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The impact of air pollution alert services on respiratory diseases: generalized additive modeling study in South Korea

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Abstract

To reduce human exposure to particulate matter (PM), governments have enacted various preventive measures, to which a warning system is central. To the best of our knowledge, we are the first to assess the effectiveness of mobile-based warning systems on respiratory health outcomes, examining two types of $PM_{2.5}$ (particles less than 2.5 μm in diameter) alerts via text messaging systems: Wireless Emergency Alert (WEA) and Air Quality Information Text (AIT) as employed in South Korea from January 2015 to October 2019. We used a generalized additive model to control the non-linear relationship between the $PM_{2.5}$ level and the number of hospital visits and admissions for four respiratory sicknesses—chronic obstructive pulmonary disease, respiratory tract infection, asthma, and pneumonia—while deciphering how such visits and admissions are reduced by the warning systems. Our results found that both systems reduced the number of new patients with the four sicknesses at a 5% statistical significance level. Of the two, WEA was found to be more effective than AIT. The former reduced the number of new patients by 16.4%, while the latter did so by 2.8%. WEA is for everyone with a cell phone connection. By sending simple and direct alerts to a broader range of people, WEA would help people to reduce the chance of short-term exposure to PM in general. The findings provide evidence with policy implications regarding air pollution adaptation.

1. Introduction

Particulate matter (PM) is known to be harmful to human health. Fine (particles less than 2.5 μm in diameter) and ultrafine PM (particles less than 0.1 μm in diameter) PM is not filtered by the nasal mucosa but penetrates directly into the lungs, aggravating respiratory conditions and potentially leading to more detrimental respiratory diseases, such as chronic obstructive pulmonary disease (COPD), respiratory tract infection (RTI), asthma, pneumonia, and lung cancer (Neuberger *et al* 2004). Globally, from 2017 to 2019, the number of premature mortalities increased 6.24% (from 3882 444 to 4140 971 deaths) and 2.55% for the rate of disability-adjusted life years (DALYs) (from 1488 to 1527 DALYs per 100 000) owing to ambient PM (GBD 2019, Risk Factors Collaborators 2020).

Many governments, such as those of the United Kingdom, European Union, United States, China, and South Korea have implemented multi-pronged efforts to lower the emission of PM and to reduce human exposure to it. Commonly adopted benchmarks are called 'air quality indexes' and indicate concentration levels and their degree of health damage (Kyrkilis *et al* 2007, Mason *et al* 2019, Olstrup *et al* 2019). Countries have modified the World Health Organization (WHO) standard to reflect their own environmental contexts and set national emission ceilings accordingly to regulate the sources of emission, for example, heavy-duty vehicles and factories burning coal and other solid fuels (EU 2008, Heal *et al* 2012, Kuklinska *et al* 2015).

In order to reduce human exposure to PM, various preventive measures are enacted, to which warning systems are central. According to the

Protective Action Decision Model, when people face environmental hazards, they determine protective actions inspired by an understanding of the associated risk and a warning provided by an accurate and trustworthy source (Lindell and Perry 2012). Likewise, in order for people to follow preventive protocols on days with high levels of PM, they need to recognize the risk of PM and they need to be alerted at the right time (Choi *et al* 2019, Yoon 2019).

With the development of information technologies, warning methods have been expanded from traditional media such as TV, radio, and internet to cell phone text messages and smartphone applications. While each of those channels contributes to the overall alert system differently, with its own target audiences (Mayhorn and McLaughlin 2014), the mobile-based Wireless Emergency Alert (WEA) system is known as one of the most direct approaches (Kim *et al* 2019a). WEA sends text messages to all mobile devices within the coverage area of a base station using the cell broadcasting service, thus people learn immediately of a potential threat they are facing in their current location (Aloudat and Michael 2011). Because the cell phone distribution rate has been rapidly increasing, the WEA method is effective at reaching a vast number of people. WEA is currently being used for public measures of air quality control in many places, such as Korea, the United States, Canada, and Hong Kong.

Air Quality Information Text (AIT) messaging is another mobile-based alert system that serves people who have subscribed to it (Jasemzadeh *et al* 2018). AIT uses a point-to-point method that individually transmits messages to a user by short message service (SMS) through a dedicated channel (Fernandes 2008), thus it requires a higher cost and a longer time (Ministry of the Interior and Safety 2015). AIT has been employed in many countries, such as Iran, Korea, the United Kingdom, and the United States.

Despite their dominance, such mobile-based air pollution alert systems have received diverging evaluations, and negative ones prevail. In Portland, Oregon, U.S., a study of the air pollution alert system investigated by telephone surveys claimed that advisory messages did not sufficiently motivate people to change their behavior; only 10.5% of the respondents reported changing behavior in response to the alarm (Semenza *et al* 2008). Also, according to a study analyzing the frequency of alerts, too many alerts led to alert fatigue and made people become insensitive and unable to recall the content of a message (Baseman *et al* 2013). When the numbers and types of alarms are excessive, it becomes harder to discern the gravity of each. In Korea, the WEA went off 137 times from January to March 2019 for PM-related alerts, which is 58% of the total of 235 times alerts were issued during that period (Kang 2019); people may opt out of receiving such frequent messages (Gonzales *et al* 2014).

Many PM-related studies have focused on the relationship between the PM level and its health effects (Neuberger *et al* 2004, Katanoda *et al* 2011, Liu *et al* 2017, Dastoorpoor *et al* 2019, Olstrup *et al* 2019). In terms of public interventions, most of the studies have focused on the effects of PM reduction measures (Huang *et al* 2018, Han *et al* 2020), while only a few have assessed those of adaptation measures (Chen *et al* 2013, Zou *et al* 2019). In particular, in those cases in which the alert system was the subject—for example, updates of Air Quality Index and Air Quality Health Index in regional newspapers, websites, and smartphone applications—the effect was analyzed by comparing people's behavior and/or the respiratory health outcomes before and after its introduction (Lyons *et al* 2016, Chen *et al* 2018, Li *et al* 2019, Mason *et al* 2019).

Such an approach, however, cannot suggest detailed insights into the system, such as individuals' immediate responses to the alert and the consequential effects, while controlling for other factors that simultaneously influence protective behaviors (Jasemzadeh *et al* 2018, Mason *et al* 2019). In cases when multiple public measures are deployed during the study period, it is difficult to discern the individual effect of each. In addition, despite the current prevalence of the mobile-based PM alert systems, their effect on behavioral change has been analyzed, but their effect on respiratory health outcomes has not (Semenza *et al* 2008). The mobile-based system is quite different from other systems, because we know for certain that the majority of the public receives the warning, thus the so-called treatment-on-the-treated effect on health can be clearly revealed.

Against this backdrop, we aim to assess the effectiveness of the mobile-based warning system, the $PM_{2.5}$ alert via text message, on respiratory health. We use the generalized additive model (GAM) to control the non-linear relationship between the $PM_{2.5}$ level and the number of hospital visits and admissions for respiratory symptoms and diseases (respiratory sicknesses hereafter) while deciphering how that measure is reduced by the warning systems. The spatial scope of the study is South Korea, and the temporal scope is from 1 January 2015 to 31 October 2019.

The report is structured as follows. Section 2 provides our analytical design, including research question, study site, data and sample, GAM, and models and variable. After discussing the analytical results in section 3, we discuss our conclusions and the policy implications in section 4.

2. Analytical design

2.1. Research question

This study investigates whether $PM_{2.5}$ alert messages affected the number of hospital visits and admissions for respiratory sicknesses in South Korea, from January 2015 to October 2019, using GAM. We answer the

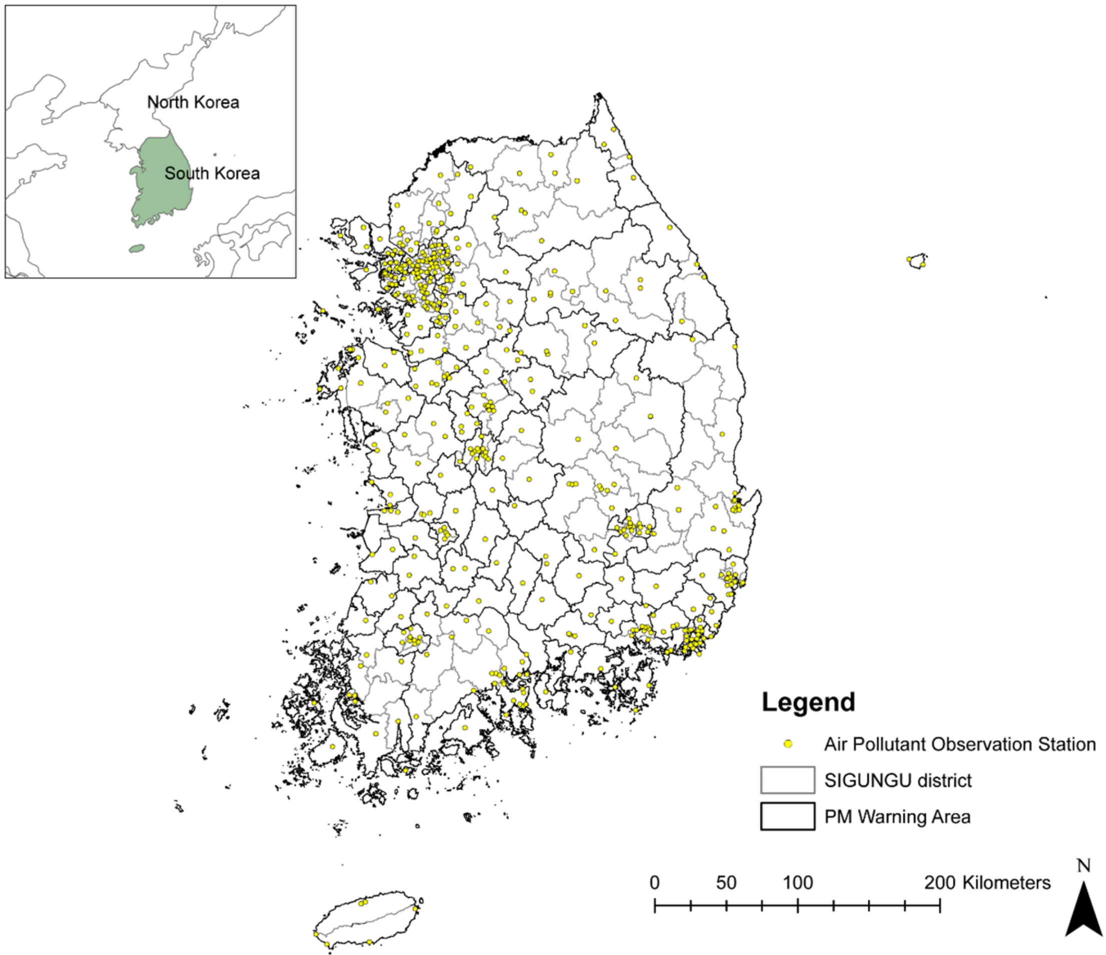

Figure 1. The study site: South Korea. The PM warning area and air pollutant observation stations on the map are shown as of 2019. In the analysis, the PM warning areas were different by year, and stations were added/removed month by month.

following research questions: (a) Do the two types of $PM_{2.5}$ alert message system—WEA and AIT—reduce the number of new patients with respiratory sicknesses? (b) Do the effects of alarms differ by the type of respiratory sickness (COPD, RTI, asthma, and pneumonia)? We hypothesize that alerts discourage people from outdoor activities so as to avoid exposure to PM, consequently reducing the number of hospital visits and admissions for respiratory sicknesses.

2.2. Study site

The study site is South Korea (figure 1). $PM_{2.5}$ in South Korea deserves greater attention, since the level there is the highest among OECD countries and ranked 26th among all countries in the world in 2019 (Visual 2020). In 2019, the annual average $PM_{2.5}$ concentration in South Korea was 24.78 $\mu g\ m^{-3}$, which is more than twice the WHO recommendation of 10 $\mu g\ m^{-3}$. The reason for such unfavorable conditions is the high population density and the high proportion of urbanized area; 82% of the population lives in urban areas (United Nations 2018, Kim *et al* 2019b). As the population is concentrated in urban areas, so as the sources of air pollutants, such as construction activities, traffic congestion, industrial and power generation plants (Cho and Choi 2014, Murray *et al* 2020).

The Korean government enacted the *Special Act on the Reduction and Management of Fine Dust* in 2018 and implemented a comprehensive plan for PM management. Under the act, the detrimental effects of PM_{10} and $PM_{2.5}$ were recognized, and their levels began to be reported and forecast through a public air pollution alert system. The predicted $PM_{2.5}$ level is divided into four grades: good (from 0 $\mu g\ m^{-3}$ to 15 $\mu g\ m^{-3}$), normal (from 16 $\mu g\ m^{-3}$ to 35 $\mu g\ m^{-3}$), bad (from 36 $\mu g\ m^{-3}$ to 75 $\mu g\ m^{-3}$), and very bad (over 76 $\mu g\ m^{-3}$). People can access real-time information through online website and smartphone applications. An alert is issued as a watch or a warning when the measured concentration exceeds 75 $\mu g\ m^{-3}$and 150 $\mu g\ m^{-3}$, respectively, for more than 2 h. In February 2019, another alert category, emergency reduction measure, was created; it is issued when the current day's measured $PM_{2.5}$ concentration and the next day's predicted $PM_{2.5}$ concentration both exceed 50 $\mu g\ m^{-3}$ (Ministry of Environment 2019) (table 1).

Table 1. $PM_{2.5}$ alert standards by concentration level.

Level	Method	Criteria
Emergency reduction measure	WEA	(a) The average concentration on the day exceeds 50 μg m^{-3} and the average concentration for 24 h on the next day is expected to exceed 50 μg m^{-3} or (b) The alert of watch or warning was issued, and the average concentration for 24 h on the next day is expected to exceed 50 μg m^{-3} or (c) The concentration is predicted to exceed the average concentration of 75 μg m^{-3} for 24 h the next day
Watch	AIT	The average concentration per hour is more than 75 μg m^{-3} and lasts 2 h
Warning	AIT and WEA	The average concentration per hour is more than 150 μg m^{-3}and lasts 2 h

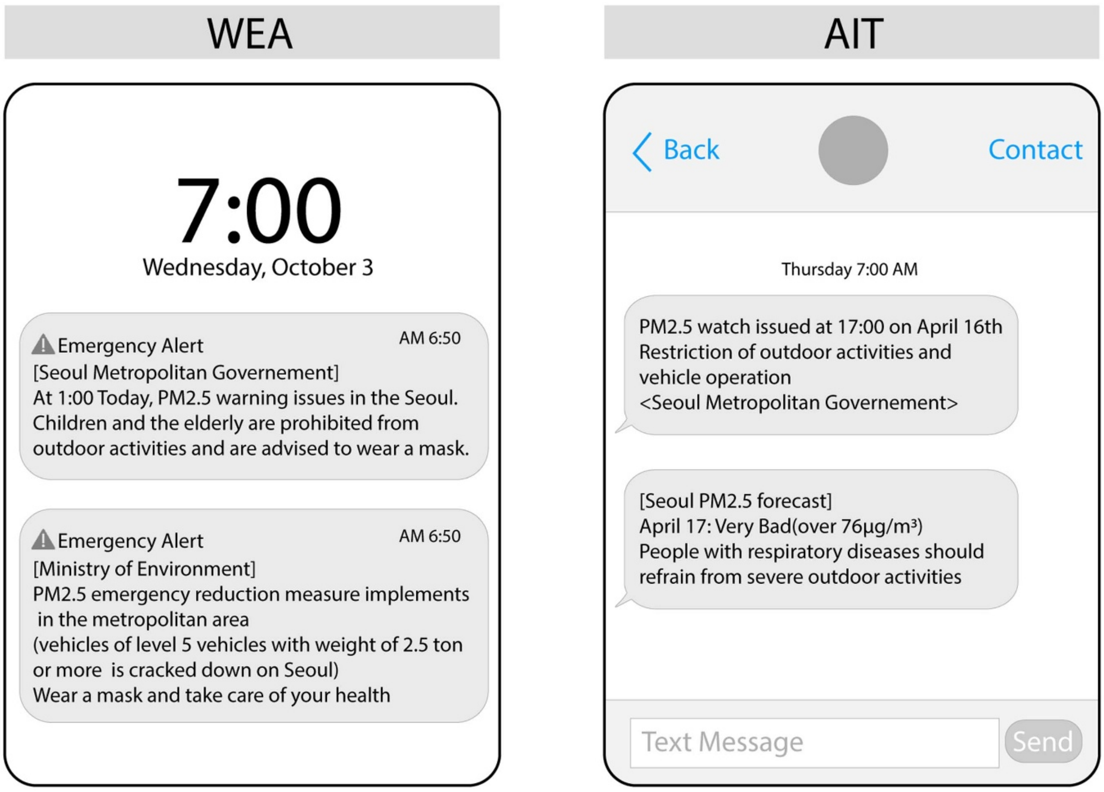

Figure 2. Examples of the alert messages issued through WEA and AIT regarding the alert level (emergency reduction measure, watch, warning) and behavioral guidelines.

In Korea, both of the two aforementioned mobile-based warning systems are deployed: WEA and AIT (figure 2). They are operated by different entities, hence the differences in the transmission method, in the necessity for a subscription, and in the levels of the alerts. WEA messaging is organized by the Ministry of the Interior and Safety and sent by local governments. WEA transmits the alert to all people who have mobile phones (Ministry of the Interior and Safety 2015). AIT messaging is managed by the Korea Environment Corporation (K-eco) and local governments, and sends alerts via SMS only to those who subscribe. The subscribers to the service can customize the information that they wish to receive, including the area, the type of alerts, and the current or predicted level of PM. During the study period, from January 2015 to October 2019, both types of the alert—WEA and AIT were issued simultaneously for 22 days. There are 23 and 290 days that only a single type of alert was issued—WEA and AIT respectively (table 2).

2.3. Data and sample

The spatial analytical unit is the primary local jurisdiction, city and ward, called *sigungu* in South Korea, and the temporal unit is one day from January 2015 to October 2019. The final sample size is 318 591.

Table 2. Distribution of days with WEA and AIT issuance.

	Days with WEA alert	Days without WEA alert
Days with AIT alert	22	290
Days without AIT alert	23	1470

Note: $PM_{2.5}$ alert is sent by regions, the total number of days with the table are not the same with total period of study.

The first dataset is the daily number of visits and admissions to the hospital mainly due to respiratory sicknesses (Korean Standard Classification of Diseases (KCD) codes from J00 to J99), provided by the Health Insurance Review and Assessment Service from January 2015 to October 2019 (Statistics Korea 2010). We categorized the total respiratory sicknesses (J00–J99) into four subsets: COPD (J40–J44), RTI (J00–J06, J22), asthma (J45–J46), and pneumonia (J17–J18) on the basis of the literature (Dominici *et al* 2006, Dastoorpoor *et al* 2019, Mason *et al* 2019). The second dataset is the record of alert message issuances via WEA and AIT systems. The record for WEA was provided by the National Disaster Safety Portal and Public Data Portal. The data consist of the alert date, the area code, the content of the alert message, and the alert level (emergency reduction measure or warning). The record for AIT was obtained from the website called Air Korea. This data includes the alert zone, the alert level (watch or warning), and the date and time of issuance.

We used the air quality record collected by the Korea Environment Corporation. These data consist of the average levels of $PM_{2.5}$ per hour with PM_{10}, sulfur dioxide (SO_2), carbon monoxide (CO), ozone (O_3), and nitrogen dioxide (NO_2). Air pollution monitoring networks are unevenly distributed across administrative districts, and the number of those varied over time (figure 1), from 504 stations in 2015 to 676 stations in 2019 (National Institution of Environment Research 2016, 2019). We also utilized weather records observed by the Automatic Weather System at about 510 stations in South Korea. These data include the average temperature, the average wind speed, and the maximum precipitation in a day. Additionally, to control for the effect of the number of hospitals, we used hospital statistic data provided by the National Statistical Office.

2.4. Models and variables

The GAM is an extended version of a generalized linear model (GLM). Like GLM, it allows a non-normal distribution of dependent variables (Wood 2008, Stram 2014). The advantage of GAM is its capacity to deal with nonlinear relationships between independent and dependent variables, using smooth functions (James *et al* 2013). In this study, we fitted non-linear relationship with two smoothers: thin plate regression spline and cubic regression spline. Thin plate regression spline captures automatically optimized smoothing parameters by the generalized cross-validation criterion without prior knowledge of knot placement (Larsen 2015, Wood 2003). Cubic regression spline draws a cubic spline by evenly distributing a specified number of knots using covariate values (Wood 2017). We used Akaike information criterion (AIC) and un-biased risk estimator (UBRE) to select the model with different smoothers. We used the GAM model with negative binomial distribution and log link function to address the nature of the overdispersed count data (figure 3), in order to answer our research question (Lee *et al* 2012, Feng *et al* 2016, Ardiles *et al* 2018). The final model is given as follow:

$$
\begin{aligned}
&\ln[E(\text{Respiratory\_Disease}_{it})] \\
&\quad = \beta_0 + \beta_1 \text{Both}_{it} + \beta_2 \text{Both}_{i.t-2} + \beta_3 \text{WEA}_{it} \\
&\qquad + \beta_4 \text{WEA}_{i.t-2} + \beta_5 \text{AIT}_{it} + \beta_6 \text{AIT}_{i.t-2} \\
&\qquad + \sum_{k=1}^{3} f_k\left(\text{PM}_{2.5 i \cdot (t-2(k-1))}\right) + \sum_{k=1}^{2} f_{k+3}\left(\text{PLT}_{kit}\right) \\
&\qquad + \sum_{k=1}^{3} f_{k+5}\left(\text{MTR}_{kit}\right) + f_9\left(\text{Hospital}_{it}\right) + f_{10}\left(\text{Time}_t\right) \\
&\qquad + \sum_{k=1}^{6} \beta_{k+6} \text{DOW}_k + \sum_{k=1}^{3} \beta_{k+12} \text{Season}_k + \beta_{16} \text{SGG}_i.
\end{aligned}
$$

The dependent variables are the daily number of new patients with respiratory sickness counted at location i and time t. We analyze the total respiratory disease (Total), as well as COPD (COPD), RTI (RTI), asthma (Asthma), and pneumonia (PNA), separately.

The main question variables are the issuance of alerts by the two types of alert systems: WEA and AIT. Both are specified as dummy variables; we assigned the value one on a day of alert issuance. Both indicates the days with both of the alerts are issued, WEA and AIT indicate the days with only WEA or AIT systems were active respectively. The reference group is the days with none of those alerts was issued. We also include the time lag of the days with those alerts in our model, because they could remain influential for more than a day. As the first lag has a correlation with the subject day (0.582), we employed a second lag for the issuance of alerts (Both_{t-2}, WEA_{t-2}, and AIT_{t-2}).

We considered the concentration of the air pollutants $PM_{2.5}$ ($PM_{2.5}$; μg m^{-3}), ozone (PLT_1; 0.01 ppm), and sulfur dioxide (PLT_2; ppm), which have been known to have a negative relationship with respiratory diseases. We employ second and fourth lag for $PM_{2.5}$ ($PM_{2.5(t-2)}$ and $PM_{2.5(t-4)}$). We excluded PM_{10}, carbon monoxide, and nitrogen dioxide due to high correlations with $PM_{2.5}$ (0.805, 0.569, and 0.452, respectively). Our model includes various meteorological factors (MTR), the average temperature (MTR_1; Celsius), the average wind speed (MTR_2; m s^{-1}), and

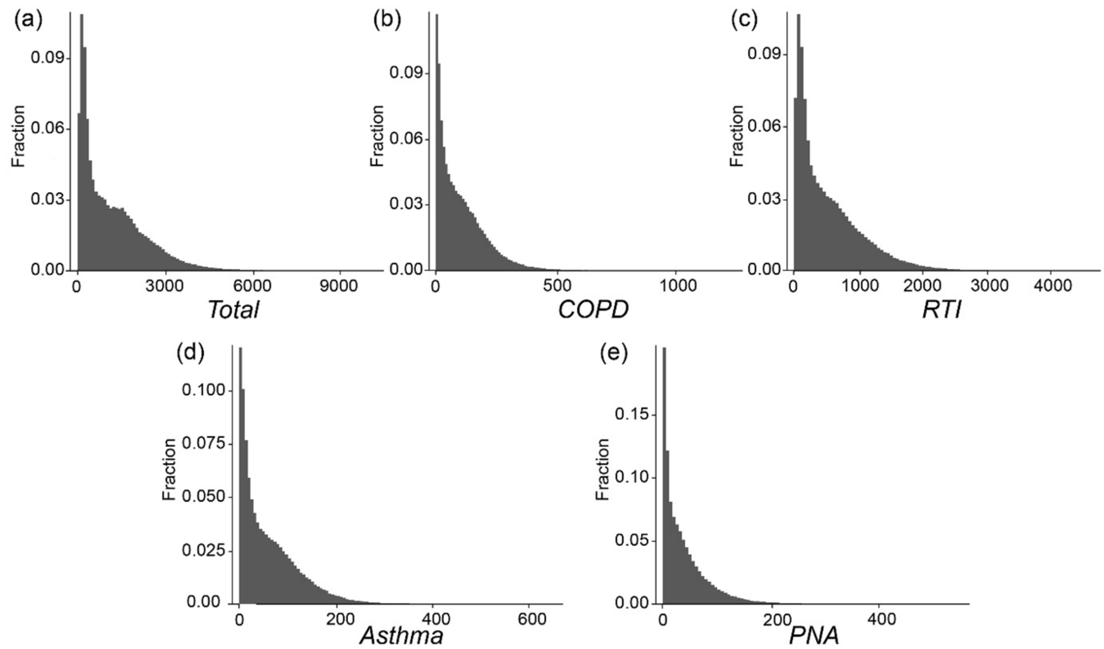

Figure 3. Distributions of the daily number of visits and admissions to the hospital mainly due to respiratory sicknesses: (a) total respiratory sicknesses, (b) COPD, (c) RTI, (d) asthma, (e) pneumonia (PNA).

total precipitation (MTR_3; mm) in a day. Strong air current tends to disperse the concentration of air pollutants, which could offset the harmful effect (Yang *et al* 2020).

For the time indicator, we specified the cumulative number of days (Time). We also considered a seasonal trend ($Season_1$ to $Season_3$; the reference is fall). The boundary layer height, wind direction, and the main cause of air pollutant depend on the season (Miao *et al* 2015, Kim *et al* 2017). With the complex effect of those factors, the average concentration of $PM_{2.5}$ also varies. $PM_{2.5}$ concentration is relatively low in summer and fall, and high in winter and spring (Park 2021). The study site saw twice as much $PM_{2.5}$ in winter compared with summer (Visual 2020). We also specified the variable of the day of the week (DOW_1 to DOW_6; the reference is Friday), because the number of hospital visits differs by the day. To control for the locational characteristics of each spatial unit, we introduced the fixed effects (SGG). We also specified the number of hospitals (Hospital) on a quarterly basis within the administrative area to scale the patients per hospital. We present the distribution of key variables in figure 4 and descriptive statistics in appendix A.

3. Results

3.1. Modeling fitting and validation

We show the results of GAMs in table 3. The results suggest that the model (3) of cubic regression spline smoother with 20 knots has the best fit among the three models. It has the highest deviance explained and the lowest AIC and UBRE score in models for all respiratory diseases. The model (1) of the thin plate regression spline has the worst fit, which has the lowest AIC and UBRE score in the four respiratory disease models excluding pneumonia. Therefore, we selected the model (3) of cubic regression spline smoother with 20 knots as the final model.

3.2. The effect of alert messages on respiratory disease

We present the analytical results in table 4. We found that the alert system significantly reduces hospital visits and admissions and that WEA has a greater impact than AIT.

First, days with the issuance of both alert systems have 8.6% lower number of new patients with respiratory diseases than days without (Coeff. $= -0.086$, $p = 0.00$). The alert systems were effective in reducing hospital visits and admissions for all individual respiratory sicknesses—COPD (Coeff. $= -0.132$, $p = 0.00$), RTI (Coeff. $= -0.100$, $p = 0.00$), pneumonia (Coeff. $= -0.080$, $p = 0.05$), and asthma (Coeff. $= -0.058$, $p = 0.00$). The effect last more than a day for only two kinds of respiratory sicknesses—RTI (Coeff. $= -0.074$, $p = 0.00$) and pneumonia (Coeff. $= -0.059$, $p = 0.10$).

Second, on the day of alert issuance by WEA, total hospital visits and admissions by respiratory sickness are reduced by 12.5% (Coeff. $= -0.125$, $p = 0.00$), controlling for the number of hospitals, the concentration of $PM_{2.5}$ and other air pollutants, weather, time, and AIT effects, considering a 1% significance level. This result implies that WEA may have altered the behavior of people with current and potential respiratory problems: they might refrain from outdoor activities in response to the alert. Such reduced chance of exposure to PM would prevent outbreaks of new

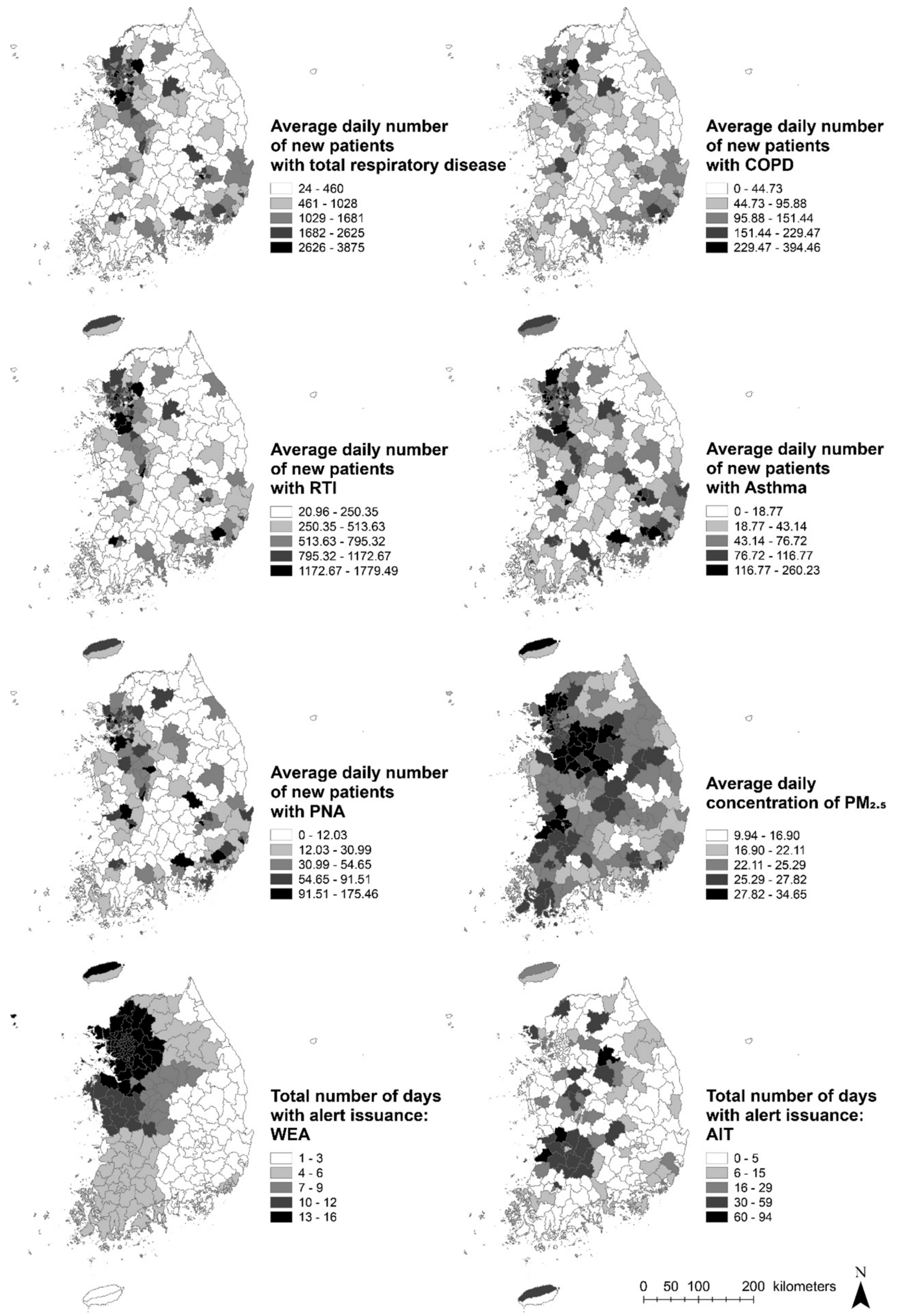

Figure 4. The distribution of average daily numbers of new patients with respiratory sicknesses (total) and with each individual respiratory sickness, average daily concentration of $PM_{2.5}$, and total number of days with alert issuances of each kind during the study period (January 2015–October 2019).

Table 3. The result of three models' fit statistics depending on smoothers.

Smooth construct	Fit statistics	Total	COPD	RTI	Asthma	Pneumonia
Model (1): thin plate regression spline	Adjusted R^2	0.868	0.805	0.850	0.821	0.807
	Deviance explained	88.2%	81%	85.7%	83.1%	83.5%
	AIC	4378 443	2991 789	3940 181	2633 103	2313 896
	UBRE	2190 053	1496 645	1970 903	1317 312	1157 685
Model (2): cubic regression spline (knots = 10)	Adjusted R^2	0.868	0.804	0.850	0.821	0.807
	Deviance explained	88.2%	81%	85.7%	83.1%	83.5%
	AIC	4378 228	2991 751	3939 926	2633 062	2314 010
	UBRE	2189 956	1496 605	1970 757	1317 268	1157 722
Model (3): cubic regression spline (knots = 20)	Adjusted R^2	0.876	0.815	0.859	0.827	0.826
	Deviance explained	88.5%	81.5%	86.1%	83.4%	84.3%
	AIC	4369 309	2984 802	3930 906	2628 102	2299 649
	UBRE	2185 538	1493 210	1966 320	1314 870	1150 639

symptoms or aggravations of existing illnesses. The effect of the alarm lasts two consecutive days, in that people seem to continue to be cautious in doing outdoor activities for at least two days after they get the WEA message. The two-day lag variable of WEA issuance is associated with a decrease in the number of new respiratory patients by 5.3% (Coeff. = −0.053, $p = 0.00$).

The WEA was effective in reducing hospital visits and admissions for all individual respiratory sicknesses examined in this study. The WEA has the highest effect on RTI, 15.5% reduction (Coeff. = −0.155, p = 0.00), followed by COPD (Coeff. = −0.130, p = 0.00), pneumonia (Coeff. = −0.100, p = 0.00), and asthma (Coeff. = −0.084, $p = 0.00$). As may be easily imagined, taking daily preventive measures inspired by alert messages would be the most beneficial in avoiding seasonal infectious diseases rather than chronic diseases (Biggerstaff *et al* 2016). However, with lower magnitude, the alert messages also worked to reduce the number of hospital visits and admission for chronic symptoms, such as COPD. Those people with chronic symptoms might be more circumspect so as not to worsen their condition (Vlaeyen and Linton 2000, Hill 2019), thus they would have been sensitive in complying with the guidelines provided by the alert. For three individual sicknesses, the duration of the alarm exceeded a day. A WEA alert issued two days prior has a reduction effect of a lesser magnitude, reducing pneumonia by 9.1% (Coeff. = −0.091, p = 0.00), followed by RTI (Coeff. = −0.075, $p = 0.00$), and COPD (Coeff. = −0.048, $p = 0.00$).

Third, on the day of AIT alert issuance, the total hospital visits and admissions for respiratory sicknesses declined by 2.5% (Coeff. = −0.025, $p = 0.00$), controlling for the aforementioned factors. Compared with the case of WEA, the current effect was 10 percentage points lower, suggesting a lower effectiveness for this type of alert message system. The two-day duration of the effect that was observed for the WEA system was not observed here. After two days, the effect of AIT disappeared. The two-day lag variable of AIT issuance is associated with an increase in the number of new respiratory patients by 2.0% (Coeff. = 0.020, p = 0.05). The AIT effects were smaller for all of four individual respiratory sicknesses. Unlike the WEA, the AIT has the highest reduction effect for one of the chronic symptoms, asthma by 3.8% (Coeff. = −0.038, p = 0.00), followed by pneumonia (Coeff. = −0.031, p = 0.10), COPD (Coeff. = −0.020, p = 0.10), and RTI (Coeff. = −0.019, $p = 0.10$).

By comparing the effects, we revealed that alert messaging through WEA is more effective than AIT. This difference can be attributed to the target audiences. Whereas WEA is for everyone with a cell phone connection, AIT is only for subscribers who are willing to receive more information regarding air quality, such as both predicted and current concentrations of $PM_{2.5}$. The request-based alert system has a clear limitation. According to the results of a survey conducted in 2017 in a city in the Seoul Metropolitan Area called Suwon City, 9% of the participants answered that they did not know about the AIT service, and among the rest who knew about the service, 42% had not signed up for it (Suwon City 2017). Even the number of AIT subscribers has decreased from 37 594 in 2018 to 16 785 in 2019 (Visual 2020).

Additionally, WEA and AIT are issued at different $PM_{2.5}$ concentration level. WEA is issued only at the warnings and emergency reduction measures are active, while AIT is issued even at lower levels of such criteria and thus issued more frequently. In 2019, WEA was sent 18 days while AIT was sent 33 days in Seoul (Seoul Metropolitan Government 2020). Therefore, it might be reasonable to guess that people might feel alert fatigue and be less responsive to AIT (Baseman *et al* 2013). One extant study emphasized that people do not feel the necessity of additional information because they already receive sufficient PM-related information from multiple channels, such as mobile

Table 4. Analytical results of the generalized additive model assessing the effect of WEA and AIT alert issuance on all individual respiratory sicknesses and on the total.

Variable	Total	COPD	RTI	Asthma	Pneumonia
Both	−0.086***	−0.132***	−0.100***	−0.058**	−0.080**
	(0.024)	(0.031)	(0.026)	(0.029)	(0.032)
Both_{t-2}	−0.039	−0.025	−0.074***	0.036	−0.059*
	(0.025)	(0.031)	(0.026)	(0.029)	(0.032)
WEA	−0.125***	−0.130***	−0.155***	−0.084***	−0.100***
	(0.012)	(0.015)	(0.012)	(0.014)	(0.015)
WEA_{t-2}	−0.053***	−0.048***	−0.075***	0.003	−0.091***
	(0.012)	(0.015)	(0.013)	(0.015)	(0.016)
AIT	−0.025***	−0.020*	−0.019*	−0.038***	−0.031**
	(0.010)	(0.012)	(0.010)	(0.012)	(0.012)
AIT_{t-2}	0.020**	0.022*	0.020**	0.016	−0.017
	(0.010)	(0.012)	(0.010)	(0.011)	(0.012)
$f(\text{PM}_{2.5})$	8.883***	7.446***	8.594***	8.159***	7.092***
	(10.515)	(8.888)	(10.190)	(9.695)	(8.484)
$f(\text{PM}_{2.5(t-2)})$	8.239***	6.217***	8.317***	6.500***	5.710***
	(9.789)	(7.489)	(9.877)	(7.810)	(6.913)
$f(\text{PM}_{2.5(t-4)})$	7.655***	7.862***	7.692***	8.075***	7.366***
	(9.126)	(9.357)	(9.168)	(9.598)	(8.793)
$f(\text{PLT}_1)$:O3	5.201**	4.806***	5.104**	7.032***	10.623***
	(6.4932)	(6.037)	(6.381)	(8.615)	(12.610)
$f(\text{PLT}_2)$:SO2	5.885***	7.179***	6.473***	3.659*	5.313***
	(7.110)	(8.582)	(7.780)	(4.594)	(6.456)
$f(\text{MTR}_1)$: temperature	15.167***	13.268***	14.958**	12.954***	13.513***
	(17.101)	(15.428)	(16.931)	(15.108)	(15.658)
$f(\text{MTR}_2)$:wind speed	4.445***	4.800***	4.316***	5.124***	6.366***
	(5.398)	(5.800)	(5.254)	(6.175)	(7.606)
$f(\text{MTR}_3)$: precipitation	10.736***	9.072***	10.446***	8.461***	7.515***
	(12.464)	(10.685)	(12.160)	(10.015)	(8.966)
$f(\text{Time})$	18.993***	18.987***	18.993***	18.989***	18.996***
	(19.000)	(19.000)	(19.000)	(19.000)	(19.000)
Season_1 :spring	0.004	−0.091***	0.021***	0.014**	−0.023***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)
Season_2 :summer	−0.010***	0.011**	0.019***	0.035***	0.061***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
Season_3 :winter	0.166***	0.140***	0.187***	0.177***	0.374***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)
DOW_1 :Monday	0.259***	0.265***	0.273***	0.243***	0.270***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
DOW_2 :Tuesday	−0.051***	−0.036***	−0.047***	−0.053***	−0.093***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
DOW_3 :Wednesday	−0.102***	−0.083***	−0.105***	−0.096***	−0.101***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
DOW_4 :Thursday	−0.063***	−0.049***	−0.060***	−0.074***	−0.053***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
DOW_5 :Saturday	−0.295***	−0.411***	−0.308***	−0.332***	−0.304***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
DOW_6 :Sunday	−2.144***	−2.358***	−2.044***	−2.312***	−1.581***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
$f(\text{Hospital})$	17.540***	18.582***	17.926***	18.504***	18.957***
	(18.570)	(18.946)	(18.739)	(18.922)	(18.999)
Constant	6.293***	4.173***	5.240***	3.649***	2.122***
	(0.019)	(0.024)	(0.021)	(0.023)	(0.024)
Observations	318 591	318 591	318 591	318 591	318 591
Adjusted R^2	0.876	0.815	0.859	0.827	0.826
Deviance explained	88.5%	81.5%	86.1%	83.4%	84.3%
AIC	4369 309	2984 802	3930 906	2628 102	2299 649
UBRE	2185 538	1493 210	1966 320	1314 870	1150 639

Note: parametric coefficients: coefficient and standard errors in parentheses.
Smooth terms (f(variable)): effective degrees of freedom (edf) and reference degrees of freedom (Ref.df) in parentheses.
PLT: air pollutant, MTR: meteorological factor, DOW: day of the week.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

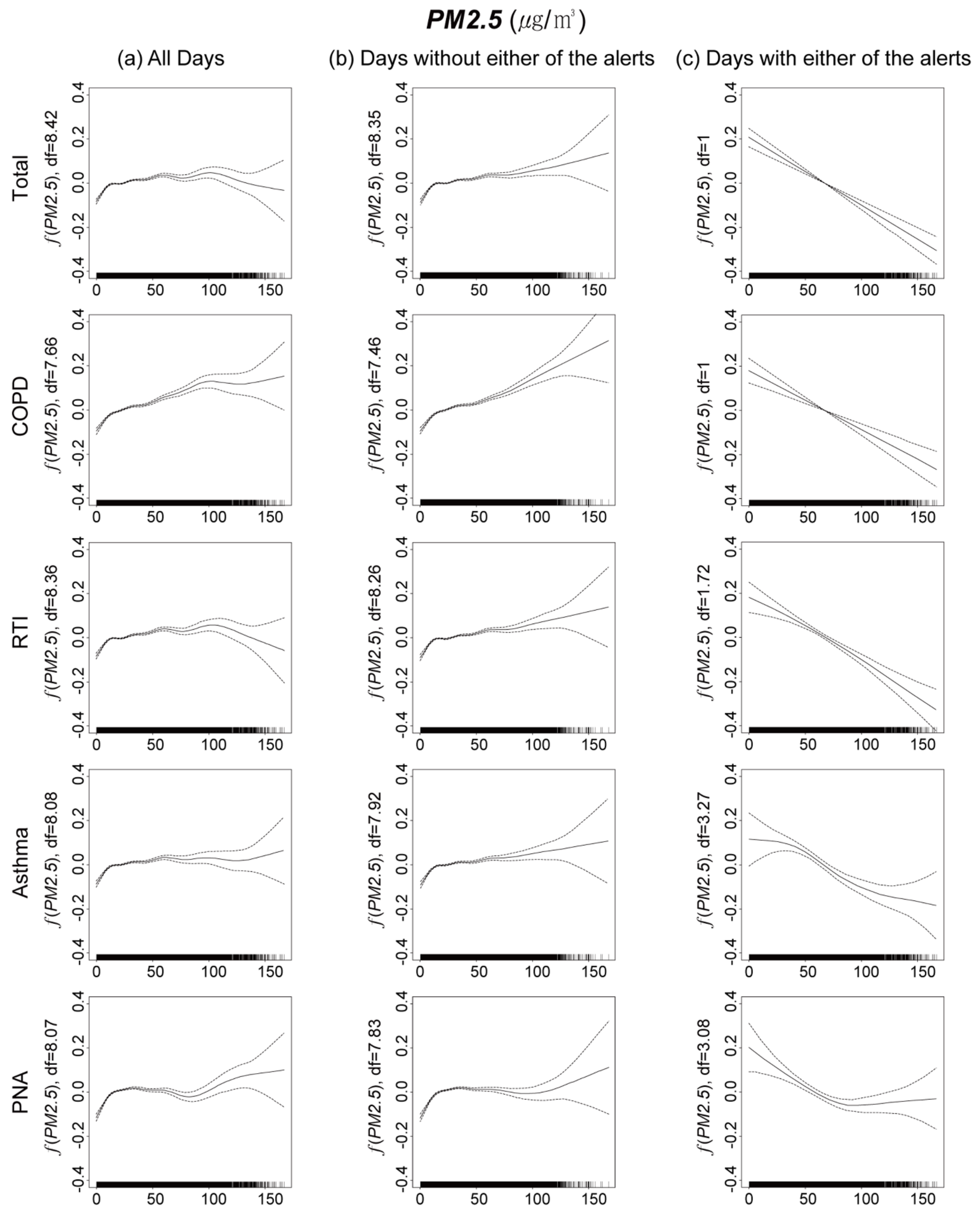

Figure 5. Estimated smooth function and 95% CI of the $PM_{2.5}$ by individual respiratory sicknesses and for total of all sicknesses. (a) Entire study period ($n = 1{,}761$), (b) days with either one of the alerts ($n = 291$), (COPD: chronic obstructive pulmonary disease, RTI: respiratory tract infection, PNA: pneumonia).

phone applications, newspapers, and outdoor electronic boards (Min 2019). Moreover, we speculated that the way of WEA delivery is more effective than that of the AIT. WEA drew people's attention as it comes as pop-up message with vibration and alarm sounds, while AIT comes in general SNS text message style, often could be confused with other messages.

While the AIT system seems redundant, interestingly, it complements the WEA system to contribute to overall protective measures. WEA has the largest reduction effect on the number of new patients with seasonal infectious diseases, while AIT was effective for chronic diseases. By sending simple and direct alerts to a broader range of people, the former would help people to reduce the chance of short-term exposure to PM in general. The latter, however, might be mostly of interest to people with underlying medical conditions, particularly those related to the respiratory system, who would subscribe to receive additional information on PM and follow detailed guidelines to care for themselves.

Table 5. Comparing the WEA effect by adding the alert category.

Variable	Entire study period	Before February 2019	After February 2019
WEA	-0.125^{***}	-0.123^{***}	0.026
	(0.012)	(0.020)	(0.017)
WEA_{t-2}	-0.053^{***}	-0.032	0.030^{*}
	(0.012)	(0.020)	(0.018)
Constant	6.293^{***}	6.467^{***}	6.302^{***}
	(0.019)	(0.022)	(0.155)
Observations	318 591	254 356	64235
Adjusted R^2	0.876	0.875	0.902
Deviance explained	88.5%	88.4%	89.4%
AIC	4369 309	3513 482	850 370.5
UBRE	2185 538	1757 540	425 768.7

$^{***}p < 0.01$, $^{*}p < 0.1$.

In order to visualize the effects of the two alert systems and to speculate about the counterfactual condition, we stratified the sample into three groups and plotted the relationship between the number of hospital admissions and visits for respiratory sicknesses and $PM_{2.5}$ concentration in figure 5 for (a) the entire study period of 1761 days, (b) the 1761 days when either type of alert was not issued, and (c) the 291 days when either type of alert was issued. Because there was at least one region where the $PM_{2.5}$ alert was not issued, the number of days of the first two conditions are the same.

First, for the entire study period, short-term exposure to $PM_{2.5}$ did not have a noticeable effect on the number of new patients with all individual respiratory sicknesses (figure 5(a)). When we control the alert issuance, a higher $PM_{2.5}$ concentration does not necessarily lead to an immediate increment of those patients. Second, for days without either of the alerts (figure 5(b)) the number of patients increased according to the concentration of $PM_{2.5}$, as suggested in the previous studies (Neuberger *et al* 2004). Part of the reason might be the preventive protocols that individuals follow, such as refraining from outdoor activities in face of the high risk of PM. In the condition of high $PM_{2.5}$ concentration when alert is issued, the alert system may have guided them. The negative relationship becomes apparent in that, on the days of higher average PM level, more jurisdictions issued alerts to warn people, consequently the number of new patients gets even lowered compared to the days of low PM levels (figure 5(c)). This is obvious evidence of the effectiveness of the warning.

We found that time and season were the other factors that influence the number of new patients. The number of respiratory disease outbreaks changes by season. In winter, the number of hospital visits and admissions for respiratory sicknesses is higher by 16.6%, compared with that of the autumn, the reference group (Coeff. $= 0.166$, $p = 0.00$). On the other hand, the number of such new patients declined in the summer by 1.0% (Coeff. $= -0.010$, $p = 0.00$). Since hospitals have different operating hours for each day of the week, the number of respiratory patients varies by the day of the week; 25.9% (Coeff. $= 0.259$, $p = 0.00$) more people go to the hospital for the aforementioned sicknesses on Monday, while 10.2% (Coeff. $= -0.102$, $p = 0.00$) and 6.3% (Coeff. $= -0.063$, $p = 0.00$) fewer people do so on Wednesday and Thursday, compared with Friday.

3.3. The change of WEA quality

We investigated whether the added alert category—emergency reduction measures—changed the effects of WEA alert, by dividing our study period into the two; before and after February 2019 (table 5). After the day, the reduction effect of WEA was 14.9% lower than before. While the WEA issuance before February 2019 is associated with a decrease in the number of new respiratory patients by 12.3% at a 1% significance level (Coeff. $= -0.123$, $p = 0.00$), after the day, it has an increase effect by 2.6% but does not have statistical significance (Coeff. $= 0.026$, $p = 0.13$). We reasoned that this is not a sufficient period to reveal the effect of WEA change in additional categories. After February 2019, WEA issued only the 13 times. Therefore, it should be evaluated after a more sufficient period of time to identify the effect of the improvement.

4. Conclusion and discussion

In this research, we attempted to investigate the effect of $PM_{2.5}$ alert messages on reducing the number of new patients with respiratory sicknesses, presumably by encouraging preventive behaviors. In particular, we compared the two methods of alert distribution—the WEA and AIT systems—for their effects on the four common respiratory sicknesses: COPD, RTI, asthma, and pneumonia. We used GAM to account for the non-linear relationship between the number of new patients and covariates such as weather and air pollutants.

Our results confirmed that the alert message has a statistically significant reduction effect on new patients with the four respiratory sicknesses. Of the two systems, WEA was found to be more effective than AIT. The former reduced the total number of new patients with respiratory sicknesses by 12.5%, while the latter did so by 2.5%. In terms of the duration of the effects, the effect of WEA lasted for two days for all individual respiratory sicknesses.

This study is a rare attempt to reveal the effect of the newest air pollution warning system, the mobile-based alert messaging. To the best of our knowledge, this study is the first to analyze the relationship between a mobile-based alert system and its immediate health outcomes on a daily basis. Compared with existing studies, the current analytical results suggest that mobile-based alert systems perform better than other adaptive policy measures, such as news, smartphone applications, websites, and outdoor electronic boards, although the spatial and temporal context of each study differs, and the generalization is limited (Lyons *et al* 2016, Saberian *et al* 2017, Li *et al* 2019, Mason *et al* 2019). A part of the larger magnitude effect we derived might be due to the directness of the system by its very nature. Since mobile phone text messages allow public notification to reach people at the most personal level (Aloudat and Michael 2011, Kim *et al* 2019a), we can assume that the ratio of the treatment-on-the-treated effect over the treatment effect could be relatively high.

Such findings provide evidence for policy implications regarding air pollution adaptation. First, by comparing the effectiveness of the vast range of adaptation measures deployed in the country, resources should be concentrated on the ones that work best. Currently, many of those measures have similar or overlapping functions. Even the two different systems analyzed in this study, WEA and AIT, have much overlapping content, while the latter has not even attracted public attention and is underused. Implementation of policies requires a large amount of funding and human resources; therefore, those should be consolidated, prioritizing the most effective approaches. Second, when people get an alert message, they are more likely to check the actual PM level and decide whether to alter their outdoor activity plans. Therefore, it is important to ensure the reliability of the alert by following a national guideline. However, municipalities often act at their own discretion (Kim and Lee 2020). For example, alerts through WEA should be sent at the levels specified for the warning and the emergency reduction measure, but local governments frequently send alerts at a lower level. Such practices may cause alert fatigue and thus reduce the reliability of alert systems. Finally, in order to increase the reliability of alerts, the PM warning area, which is the regional criterion for alert transmission, needs to be readjusted. The PM warning area is still set wider than the location of the observatory, and alerts are sent based on the average concentration of the area. Some area would receive unnecessary alerts or the other would not receive necessary alert depending on the local deviation from the average (figure 1). Therefore, local governments should consider adjusting this to provide people with air pollution information tailored to their region.

This research has some limitations. First, our analyses could not reveal the underlying reasons behind the association between the PM alerts and the reduced number of the patients. We can attribute the positive health outcomes to the alert system, one of the adaptive measures that encourages people's preventive behavioral changes, however, we could not rule out other types of measures, for example, those of reducing pollution emission. When the PM level gets higher, it is recommended to take public transportation, shorten operating hours at large business sites operated by public institutions. The number of road washout and dust cleaning is also increased. Since both measures are active simultaneously, separating individual effects requires additional data collections and more advanced analytical strategies. Second, the health outcome we considered, the number of hospital visits and admissions, is one of the conservative indicators of the policy effects. The effect could have been measured as more minor forms, such as the pattern of non-prescription medication consumptions, and those could also have been considered to present more comprehensive perspectives.

Finally, for reasons of privacy, we could not take into account personal characteristics. People respond differently to an alert depending on their prior experience, pre-existing beliefs, costs of compliance, and other personal factors (Mayhorn and McLaughlin 2014). In particular, it is well known that children and some elderly groups have lower risk cognitive levels (Neidell 2009). Young children are susceptible to air pollution due to a lot of outdoor activity with their lungs not fully developed, and the elderly are at high risk of health complications at high level of pollutants (Ward and Beatty 2016). Further study will be necessary to refine the alert system for better performance for diversified groups among the population, using more detailed demographic information.

Data availability statement

The data generated and/or analyzed during the current study are not publicly available for legal/ethical reasons but are available from the corresponding author on reasonable request.

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Appendix A. Descriptive statistics

	Entire study period (Obs. = 318 591)				Days without either of the alert (Obs. = 314 852)				Days with either of the alert (Obs. = 304)			
Variable	Mean	Std. dev.	Min.	Max.	Mean	Std. dev.	Min.	Max.	Mean	Std. dev.	Min.	Max.
Total	1132.61	1108.82	0	10 579	1132.37	1109.31	0	10 579	1069.10	1052.30	3	6012
COPD	100.83	101.1	0	1285	100.73	101.03	0	1285	94.31	97.66	0	589
RTI	513.34	507.51	0	4817	513.24	507.80	0	4817	465.34	437.73	1	2,426
Asthma	59.82	60.11	0	639	59.83	60.11	0	639	57.27	63.29	0	439
Pneumonia	37.46	43.07	0	572	37.47	43.09	0	572	34.55	35.29	0	175
$PM_{2.5}$	24.2	14.96	0	166.45	23.62	13.77	0	149.54	89.54	27.43	19	166.45
$PLT_1 : O_3$	2.89	1.37	0.1	12.49	2.89	1.37	0.1	12.49	3.07	1.53	40.38	7.31
$PLT_2 : SO_2$	0	0	0	0.04	0.00	0.00	0	0.04	0	0	0	0.02
MTR_1 : temperature	13.58	9.83	−19.87	34.36	13.68	9.83	−19.87	34.36	4.92	3.54	−3.73	16.23
MTR_2 : wind speed	1.81	1.14	0	17.4	1.81	1.15	0	17.40	1.17	0.61	0.05	4.6
MTR_3 : precipitation	3.34	12.4	0	358.5	3.37	12.46	0	358.5	0.01	0.19	0	3.24

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