCR). Normalization using fecal markers like Pepper Mild Mottle Virus (PMMoV) addresses variability in human waste contributions, enhancing data reliability. While WBE provides a cost-effective and broad population-level surveillance method, challenges remain in standardizing protocols and adapting to diverse wastewater characteristics. This review underscores WBE's role in pandemic preparedness, its application to emerging infectious diseases, and future research directions to improve sensitivity, develop robust normalization techniques, and establish scalable methods for global public health. WBE serves as a critical framework for rapid response to infectious disease outbreaks.

키 워 드 : SARS-CoV-2, 하수기반역학, COVID-19, 팬데믹, 검출

Key words : SARS-CoV-2, Wastewater-based epidemiology, Coronavirus disease-19, Pandemic, Detection

1. 서 론

코로나바이러스는 호흡기 감염증을 발생시키는 호흡기 바이러스 (respiratory virus) 중 하나로, 지속적인 변이 바이러스의 출현이 보고되고 있는 바이러스 종 중 하나이다. 2002 - 2003년 중증급성호흡기증후군 (Severe acute respiratory syndrome, SARS)를 시작으로 2012년 중동호흡기증후군 (Middle east respiratory syndrome, MERS), 2019년 12월 경 중국 우한시에서 발생한 것으로 추정되는 신종 호흡기 감염병인 COVID-19까지 사회적·경제적으로 큰 영향을 발생시켰다. COVID-19는 코로나바이러스의 변이형인 제2형 중증급성호흡기증후군 코로나바이러스 (Severe acute respiratory syndrome coronavirus 2, SARS-CoV-2)의 감염에 의해 발생하는 질병이다. SARS-CoV-2 바이러스는 외피 (Envelop)을 보유한 단일 가닥의 RNA로 구성되어 있으며, 기존 바이러스에 비해 상대적으로 감염성과 무증상 잠복 감염자의 높은 비율로 국내를 비롯한 세계로 감염이 확산되었다 (Westhaus et al., 2021; Monteiro et al., 2022; Oran et al., 2020). 국내에서는 감염자는 2020년 1월 첫 감염사례가 보고되었으며, 지속적인 확산 추세 및 영향에 따라 세계보건기구 (WHO)에서는 2020년 3월, COVID-19를 팬데믹 질병 (Pandemic disease)로 선언하였다.

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대한민국의 경우 2020년 2월 1차 대유행을 시작으로 2022년 7월까지 총 6차례의 대규모 유행기를 거쳤으며, 4차 대유행부터는 SARS-CoV-2의 변이형인 델타 및 오미크론 변이 기반 바이러스가 유행을 주도하였다.

COVID-19 감염으로 인한 유증상자 및 검사를 통한 확진자가 급속히 증가함에 따라, 감염 예방 및 확산 방지, 신속하고 정확한 정보 제공을 목적으로 국내에서는 전수감시체계 (Mandatory surveillance systems)가 도입되었다. 전수감시체계의 경우 감염병 병원체 확인기관의 의무 신고를 기반으로 실제 환자 데이터를 수집할 수 있다는 장점이 있으나, 환자 신고에 의존하기 때문에 실제 감염자 수와는 차이가 발생할 가능성이 있다 (Jang et al., 2023; Gonzalez et al., 2020). 또한, 신고 기반 시스템의 경우 국가 또는 지역사회 내 COVID-19의 확산을 시공간적으로 분석하는 데에는 어려움이 있으며, 많은 인력과 시간이 소요된다는 단점이 있다(Islam et al., 2023). 이러한 한계를 극복하기 위하여 네덜란드, 독일, 호주, 미국 등 다양한 국가에서 하수기반감시(Wastewater-based surveillance, WBS)를 감염병 감시에 적용하기 시작하였으며, WHO에서도 2022년 4월 이를 새로운 감시 기술로 인정하고, 하수기반 COVID-19 감시 지침을 발표하였다 (WHO, 2022). 실제로 COVID-19 확산에 따라 SARS-CoV-2 RNA의 하수 내 검출이 보고되고 있었으며, 특히 하수 내 인간 분비물 중 대변에서의 SARS-CoV-2 RNA 검출이 대부분을 차지하고 있다. 이러한 SARS-CoV-2의 하수 기반 감시는 COVID-19의 증상 발현과 상관없이 잠복기부터 유증상자, 무증상자 단계의 환자까지 광범위한 분석이 가능하여 특정 지역의 인구 내 감염자 비율 추정과 사생활 침해 없이 감염병 확산 및 조기 예측이 가능한 장점이 있다(Medema et al., 2020; Hemalatha et al., 2021). 이후, 하수기반 감시체계를 활용하기 위하여 하수 내에서 SARS-CoV-2 바이러스를 검출하기 위한 다양한 연구들이 수행되었으나, 지역 하수 성상 및 RNA 추출 및 농축 방법, 사용되는 프라이머/프로브에 따라 결과는 상이한 것으로 알려져 있다.

따라서, 본 연구에서는 최근 감염병 감시 분야에서 주목되고 있는 하수기반역학 및 SARS-CoV-2 검출을 위한 하수기반역학 연구의 최신 동향에 대한 정보를 제공하고, 이후 연구 방향에 대해 고찰하고자 한다.

2. SARS-CoV-2 대상 하수기반역학 연구 동향

2.1 역학의 배경

역학(Epidemiology)은 인구집단 내에서 질병의 분포 양상을 분석하고, 원인 규명 및 통제와 관련한 연구를 수행하는 학문이다. 역학의 기원은 1854년 Snow의 콜레라 원인과 전파 양상을 감염지도 작성을 통해 규명한 연구 (Snow, 1856)로 이후 전염병 연구의 기본으로 설정되었다. 이후, 통계학 및 데이터 분석 기법이 도입되면서, 도입 범위가 확장되었으며, 현재는 감염병 대유행 조사, 지역 내 만성 질환 연구, 임상 연구를 비롯하여 보건 및 건강정책 개발, 인구 건강 관리 등 다양한 질병과 건강 문제를 다루고 해결하는 연구에서 활용되고 있다.

Satman, et al. (2002)는 터키 전역에서 당뇨병 유병률(Prevalence rate)을 조사하여 지역 간 차이 및 인구 특성, 생활 방식 등과의 잠재적 관계를 연구하였다. 국내에서도 당뇨병 유병률의 통계 기반 역학 분석을 수행하고 있으며, 19세 이상 성인 기준 당뇨병의 유병률이 지속적으로 증가할 것으로 추정하였다 (Yang et al., 2021). 이와 같은 만성 질환뿐만 아니라 신종 감염병인 SARS를 시작으로 조류인플루엔자(Avian influenza), MERS, COVID-19까지 지속적으로 전세계적인 감염병 위험이 증가하고 있으므로, 유행 가능성을 조기에 예측하고, 감염 위험 요인 파악 및 규명을 통한 방지를 위한 역학 조사의 중요성이 대두되고 있으며, 역학의 중요성 역시 강조되고 있는 추세이다.

2.2 하수기반역학의 배경

하수기반역학(Wastewater-based epidemiology, WBE)은 하수처리장의 유입수에서 수집된 인간 대사산물 (Metabolites) 및 화학 물질 표지자를 분석하여 해당 하수 집수구역 거주자의 생활 패턴과 건강 상태를 예측하는 방법이다 (그림 1).

초기에는 WBE가 지역사회 내에서 코카인(Cocaine), 헤로인 (Heroin) , 케타민 (Ketamine) , 대마초 (Cannabis)와 같은 불법 마약류 및 카페인과 담배, 알코올과 같은 합법 마약류의 사용 패턴을 분석하는 데 활용되어 지역 주민의 건강 상태와 범죄 조직의 활동을 모니터링하는 수단으로서 시작되었다(Zuccato et al., 2005; Been et al., 2015; Castiglioni et al., 2015; Löve et al., 2022). 이후 WBE는 마약류 외에도 하수에서 인구 건강

상태를 반영하는 다양한 생물학적•화학적 지표를 분석하며 시공간적 모니터링이 가능하고 기존의 역학조사 방식에 비해 효율적이며, 개인정보 침해 우려가 없다는 장점 덕분에 다양한 분야로 활용 범위를 넓혔으며, 최근에는 WBE가 의약품 및 개인위생용품(pharmaceuticals and personal care products, PPCPs), 산업용 화학물질, 스트레스 및 식품 소비를 나타내는 생화학적 마커, 병원체, 항생제 내성(antimicrobial resistance) 마커까지 검출할 수 있게 되면서, 인구 건강의 여러 측면을 평가하고 이를 기반으로 다양한 정보를 제공하는 중요한 위치를 차지하게 되었다 (Choi et al., 2018).

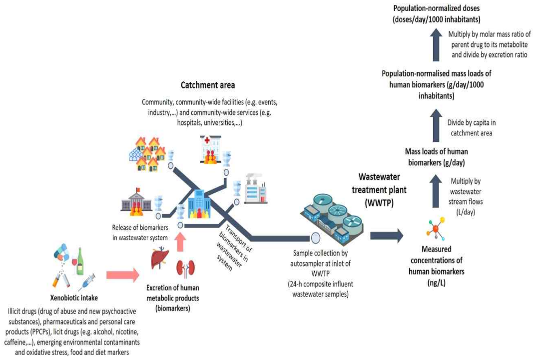

그림 1. WBE의 분석 구조 개요
(Boogaerts et al., 2021)

특히 국내・외에서는 하수 내에서 검출되는 주요 바이러스로 알려져 있는 노로바이러스(Norovirus), 아데노바이러스(Adenovirus), 로타바이러스(Rotavirus), 인플루엔자 A(H1N1)과 같은 장내 바이러스의 감시를 통해 유행 가능성을 조기에 예측하는 수탁으로서 WBE가 주목을 받았으며, 전세계적 유행을 보인 COVID-19 이후 중요성이 더욱 강조되고 있다 (Wani et al., 2023). 현재 여러 국가 및 지역에서 자체적으로 COVID-19 및 타 감염병의 대응을 위하여 WBE를 도입하였으며, 국내에서도 2023년 4월을 시작으로 질병관리청 주도 하수기반 감염병 감시 사업을 수행하여, 현재 일상기반 전수감시를 보완하는 수단으로서 활용하고 있다. COVID-19와 같은 신종 감염병의 하수기반 모니터링 체계의 신속한 구축을 위해서는 감염병의 유행 정도, 바이러스의 구조, 하수의 물리・화학적 특성에 따른 검출 방법의 개발 등 다양한 연구들이 지속적으로 수행되어야 한다.

2.3 SARS-CoV-2 검출을 위한 하수기반역학 연구

하수 내 SARS-CoV-2 검출은 2020년 초기 네덜란드와 호주에서 처음으로 수행 및 보고되었으며, 하수 내 SARS-CoV-2 RNA 농도와 COVID-19 확진자 사이에 유의미한 상관관계를 도출하였다 (Medema et al., 2020; Ahmed et al., 2020). 이후 미국, 스페인, 프랑스, 일본, 인도, 독일, 이탈리아를 비롯하여 전세계적으로 하수 내에서 SARS-CoV-2 검출이 확인되며, COVID-19 감시를 위한 WBE 감시체계 마련 연구가 집중적으로 수행되었다.

Ahmed et al. (2020)은 하수 대상 SARS-CoV-2 검출을 위해 유사한 계열의 바이러스인 MHV (Murine Hepatitis Virus)를 활용한 최적 농축 방안을 고안하였으며, 그 결과 음전하 막 여과법이 65.7%의 회수율을 보여 농축 방안으로서 권장되었다. 추가로 한외여과법(Medema et al., 2020), PEG (Polyethyleneglycol) 침전법 (Wu et al., 2020), 원심분리법 (Wurtzer et al., 2020) 등을 활용한 하수 내 SARS-CoV-2 RNA 검출 연구와 농축 방법에 따른 검출 민감도, 처리 소모 시간, 비용 등을 비교 분석한 연구가 수행되었다. Barril et al. (2021)은 Aluminum polychloride를 활용한 응집법과 PEG 침전법 간의 SARS-CoV-2 검출량 분석 결과 응집법인 15.6% 가량 높은 검출량을 보였으며, Zheng et al. (2022)의 연구에서는 총 8가지의 농축 방법을 비교 분석하였을 때, 원심분리법이 25%로 가장 높은 회수율을 나타냈다고 보고하였다. 상기 연구 결과를 참고하였을 때, 다양한 유기물과 무기물이 혼합되어 있어 복잡한 성상을 보유한 하수의 특성상 각 환경에 따른 최적 농축 방안에는 차이가 있음을 확인하였으며, 기존에 제시된 바이러스 농축 방안의 경우에는 비용과 시간이 다량 소모되는 경우가 많아 비교적 저렴하고 신속한 새로운 SARS-CoV-2 대상 바이러스 농축 방안에 대한 연구가 필요한 실정이다.

또한, 적합한 프라이머/프로브 설정에 대한 연구도 지속적으로 수행되었다. 일반적으로 SARS-CoV-2 RNA 검출에는 Nucleocapsid 유전자를 대상으로 증폭하는 N1, N2, N3 프라이머/프로브와 외피 유전자를 대상으로 하는 E, 복제와 관련 있는 RdRp 유전자를 대상으로 하는 RdRp gene 등 다양한 프라이머가 사용되나 (Lu et al., 2020) (그림 2) 어떤 프라이머가 SARS-CoV-2 검출에 효과적인지에 대해서는 연구마다 상이한 결과가 도출되었다.

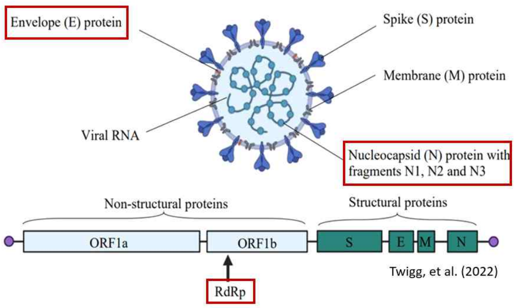

그림 2. SARS-CoV-2 프라이머/프로브의 증폭 대상 영역 (Twigg et al., 2022)

마지막 단계인 SARS-CoV-2 RNA의 정량 분석 시에는 주로 qPCR(Quantitative PCR) 장비가 사용되고 있으나, 상대적으로 민감도가 낮고, 방해물에 대한 PCR 반응 효율 감소, 검량선 작성을 통한 농도 정량법 등의 단점 때문에 최근에는 검출 민감도를 향상하고 PCR 반응 효율이 높은 ddPCR (Droplet digital PCR), Plate-based dPCR 등 최종 정량 분석에서도 다양한 기기들이 활용되고 있는 추세이다 (그림 3).

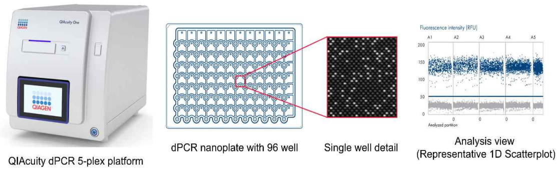

그림 3. Plate-based digital PCR의 정량 원리

2.4 분변 지표를 활용한 SARS-CoV-2 농도의 정규화 연구

SARS-CoV-2 바이러스의 경우, 장내에서도 분해되지 않고 지속되는 특성이 있어 인간의 대변 및 소변을 통해 배출되어 하수로 유입된다. COVID-19 증상의 발현 후 3-4주간 대변에서 SARS-CoV-2가 검출될 가능성이 높으며, 이는 감염자뿐만 아니라 무증상자까지 포함한다. 그러므로 하수 내 인간 대변의 양으로 인해 SARS-CoV-2의 검출량 변동 가능성이 높은 것으로 알려져 있으며 (Crank et al., 2022), 이에 따라 특정 지역 내 이동을 통한 생활 인구 및 유동 인구 변화에 따른 하수 내 분변 배출량을 하수기반 모니터링에 반영하기 위하여 CDC와 유럽위원회 등 국제기구에서는 하수 내 인간 대변의 양을 추정할 수 있는 분변 지표(Fecal indicator)를 활용하여 검출된 SARS-CoV-2 농도를 정규화(Normalization)하는 과정을 권고하였다.

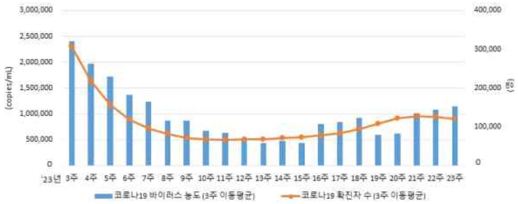

그림 4. SARS-CoV-2 하수기반 역학 분석 예시 (질병관리청, 2023)

하수기반역학 연구 분야에서 일반적으로 활용되는 분변지표로는 고추약한모틀바이러스(Pepper mild mottle virus, PMMoV)와 분변 대장균군(Fecal coliform bacteria) 등이 있으며, 이 중 PMMoV가 국제 기구에서 분변 지표로서 활용하도록 권장되고 있다 (Zhan et al., 2022). PMMoV는 고추, 피망, 파프리카를 비롯한 가지과 작물에서 주로 발생하는 식물 병원성 바이러스로, 계절적 변화에 영향이 거의 없고, 하수를 비롯하여 다양한 환경 조건에서 안정적으로 검출되는 특성이 있다. 또한, 고추나 피망, 파프리카와 같은 일상에서 빈번하게 섭취하는 식물을 숙주로써 활용하기 때문에 하수 내 인간 분변에서 매우 풍부한 농도로 쉽게 검출되는 바이러스군으로 알려져 있다 (Rosario et al., 2009). PMMoV 이외에도 SARS-CoV-2 농도의 정규화를 위하여 Bacteroides HF183, 16S rRNA(ribosomal RNA), 18S rRNA, Beta-2-Microglobulin, 분변대장균군, 크로스-어셈블리 파지 (CrAssphage) 등이 정규화 지표로서 활용 가능성이 있는지 평가되었으며, 화학적 인구 표지자인 크레아틴 (Creatine), 카페인 (Caffeine), 파라잔틴 (Paraxanthine) 등을 적용한 연구가 수행되고 있으나 (Hsu et al., 2022), 지역 내 COVID-19 모니터링을 위한 최적 분변 지표는 특이적인 하수 시스템에 따라 변동 가능성이 크므로 (Mitranescu et al., 2022), 연구를 통한 최적 지표의 설정이 필수적이며, 다양한 하수에 적용될 수 있는 정규화 지표를 발견하기 위한 분변 지표

연구가 지속적으로 이루어져야 할 필요성이 있다.

3. 결과 및 시사점

전 세계적으로 COVID-19 팬데믹에 대응하기 위해 하수기반 COVID-19 모니터링이 새로운 감염병 감시체계로 도입되었으며, 관련 연구가 지속적으로 증가하고 있다. 하수에서 SARS-CoV-2 RNA를 검출하는 과정은 하수의 성상, 특성, 바이러스 농도 등 다양한 환경적 요인의 영향을 받으므로, 각 지역의 하수 특성에 적합한 검출 방법에 대한 연구가 필요하다. 특히, 장기적인 COVID-19 모니터링에서 중요한 단계는 SARS-CoV-2 RNA 농도를 정규화하는 과정으로, 현재 대표적인 분변 지표인 PMMoV를 활용한 정규화 연구가 활발히 진행되고 있다. 그러나 PMMoV 기반 정규화는 qPCR을 이용한 정량화가 필수로, 시간이 오래 걸리고 비용이 많이 드는 한계가 있다. 이에 따라, 정량 분석이 qPCR보다 민감도가 높은 dPCR의 활용과 분석이 간단한 새로운 분변 지표를 개발하고 선정할 필요성이 제기되고 있다. 또한, 다양한 검출 방안의 연구 대상 하수처리장 확대, 계절 변화, COVID-19의 유행 수준을 반영한 정기적 시료 채취 등의 일반화 과정을 통해 지속적인 보완이 필요하다. 또한, 정규화를 수행한 SARS-CoV-2 농도와 COVID-19 감염자가 적은 상태에서의 장기간 분석을 통한 모니터링 연구 또한 병행되어야 할 것이다. 이처럼 하수기반역학의 경우 COVID-19뿐만 아니라 추후 국가 및 지역사회 내에서 새롭게 발생할 수 있는 감염병에 대한 신속한 대응체계 마련에 기여할 수 있을 것으로 생각된다 (그림 5).

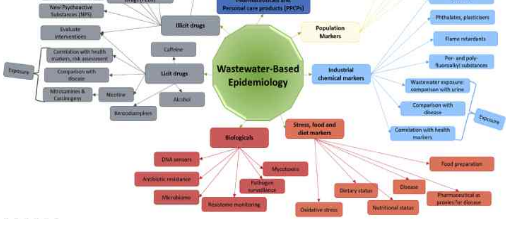

그림 5. WBE의 최근 및 추후 연구 방향 관련 마인드맵 (Choi et al., 2018)

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부 록

「도시과학」논문편집규정
「도시과학」편집위원회

「도시과학」 논문편집규정 (2017. 6. 30. 개정)

1. 기고하는 원고는 도시과학에 관한 학술논문을 포괄적으로 포함하며, 다른 학술지에 게재를 위하여 심사를 의뢰한 논문이나 혹은 다른 학술지에 게재한 논문과 중복된 논문은 기고할 수 없다.

2. 논집에 기고하였다가 '게재불가' 판정을 받은 원고는 판정일로부터 3개월 이내에 재기고할 수 없다. 제약기간이 지난 뒤에는 논문의 주제와 내용을 대폭 수정하고 처음 기고한 일자를 표시하고 '재기고'임을 명기하여 다시 기고할 수 있다. 원고는 수시로 접수한다.

3. 기고 원고는 한글프로그램을 사용하며 제목, 저자, 초록, 본문, 참고문헌, 부록의 순으로 구성한다. 원고는 한글 사용을 원칙으로 하되 뜻을 명확하게 하기 위해 한자를 쓰는 경우에는 한글 뒤에 괄호를 하고 한자를 쓴다. 다만, 외국의 연구자의 경우 이름은 원어로 쓴다. 초록은 20행 이내로 작성한다.

4. 기고 원고는 A4용지에 단면으로 출력하며 원고의 전체분량은 200자 원고지 125매(25,000자)를 원칙으로 하되, 이를 초과할 경우에는 초과 200자 원고지 5매 (1,000자)당 1만 5천원의 인쇄비를 징수한다(한글프로그램에서: 파일-문서정보-문서분량-원고지로 체크). 단, 전체 원고분량은 200자 원고지 175매를 초과할 수 없다. 분량이 초과된 원고는 투고할 수 없다.

5. 심사용 원고의 본문, 각주와 참고문헌에 필자의 이름 등 필자가 누구인지 확인할 수 있는 글은 공란 없이 삭제한다. 보관용 원고(1부)의 표지에는 논문제목(국, 영문), 성명(국, 영문), 소속기관 및 직위, 연락주소, 전화(직장, 자택), 팩스번호, e-mail 주소를 기재한다.

6. 원고작성을 위한 편집용지, 문단모양, 글자모양은 다음과 같다.

● 편집용지 및 글자모양

용지종류		용지여백	
종류	사용자 정의	위쪽	22
폭	190	아래쪽	5
길이	260	왼쪽	20
용지방향	좁게	오른쪽	20
제책	한쪽	머리말	13
본문 다단형식	다단	꼬리말	10
적용범위	전체	제본	0

<table>
<tr><th colspan="3">본문(각주)문단모양</th><th colspan="2">글자모양</th></tr>
<tr><td rowspan="2">여백</td><td>왼쪽</td><td>0pt</td><td>글꼴</td><td>휴먼명조</td></tr>
<tr><td>오른쪽</td><td>0pt</td><td>크기</td><td>9pt</td></tr>
<tr><td rowspan="3">간격</td><td>줄간격</td><td>130%</td><td>장평</td><td>100%</td></tr>
<tr><td>문단위</td><td>0pt (2)</td><td>자간</td><td>0%</td></tr>
<tr><td>문단아래</td><td>0pt (2)</td><td>각주크기</td><td>8pt</td></tr>
<tr><td>첫째줄</td><td>들여쓰기</td><td>10pt (0)</td><td>각주줄간격</td><td>130%</td></tr>
<tr><td rowspan="2">정렬</td><td>정렬방식</td><td>양쪽혼합</td><td>각주 장평</td><td>100%</td></tr>
<tr><td>낱말방식</td><td>0</td><td>각주 자간</td><td>0%</td></tr>
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● 제목

- 국문논문은 국문, 영문 순으로 작성하고, 영문논문은 영문으로만 작성한다.
- 국문제목: HY견고딕 15pt, 장평 98%, 자간 -10%, 줄간격 130%, 가운데정렬
- 영문제목: 신명조 10pt, 진하게, 장평 98%, 자간 -10%, 줄간격 130%

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- 국문저자명: 중고딕 9pt, 장평 98%, 자간 -10%, 줄간격 130%, 가운데정렬
- 영문저자명: 신명조 9pt, 진하게, 장평 98%, 자간 -10%, 줄간격 130%
- 저자명 별로 오른쪽에 *, ** 등을 표시한 후 논문 첫페이지 하단 각주에 저자의 소속을 표기한다(단, 교신저자에 한하여 Corresponding Author (이메일주소)를 명기한다).
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- 요약제목은 Abstract 로 표기하고 영문으로 150~200단어 정도 작성한다.
- 요약제목: 신명조 8pt, 진하게, 130%, 첫 문자만 대문자
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- 주요어는 ‘키워드’, ‘Key Words’로 표기하고 영문요약의 아래에 4~6개 단어로 표기한다.
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● 장/절/항 제목

- 장 제목: HY견고딕 10pt, 줄간격 130%, 문단위 10pt, 문단아래 5pt
- 절 제목: 중고딕 9pt, 진하게, 줄간격 130%, 문단아래 5pt
- 항 제목: 휴먼명조 9pt, 장평 98%, 자간 -10%, 줄간격 130%, 문단아래 5pt

● 표/그림
- 제목과 설명은 영문으로 표기하는 것을 원칙으로 한다.
- 제목 첫단어의 첫문자만 대문자로 한다.
- 표제목 글꼴: 돋움 8pt, 진하게, 줄간격 120%, 위표기, 가운데정렬
- 내용 글꼴: 중고딕 7pt, 장평 95%, 자간 -10%, 줄간격 120%
- 그림제목 글꼴: 돋움 8pt, 진하게, 줄간격 120% 아래표기, 가운데정렬

● 감사의 글(필요할 경우)
- 감사의글 제목: HY견고딕 10pt, 줄간격 130%, 문단위 10pt, 문단아래 5pt

7. 참고문헌은 아래의 논집 양식에 의거 작성하여야 한다.

● 참고문헌 인용방법
- 참고문헌을 인용할 때에는 해당하는 내용 옆에 ‘( )’를 하고, 그 속에 저자와 발행년도를 적는다. 본문에 저자가 나타나 있는 경우에는 발행년도만을 적으며, 발행년도가 같은 동일 저자의 문헌이 두 개 이상일 경우에는 발행년도 뒤에 ‘a’, ‘b’등을 부가하여 구분한다. 동일내용에 대해 인용문헌이 여러 개인 경우에 인용문헌의 구분은 세미콜론(;)으로 구분한다.
- 저자명은 국문문헌의 경우는 성과 이름을 모두 표기하고, 영문문헌은 Last Name을 표기한다. 인용문헌의 저자가 2인이면 2인 모두 표기하며, 3인 이상인 경우 제1 저자명만을 사용하여 “Hong et al.”과 같이 표기한다.
- 본문에 인용된 모든 참고문헌을 포함하는 것을 원칙으로 하며, 본문에서 인용되지 않은 문헌은 참고문헌에 포함시키지 않는다.

● 참고문헌 표기방법
- 참고문헌 제목: HY견고딕 10pt, 줄간격 130%, 문단위 10pt, 문단아래 5pt
- 참고문헌 본문: 휴먼명조 9pt, 줄간격 130%, 내어쓰기 15pt
- 본문에 인용 또는 언급된 참고문헌은 국내문헌과 외국문헌(동・서양의 순)으로 구분하되, 저자의 성을 기준으로 전자는 가나다순으로 후자는 알파벳순으로 배열한다.
- 참고문헌은 저자 (출판년도), 제목, 출판사항의 순서로 기재한다.

예)

홍길동 (2012), 도시정부의 정책집행에 있어서 주요 영향요인에 관한 연구, 도시과학연구 제10권, 제1호, pp.67-83.

Moynihan, D. P. (2006), Managing for results in state government, Evaluating a Decade of Reform, Public Administration Review, Vol. 66, No. 1, pp.77-89.

8. 목차의 계층을 나타내는 기호체계는 1, 1.1, 1.1.1, 1), ①의 순서를 따른다.

9. 표나 그림의 제목은 각각 논문의 전편을 통해서 일련번호를 매겨(예: Table 1., Figure 1.) 표는 윗부분에 그림은 아랫부분에 쓰고, 자료의 출처는 '자료:'라고 표시하고 아랫부분에 밝힌다.

10. 표나 그림에 대한 주는 개별주(a), b), c)의 기호 사용; 확률주인 경우에는 *p<.05, **<p.01, ***<p.001), 일반주('주:'로 표시하고 기재)의 순으로 자료 출처의 윗부분에 달아 준다(즉, 표나 그림의 하단에 개별주, 일반주, 자료의 순서가 되도록 배열한다).

11. 논문 제출은 E-mail접수와 우편접수가 가능하며, 우편접수 시에는 심사용 논문 3부와 원고 파일을 제출하여야 한다. 원고는 수시로 접수하며, 논집 편집위원회에 제출한다.

12. 최초 기고된 논문은 심사위원 3인에게 논문 심사를 의뢰한다. 초심의 종합판정은 ‘게재가’, ‘수정 후 게재’, ‘수정 후 재심사’, ‘게재불가’의 4유형으로 구분한다.

13. 초심의 종합판정 결과 ‘게재가’가 둘 이상이면 게재를 원칙적으로 ‘게재 판정’으로 인정하고, ‘수정 후 게재’가 둘 이상이면 수정을 조건으로 ‘게재 판정’을 하고, ‘수정 후 재심사’가 둘 이상이면 ‘수정 판정’으로 재심을 하며, ‘게재불가’가 둘 이상이면 ‘불가 판정’으로 게재를 하지 못한다. 다만, ‘게재판정’의 경우에도 편집위원회는 수정 및 보완을 요구할 수 있으며, 수정 및 보완이 이루어진 후에 게재를 할 수 있다.

14. 초심에서 ‘수정 후 재심사’ 판정을 받은 논문은 수정 및 보완을 한 후 수정・보완사항을 정리하여 논집 편집위원장에게 e-mail로 보낸다. 편집위원장은 수정・보완된 논문의 초심 심사위원 중 ‘수정 후 재심사’ 판정을 내린 심사위원에게 재심용 논문을 보낸다. 재심 심사위원은 ‘게재가’와 ‘게재불가’ 판정만 할 수 있다.

15. 최종 게재확정 통보를 받으면 최종원고를 e-mail로 제출한다. 최종원고의 끝 부분에는 성명(한자), 박사학위(학위명, 취득년도, 취득대학, 논문제목), 소속기관 및 직위, 학문적 관심분야(3개 이내), 최근 5년 이내의 저서 및 출간논문(3편 이내), e-mail 주소 등을 중심으로 간략한 자기 소개서를 작성・제출한다.

16. 저자는 제1저자를 제일 처음 명기하며 공동저자는 논문기여도를 고려한 순서로 명기한다. 그리고 최종원고의 끝 부분의 저자 소개 부분에 제1저자와 공동저자를 표시한다. 교신저자의 경우에도 교신저자임을 표시한다.

17. 게재가 확정된 논문이라도 편집위원회의 결정에 따라 이월하여 게재할 수 있다.

18. 발간 일자는 다음과 같다.
    1호: 매년 6월 30일자, 2호: 매년 12월 31일자

도시과학 제13권 제2호

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