

Impact of Wireless Emergency Alerts on a Floating Population: An Analysis of Panel Data from Seoul, South

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Table of Contents

Original Manuscript..... 5

Supplementary Files..... 15

 Figures 16

 Figure 1..... 17

Multimedia Appendixes 18

 Multimedia Appendix 1..... 19

 Multimedia Appendix 2..... 19

Impact of Wireless Emergency Alerts on a Floating Population: An Analysis of Panel Data from Seoul, South

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Abstract

Background: Wireless emergency alert (WEA), which delivers disaster information directly to individuals' mobile phones, has been widely used to provide information related to coronavirus disease (COVID-19) and to encourage compliance with social distancing guidelines in the COVID-19 pandemic.

Objective: This study aimed to empirically analyze the effect of WEAs on the floating population where WEAs were transmitted in the early stages of COVID-19 pandemic. As most WEA messages focus on compliance with the government's social distance guidelines, one of the goals of transmitting WEA in the COVID-19 pandemic is to control the floating population at an appropriate level.

Methods: We investigate the empirical impact of WEA on the floating population across 25 districts by estimating a panel regression model at district-hour level with a series of fixed effects. Main independent variables are the number of instant WEAs, the daily cumulative number of WEAs, the total cumulative number of WEAs, and information extracted from WEAs by a natural language processing at district-hour level. The dataset provides a fine empirical setting as WEAs were sent by different local governments with various district-hour level data, which is identifiable.

Results: The estimates of the impact of WEAs on the floating population are significantly negative (-0.012, $P < .05$ to -0.0144, $P < .05$) across all specifications, implying that the floating population decreases when people receive WEAs. Although the coefficients of DCN (daily cumulative number of WEAs) are also negative (-0.0034, se:0.0035 to -0.0052 se:0.0035) across all models, they are insignificant. The effect of WEAs on the floating population are doubled (-0.0254, $P < .05$ to -0.0331, $P < .01$) when the first 82 days of observations were used as subsamples to reduce the possibility of people blocking WEAs.

Conclusions: Our results suggest that issuing WEAs and distributing information related to COVID-19 to a specific district reduced the floating population of that district. Furthermore, among the various types of information in the WEAs, location information was the only significant information, which causes a decrease in the floating population. Our findings provided a plausible mechanism by which WEA could effectively suppress infectious disease by providing the empirical evidence that the transmitting WEAs affected the reduction of the floating population in the COVID-19 pandemic.

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Original Paper

Sungwook Yoon (Korea Information Society Development Institute, Jincheon, South Korea), Hyungsoo Lim (Hong Kong University of Science and Technology, Kowloon, Hong Kong), Sungho Park (SNU Business School, Seoul National University, 1 Gwanak-ro, Gwanak-gu, Seoul National University, Seoul, 08826, Korea, Corresponding author; spark104@snu.ac.kr, 82-2-880-6949)

Impact of Wireless Emergency Alerts on a Floating Population: An Analysis of Panel Data from Seoul, South Korea

Abstract

Background: Wireless emergency alert (WEA), which delivers disaster information directly to individuals' mobile phones, has been widely used to provide information related to coronavirus disease (COVID-19) and to encourage compliance with social distancing guidelines in the COVID-19 pandemic. The floating population refers to the number of people temporarily staying in a specific area, and this demographic data can be a useful indicator to understand the level of social distancing people are complying during the COVID-19 pandemic.

Objective: This study aimed to empirically analyze the impact of WEAs on the floating population where WEAs were transmitted in the early stages of the COVID-19 pandemic. As most WEA messages focus on compliance with the government's social distance guidelines, one of the goals of transmitting WEA during the COVID-19 pandemic is to control the floating population at an appropriate level.

Methods: We investigated the empirical impact of WEA on the floating population across 25 districts in Seoul by estimating a panel regression model at the district-hour level with a series of fixed effects. The main independent variables are the number of instant WEAs, the daily cumulative number of WEAs, the total cumulative number of WEAs, and information extracted from WEAs by a natural language processing at the district-hour level. The dataset provides a fine empirical setting as WEAs were sent by different local governments with various district-hour level data, which is identifiable.

Results: The estimates of the impact of WEAs on the floating population are significantly negative (-0.013 , $P=.02$ to -0.014 , $P=.01$) across all specifications, implying that an additional WEA issuance reduces the floating population by 1.3% (-100%) to 1.4% ($-100(1-e^{-0.014})$). Although the coefficients of DCN (daily cumulative number of WEAs) are also negative (-0.0034 , $P=.34$ to -0.0052 , $P=.15$) across all models, they are insignificant. The impact of WEAs on the floating population are doubled (-0.025 , $P=.02$ to -0.033 , $P=.005$) when the first 82 days of observations were used as subsamples to reduce the possibility of people blocking WEAs.

Conclusions: Our results suggest that issuing WEAs and distributing information related to COVID-19 to a specific district was associated with a decrease in the floating population of that district. Furthermore, among the various types of information in the WEAs, location information was the only significant information, which was related to a decrease in the floating population. Our study made important contributions. First, this study measured the impact of WEAs with a fine empirical setting. Second, this study added to the existing literature on the mechanism for how WEAs can affect public response. Lastly, our study provided important implications for making optimal WEAs, which suggests that location information should be included.

Keywords: Wireless emergency alert; Floating population; Social distancing; COVID-19; Empirical identification.

Introduction

The frequency of disasters and the scale of the damage have increased dramatically over the decades. Natural disasters related to climate, weather, or water hazard have increased more than fivefold over the past 50 years. Such incidents have resulted in approximately 115 casualties and \$202 million in damage per day [1]. Likewise, man-made disasters, including criminal attacks (e.g., shooter incidents and terrorist attacks), human-based technological incidents (e.g., building or bridge collapse), and events related to the manufacture, transportation, storage, and use of hazardous materials have also increased significantly over the past 50 years. Moreover, the number of occurrences was estimated to have increased sixfold or more, whereas the amount of damage increased by approximately 189 times [2].

Along with a significant number of disasters, the importance of wireless emergency alert (WEA) to rapidly deliver disaster information is emphasized. Many countries, including the United States, Japan, and South Korea have adopted WEA as a disaster information delivery system channel. This is because WEA operates as a cell broadcast service (CBS) system that can send messages to multiple mobile phone users in a defined area simultaneously. Information is delivered directly to an individual's cell phone; hence, it can be easily accessed through an individual's mobile phone without the hassle of searching.

Recently, WEAs have been actively used to prevent the spread of COVID-19 since early 2020 [3]. In the United States, Utah and Massachusetts have issued WEAs reminding the safety rules related to coronavirus disease (COVID-19) [4-5]. In New Zealand, WEAs were sent to mobile phone users across the country in the name of the "National Emergency Management Agency." [6] Taiwan also used a cell-based mass texting system known as the public warning CBS to share information on COVID-19 [7].

One of the most efficient ways to respond to a disaster situation is to evacuate people from the danger zone to a safer location. Therefore, it is necessary to monitor changes in the flow of public movement, including the floating population, among the various public responses that occur during such disasters. Along with growing frequent disasters, there is increasing demand for countries or local governments to examine the impact of WEA as it could be one of the solutions to prevent severe damages from emergent events. WEA is an information delivery channel optimized for this purpose, enabling people in a specific area to receive disaster notifications on their cell phones and prompting them to evacuate. Therefore, analyzing the relationship between the issuance of WEAs and the size of the floating population in a given area is the most intuitive and effective way to measure the policy performance of sending WEAs, which provides important implications for developing future policies. However, little is known about the impact of WEAs on people's behavior because granular datasets of the focal outcome variable at various regions, and short-time levels are unlikely available (e.g., the real-time population at a specific time in a particular region). Only a few studies have examined the impact of WEAs, and they focused on either the impact of a single region [8] or simply compared the delivering and non-delivering regions [3].

We empirically investigated the associations between WEAs and the floating population in 25 districts in Seoul, the largest metropolis in South Korea, in the early stage of the COVID-19 pandemic for 13 months from January 2020 to January 2021. The floating population denotes the transient influx of individuals within a defined area, and this metric serves as a pivotal indicator, offering perspectives on the adherence to social distancing protocols during the COVID-19 pandemic. As most WEA messages focus on compliance with the government's social distance guidelines, we can safely say that the goal of transmitting WEA in the COVID-19 pandemic is to control the floating population at an appropriate level.

Methods

Dataset

In May 2005, the South Korean government established a nationwide WEA transmission system for the first time in the world, and since 2013, the WEA reception function has been mandatory for all mobile phones. WEA operates as a CBS system, a method of simultaneously sending messages to multiple mobile phone users in a defined area. CBS is a one-to-many geo-targeted and geo-fenced messaging service, unlike a short message service.

Since the establishment of the WEA transmission system, only the central government has had the authority to send WEAs, but this authority was extended to local governments in 2019 with an amendment to the relevant law. Since then, local governments have sent WEAs related to natural disasters, such as storms, floods, conflagrations, and other issues in their jurisdictions. WEA sending standards and the composition of contents are the subjects of the authority's autonomy. Unlike WEAs sent by the central government, those from the local governments are sent only to their jurisdictional areas.

We have collected 6,442 WEAs sent by each local government in the designated district (*Gu*—administrative district in Seoul, and there are 25 of them) in Seoul for 13 months from January 2020 to January 2021. Detailed WEAs were extracted from the “Public Data Portal” built by the Ministry of the Interior and Safety of South Korea government. The empirical period covers the early stage of the COVID-19 pandemic in South Korea.

To investigate what kind of information should be included in WEAs, we extract information from WEAs using natural language processing. The first information extracted from WEAs is whether or not the WEAs contain location information. The second indicates whether WEAs have up-to-date information. The third indicates whether WEAs have information on hand (e.g., number of confirmed cases). The final one indicates whether WEAs have disease information (e.g., detailed information on COVID-19).

For the dependent variable, we use the estimated floating population provided by SK Telecom, which has the largest number of subscribers in South Korea, at the district-hour level during the same period. We summarized the materials which aids in the understanding of our dependent and independent variables into Multimedia Appendix 1.

Empirical Model

We specify our empirical model at the region-hour level as follows:

$$y_{it} = \alpha_0 + \alpha_1 N_{it} + \alpha_2 DCN_{it} + \alpha_3 TCN_{it} + \beta X_{it} + \theta_{it} + \varepsilon_{it}, \quad (1)$$

where y_{it} denotes the dependent variable in district i at time t ; N_{it} indicates the number of WEAs in district i at time t ; DCN_{it} indicates the daily cumulative number of WEAs in district i until time t (excluding the number of WEAs at time t); TCN_{it} indicates the total cumulative number of WEAs in district i until time t since January 1, 2020; X_{it} indicates the information extracted from WEAs with a natural language processing; and θ_{it} indicates the group of fixed effects that includes district-fixed effects, time-fixed effects, and the joint district and time-fixed effects. To control the effect of unobservable factors (e.g. daily work commute), we include these granular region, weekday, and hour-fixed effects. This specification can alleviate the concern about controlling unobservable factors that could affect the floating population.

The dependent variable is the floating population at time t in district i . We specify continuous variables in logarithms since they have skewed distribution (e.g., y_{it} , TCN_{it}). As appropriate, we add 1 to the variables to avoid logarithms of 0. Figure 1 shows the distribution of N and DCN during the day. The x-axis represents 24 h. For instance, 0 indicates a period from midnight to 1 AM. The y-axis represents the average N (in grey) and DCN (in light grey) across 25 districts. As shown in Figure 1,

DCN increases over time during a day as *N* is accumulated. On average, people have received 0.65 WEAs daily, and the peak time is 6 PM. Tables 1 and 2 report the summary statistics and correlations of the variables. Most of correlations are significant ($P < 0.001$) except a correlation between floating population and number of WEAs with order information as shown in Table 2. The correlations between each variable are mostly at a modest level, and considering our sample size (the number of observations in the analysis is 236,775), we conclude that each variable has different variations. We use the ordinary least square methods to estimate the unknown parameters of our empirical model.

Figure 1. *N* (number of WEAs) and *DCN* (daily cumulative number of WEAs) at hour level for WEAs issued in 25 districts of Seoul, Jan 2020 – Jan 2021.

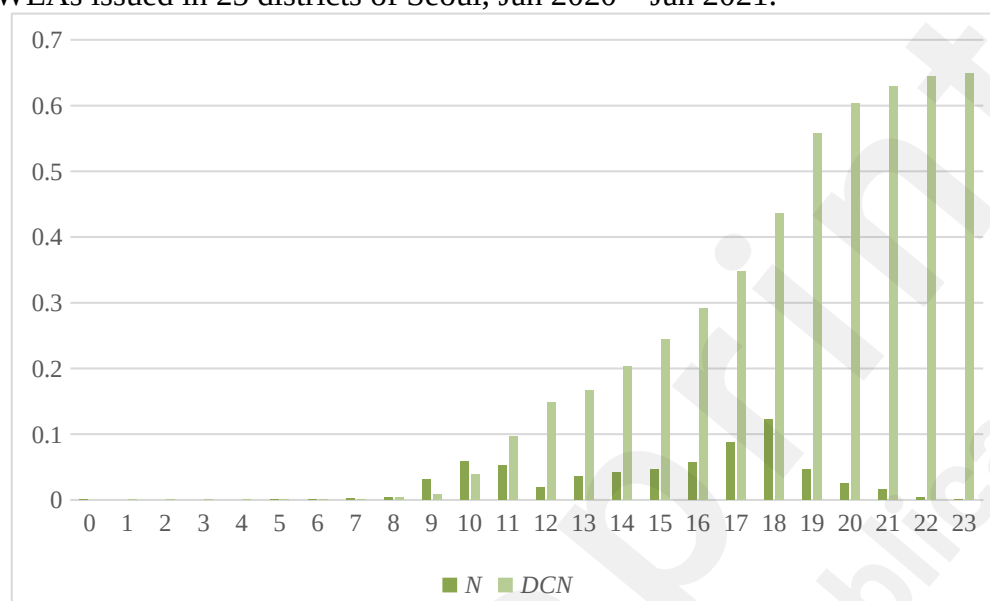


Table 1. Descriptive statistics of the floating population and WEAs across 25 districts in Seoul, Jan. 2020 – Jan. 2021.

Variables	Median	Mean	Min.	Max.
1. Floating population	319,000	327,382	94,020	1,044,150
2. Number of WEAs (<i>N</i>)	0	0.027	0	4
3. Number of daily cumulative WEAs (<i>DCN</i>)	0	0.211	0	8
4. Number of total cumulative WEAs (<i>TCN</i>)	54	84.210	0	495
5. Number of WEAs with location information	0	0.017	0	9
6. Number of WEAs with date information	0	0.007	0	8
7. Number of WEAs with order information	0	0.040	0	11
8. Number of WEAs with disease information	0	0.005	0	4

Table 2. Correlation matrix of the floating population and WEAs across 25 districts in Seoul, Jan. 2020 – Jan. 2021.

Correlation ^c	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Log (floating population)	1.000	0.016	0.028	0.153	0.005 ^a	0.029	0.001 ^b	0.015
(2) Number of WEAs (<i>N</i>)	0.016	1.000	0.042	0.106	0.564	0.437	0.805	0.400
(3) Number of daily cumulative WEAs (<i>DCN</i>)	0.028	0.042	1.000	0.265	0.014	0.025	0.028	0.005 ^a
(4) Number of total cumulative WEAs (<i>TCN</i>)	0.153	0.106	0.265	1.000	0.033	0.042	0.103	0.023
(5) Number of WEAs with location information	0.005 ^a	0.564	0.014	0.033	1.000	0.216	0.469	0.173

(6) Number of WEAs with date information	0.029	0.437	0.025	0.042	0.216	1.000	0.285	0.195
(7) Number of WEAs with order information	0.001 ^b	0.805	0.028	0.103	0.469	0.285	1.000	0.284
(8) Number of WEAs with disease information	0.015	0.400	0.005 ^a	0.023	0.173	0.195	0.284	1.000

^a Correlation is significant (P=0.01).

^b Correlation is insignificant (P=0.65).

^c All correlation are significant (P<0.001) if there is no note.

Various types of information were sent through WEAs, and natural language processing (NLP) techniques were used to extract and identify them. Sentences in WEAs were stemmed through a morphology analyzer named “Mecab” and “Okt tagger” in KoNLPY, an open-source Korean language processing package. After classifying common nouns, proper nouns, adjectives, and verbs through the morphology analyzer, informative words were extracted by specifying a list for exclusion of the stopwords and out-of-vocabulary (OOV) words in advance. The type of information included in the WEAs is identified by classifying the extracted words according to a pre-determined semantic standard (Named Entity Recognition: NER). We utilized the NER API (Application Programming Interface) in the AI API·DATA service provided by the Korea Electronics and Telecommunications Research Institute (ETRI), and this API is known to have a high performance of 89.4% in Korean NER [9].

Ethical Considerations

To compile the data set used in this study, publicly available information was collected via Ministry of the Interior and Safety of the Republic of Korea. We received confirmation of exemption from the Public Institutional Bioethics Committee designated by the Ministry of Health and Welfare of the Republic of Korea (P01-202309-01-043).

Main Results

Parameter estimates of our empirical model are shown in Table 3. We include district, weekday, hour, and joint district-hour fixed effects in all regressions.

Table 3. Parameter estimates of the main empirical model: Panel regression model using WEAs and the floating population at the district-hour level with a series of fixed effects.

	(1) Base	(2) With <i>TCN</i> ^b	(3) With <i>TCC</i> ^c	(4) With Day
<i>N</i>	-0.014 (0.0053; P=.01)	-0.013 (0.0050; P=.02)	-0.013 (0.0048; P=.01)	-0.013 (0.0050; P=.02)
<i>DCN</i> ^a	-0.0052 (0.0035; P=.15)	-0.0034 (0.0035; P=.34)	-0.0039 (0.0034; P=.26)	-0.0037 (0.0035; P=.30)
<i>Log (TCN)</i> ^b		-0.0019 (0.0005; P=.002)		
<i>Log (TCC)</i> ^c			-0.0012 (0.0006; P=.06)	
<i>Log (Day)</i>				-0.0033

				(0.0010; P=.004)
Region FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Region $\times$ weekday $\times$ hour FE	Yes	Yes	Yes	Yes
Observations	236,775	236,775	236,775	236,775
R-squared	0.804	0.804	0.804	0.804
Adjusted R-squared	0.804	0.804	0.804	0.804

^a *DCN* denotes the daily cumulative number of WEAs in a specific district.

^b *TCN* denotes the total cumulative number of WEAs in a specific district since January 1, 2020, the beginning of the observation period.

^c *TCC* denotes the total number of confirmed cases of COVID-19.

As shown in the first row of Table 3 (*N*), the estimates are significantly negative across all models, implying that when people receive WEAs, the floating population decreases. Based on the estimate in column (2), one increase in WEA is related to a reduction of the floating population by 1.3% ($100(1 - e^{-0.013})$). Other specifications yield similar results, ranging from 1.3% ($100(1 - e^{-0.013})$) to 1.4% ($100(1 - e^{-0.014})$). Although the coefficients of *DCN* are also negative across all models and related to a reduction of the floating population from 0.34% ($100(1 - e^{-0.0034})$) to 0.52% ($100(1 - e^{-0.0052})$), they are insignificant. To check the impact of cumulative WEAs, we incorporated the *TCN* into the main specification, as shown in column (2) of Table 3. The results show that cumulative WEAs are also negatively correlated with the floating population. We replaced *TCN* with *TCC* (total number of confirmed cases of COVID-19) and *Day* (daily time trend) to check the robustness and summarize the results in columns (3) and (4) of Table 5, respectively. We used the variables related to *TCN*, *TCC*, and *Day* separately due to their high correlation (0.963 between $\log(TCN)$ and $\log(TCC)$; 0.902 between $\log(TCN)$ and $\log(Day)$; and 0.899 between $\log(TCC)$ and $\log(Day)$). As shown in columns (3) and (4), *TCC* and *Day* have negative impacts on the floating population like *TCN*.

We conducted several robustness checks with subsamples and different specifications. The results of robustness checks are consistent with our main findings. Subsequently, we perform two falsification tests, and we found that our results do not hold when using incorrect variables in terms of district and timing. Detailed information and results of the robustness checks and falsification tests are summarized in Multimedia Appendix 2.

Discussion

Principal Results

This study empirically measured the association between details of issuing WEAs and the granular region-hour-level estimated floating population changes in 25 districts in Seoul, South Korea. We used variations in the number and content of WEAs independently managed by local authorities to empirically measure the WEA impact. By estimating a panel-data model with a series of fixed effects, we found robust evidence that issuing WEAs is related to the reduction of the floating population of districts in Seoul, South Korea. A collection of robustness and falsification tests show that our findings are robust. Furthermore, we found that location is the only significant information among various information extracted from WEAs, which is associated with a decrease in the floating population.

The information necessary for disaster response must be delivered promptly and accurately to

overcome disaster situations. WEAs, which deliver disaster information directly to the recipients' mobile phones, have become a major means of providing disaster information. One of the most efficient ways to respond to a disaster situation is evacuating people from dangerous areas to safe locations. Therefore, a major objective of issuing Wireless Emergency Alerts (WEAs) is to control or reduce the floating population in hazardous areas to an appropriate level. These policy objectives gained further prominence during the COVID-19 pandemic, as the primary content of WEAs at the peak of the pandemic emphasized practicing social distancing and avoiding densely populated areas. Hence, an intuitive approach to measuring the impact of WEAs is to examine the relationship between the number of WEAs sent and the size of the floating population in a given area. Our empirical dataset is ideal for our study due to the following reasons: (1) The dataset provides a fine empirical setting to measure the impact of WEAs as different local governments sent WEAs with various region-hour-level data of districts in Seoul, South Korea, which are identifiable. (2) The dataset contains granular information on floating populations at various region-hour-level data, which are compatible with the dataset of WEAs. (3) WEAs are mandatory for mobile users. Lastly, (4) the empirical dataset fully covers the COVID-19 pandemic in South Korea since the first confirmed case was reported, which provides us with a clear impact in a long enough range. Overall, our empirical data are ideal for studying our research question.

This study makes several contributions. First, this study offers new empirical evidence on the impact of Wireless Emergency Alerts (WEAs), advancing previous research that mainly relied on hypothetical scenario surveys due to limited WEAs and challenges in identifying key variables [10, 11, 12]. Earlier studies, particularly those examining COVID-19, faced difficulties in robust statistical analysis and data collection reflecting public responses [3, 13]. Unlike prior work that focused on a few regions or solely on the number of WEAs, this study stands out by analyzing variations in the number and content of WEAs across different regions due to regions' independent authorities to issue them [8].

Second, this study provides a plausible mechanism for how WEA can reduce other focal outcomes, such as the number of infections and deaths [3], which remains unclear. Previous studies revealed that population density has a strong correlation with the number of infections and deaths from COVID-19 [14-17]. Transmitting WEAs reduces the floating population in the area where WEAs are sent, and consequently reduces the confirmed COVID-19 cases and deaths.

Lastly, our study provides important implications for developing a policy on making an optimal WEA to prevent national disasters or pandemics, which suggests that location information should be highlighted rather than other information (e.g., date and general information).

Limitations

This study has some limitations due to technical issues with the WEA system and the difficulty in obtaining datasets. This study observed the relationship between the transmission history of WEAs in districts and the change in the floating population. However, we cannot confirm whether the person who received WEAs has moved to a safe place, which makes it hard to argue the causal relationship. To supplement this limitation, we require an additional dataset that can check the WEA confirmation time and movement history through personal-level mobile phone log records.

We used the estimated floating population provided by SK Telecom as a dependent variable. However, it's worth noting that while SK Telecom has the largest number of subscribers with a market share of 44.3% as of 2021 [18], the floating population they estimate and provide may differ from the actual floating population. We conducted an additional analysis using the floating population provided by the Seoul local government as the dependent variable, and the results are summarized in Multimedia Appendix 2. The implication of this study remained consistent even when analyzed with an additional dataset.

This study focused on WEAs and the floating population of 25 districts in Seoul, the capital and largest city of South Korea. For a more generalized conclusion about the effectiveness of WEAs, it is

necessary to expand and analyze the dataset to include more regions in future studies.

WEA can be blocked by changing the mobile phone settings; in that case, the impact of transmitting WEAs on behavioral responses may vary. Nevertheless, due to technical constraints, the government cannot collect data on the rate of the WEA blockade. The WEA sending system should be advanced so that the WEA reception/blocking rate can be aggregated and used for policy formulation.

Conclusions

This study analyzed the impact of WEAs sent in the 25 districts of Seoul on the changes in the floating population in those areas, utilizing the fact that the content of the WEAs sent during the COVID-19 pandemic was focused on compliance with social distancing guidelines. The results showed that issuing WEAs and distributing information related to COVID-19 to a specific district in Seoul, South Korea was related to the reduction of the floating population of that district. Furthermore, among the four types of information (location, date, order, and disease) in the WEAs, location information was the only significant information, which was associated with a decrease in the floating population. Contrasting with prior studies that couldn't generalize findings by using hypothetical survey results or analyzing WEAs and the floating population in a single region, this study empirically elucidates the impact of WEAs on public behavior by examining the number and content of region-hour level messages sent by 25 districts with independent dispatch authority, along with the corresponding changes in the floating population.

Our findings provided a plausible mechanism by which WEA could effectively suppress infectious diseases by providing the clues that transmitting WEAs was related to the reduction of the floating population during the COVID-19 pandemic. Our finding focused on a correlational relationship rather than a causal one as researchers are unable to observe whether people who received WEAs have moved to safer places.

We hope that this research will spur further investigation into the sophisticated measurement of the WEA impact and the establishment of disaster response systems.

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Conflicts of Interest

Non declared

Abbreviations

WEA: Wireless emergency alert

CBS: Cell broadcast service

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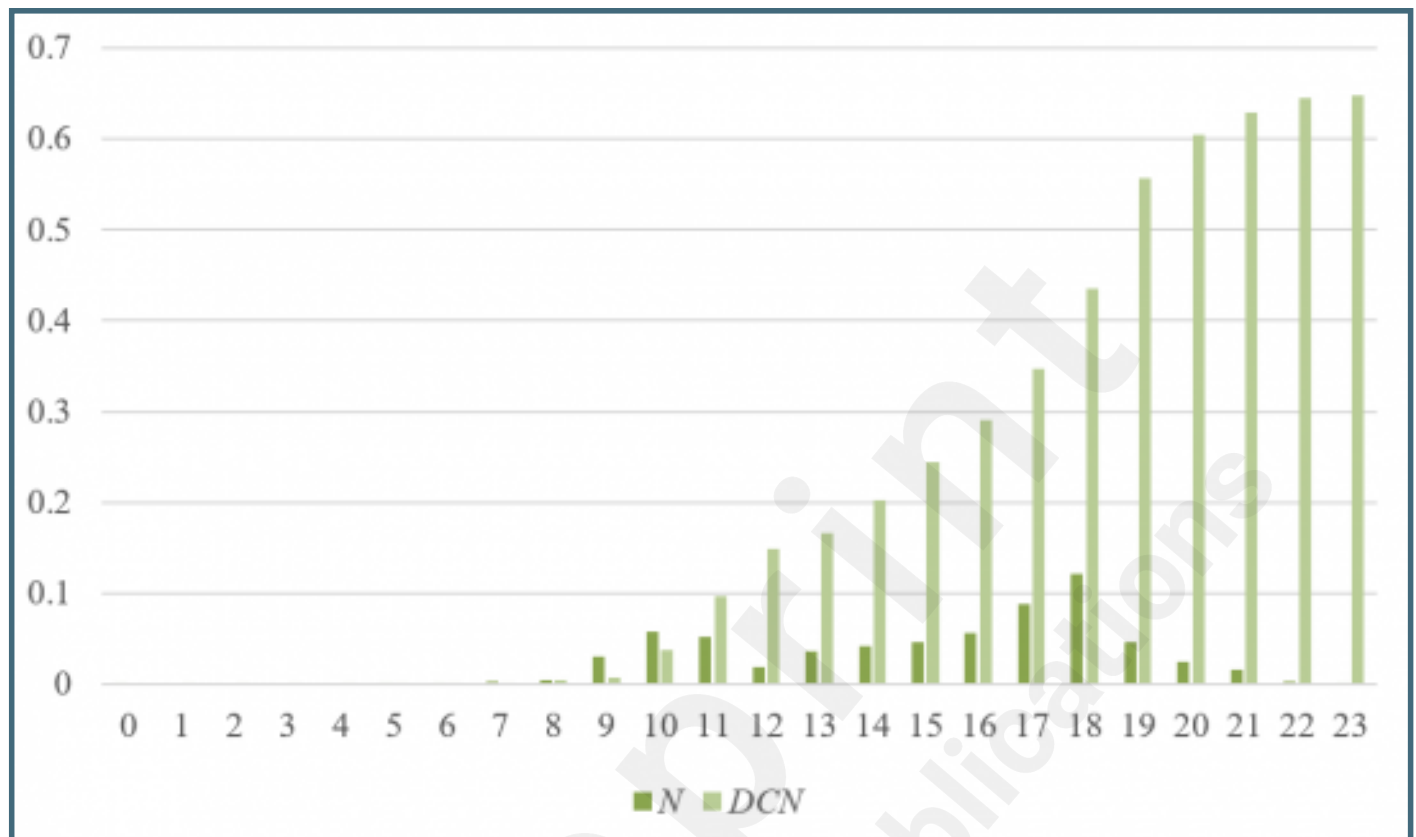
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Supplementary Files

Figures

N (number of WEAs) and DCN (daily cumulative number of WEAs) at hour level for WEAs issued in 25 districts of Seoul, Jan 2020 – Jan 2021.



Multimedia Appendixes

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