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Forecasting COVID-19 cases by assessing control-intervention effects in Republic of Korea: A statistical modeling approach

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Abstract  The Coronavirus disease of 2019 (COVID-19) is an ongoing public health concern worldwide. COVID-19 infections continue to occur and thus, it is important to assess the effects of various public health measures. This study aims to forecast COVID-19 cases by geographical area in Korea, based on the effects of different control-intervention intensities (CII). Methods involved estimating the effective reproduction number ($R_t$) by Korean geographical area using the SEIHR model, and the instantaneous reproduction number using statistical model, comparing the epidemic curves and high-, intermediate-, and low-intensity control interventions. Here, short-term four-week forecasts by geographical area were conducted. The mean of delayed instantaneous reproduction number was estimated at 1.36, 1.03, and 0.93 for the low-, intermediate-, and high-intensity control interventions, respectively, in the capital area of Korea from July 16, 2020, to March 4, 2021. The COVID-19 cases were forecasted with an accuracy rate of 11.28%, 13.62%, and 20.19% MAPE in Korea, including both the capital and non-capital areas. High-intensity control measures significantly reduced the reproduction number to be less than one. The proposed model forecasted COVID-19 transmission dynamics with good accuracy and interpretability. High-intensity control intervention, active case detection, and isolation efforts should be maintained to control the pandemic.

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1. Introduction

The Coronavirus disease of 2019 (COVID-19), which is caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), has been an ongoing concern since it was first reported in Wuhan, China, in December 2019 [1]. COVID-19
was declared a global pandemic by the World Health Organization (WHO) on March 11, 2020 [2]. Common symptoms include a fever, dry cough, fatigue, chills, headache, and sore throat whereas severe symptoms often indicate pneumonia, including high fever, severe cough, and shortness of breath [3]. COVID-19 has continued to spread with more than 12.79 million confirmed cases and 2,798,000 deaths being reported worldwide (in more than 220 countries) by March 31, 2021 [4].

The first Korean case was identified on January 20, 2020, in a patient who had previously visited Wuhan, China. This initiated COVID-19 transmission in Korea, after which the number of COVID-19 cases rapidly increased. According to the Korea Disease Control and Prevention Agency (KDCA), by March 31, 2021, 103,088 confirmed cases—including 1,731 deaths—had been reported [5]. The 31st case was reported in Daegu on February 18, 2020 and was, later, linked to church attendance. COVID-19 then rapidly propagated through clusters in hospitals, churches, and so on [6,7]. The Korean government raised the COVID-19 alert to the highest level on February 23, 2020 to respond to the increasing COVID-19 case numbers and facilitate implementation of comprehensive social distancing measures, including enhanced infection control measures, large-scale epidemiological investigations, rapid diagnosis, case isolation, contact tracing, quarantine, and public transportation restriction [8]. Despite these control interventions, COVID-19 infections continued to occur in many areas, including a large number in the Seoul metropolitan area [5]. Since December 2021, there have been three waves of COVID-19 outbreak in Korea [9] and thus, the virus must be closely monitored to track the progression of such outbreaks and assess the effects of various public health measures in real time.

Mathematical modeling has been used to predict the evolution of the COVID-19 pandemic and to evaluate the effectiveness of proposed and enacted interventions, particularly in terms of investigating and analyzing COVID-19 transmission dynamics. Here, many previous studies have employed both susceptible–infectious–recovered (SIR) and susceptible–exposed–infectious–recovered (SEIR) type compartmental models [10–18]. Booton et al. [10] used mathematical models to determine that all interventions—including social distancing, school closure, and lockdown—reduced the reproductive number in South West England. Similarly, Lyra et al. [15] estimated hospitalization and intensive care unit (ICU) numbers depending on social distancing intensity in Brazil. Compartmental models of COVID-19 including the infection by super-spreaders were developed in [16–18].

The most effective strategies against the COVID-19 spread were analyzed, with consideration given to the strict social distancing, contact-tracing, restriction on public gathering, and self-isolation policy set out in [19,20]. In addition, 10-day-ahead predictions of COVID-19 transmission in the United Kingdom played an important role in the reduction of new cases, capturing the decreasing trend from the model in [21]. The reproduction number is computed by fitting the model to the number of reported COVID-19 cases in 2020, shown in [22,23]. They obtained the basic reproduction number at 1.20, 1.30 in Pakistan and Kingdom of Saudi Arabia, respectively. Novel SEIR-type compartmental models have been developed to analyze the effect of the lockdown in China [24–26]. Tian et. al. found that the Wuhan lockdown delayed the outbreak in other provinces in China by 2.91 [25].

In this study, COVID-19 cases in Korea were forecasted by geographical area, based on the effects of different control-intervention intensities (CII). To the researchers’ knowledge, no previous scientific reports have forecasted COVID-19 case numbers based on control-intervention intensities (CII). In detail, the COVID-19 transmission potential—including the effective reproduction number, \( R \)—for different geographical areas in Korea, was estimated and the susceptible–exposed–infectious–hospitalized–recovered (SEIHR) mathematical model used to assess the effects of control interventions of different CII. The instantaneous reproduction number \( (r_{g, t}) \) in Korea, which can indicate the magnitudes and intensities of the control interventions required to mitigate the COVID-19 outbreak was also estimated [27,28]. Additionally, short-term forecasts were conducted using the SEIHR compartment model and renewal equations in terms with CII levels, incorporating the time lag, which reflects the effect of control interventions on the transmission dynamics of confirmed cases to the reproduction number [29,30]. The model successfully provided useful predictions, forecasting the pandemic size and characterizing the temporal changes in \( R \). Moreover, it indicated the effectiveness of potential control measures, thereby providing valuable information for public health policy makers. To the best of the researchers’ knowledge, this is the first forecasting analysis conducted based on the effects of control interventions and which analyzes simple mathematical modeling in Korea, using epidemiological data from July 2020 to April 2021.

2. Methods

An ordinary differential equation, provided by the SEIHR model, was used to describe the COVID-19 transmission dynamics in Korea. The process is summarized as follows: First, the effective reproduction number were estimated according to the time intervals using SEIHR model. Second, the instantaneous reproduction number \( (r_{g, t}) \) was calculated from the renewal equation after which, the probability distribution of \( r_{g, t} \), which reflects the effects of control intervention, was estimated. Third, the probability distribution of the delayed instantaneous reproduction number \( (r_{g, t}) \) was estimated according to the different control intervention intensities (i.e., \( x \) = low, intermediate, and high). Finally, randomly sampled reproduction numbers were applied into the SEIHR model to forecast the number of COVID-19 cases for the next four weeks (28 days) from the probability distribution defined by a given \( x \) CII (See Fig. 1).

2.1. Data collection

Daily confirmed local COVID-19 case numbers for the Republic of Korea were collected from July 2020 to March 2021, as provided by the KDCA [5]. The following eight geographical areas were analyzed: Korea (total); the Seoul Metropolitan Area (Seoul, Gyeonggi-do, Incheon), i.e. the “capital area”; Korea excluding the capital area, i.e., the “non-capital area”; the Chungcheong area (Daejeon, Chungcheongnam-do, Chungcheongbuk-do); the Gyeongbuk area (Daegu, Gyeongsangbuk-do); the Gyeongnam area (Busan, Ulsan, Gyeongsangnam-do); the Honam area (Gwangju, Jeollabuk-
do, Jeollanam-do); and the Gangwon area (Gangwon-do). The pandemic curves for the eight geographical areas are shown in Fig. 2 below (see also, S1 Table).

2.2. Social distancing in Republic of Korea

In 2020, the Korean government initiated non-pharmaceutical interventions, including social distancing and mask-wearing. Social distancing requires people to remain 1.5 m apart as COVID-19 spreads through air droplet transmission and, therefore, effectively reduces the spread of the virus. Hence, it is important to explore the geographical area–specific control effect with respect to social distancing.

On March 22, 2020, the Korean government strengthened social distancing strategies [31] and on June 28, 2020, established three different levels of distancing control interventions [32]. On November 8, 2020, public health authorities revised these guidelines, creating five levels from the original three to construct stricter guidelines for social distancing campaigns [33]. The social distancing measures implemented in Korea are described in S2 Table. This study grouped control interventions as low, intermediate, and high intensity (Table 1) with each geographical area including several cities, where the levels of control interventions were differently implemented [32,33]. CII in a geographical area is determined by following the stronger policies among cities in the area. Likewise, CII in Korea is defined by stronger policies among all cities.

For each \( g \in G = \{ \text{Korea}, \ldots, \text{Gangwon area}\} \), the vector of time interval denoted by \( T_g = \{P_1, P_2, \ldots, P_{n_g}\} \) was newly defined where \( P_i \) represents the epidemiologically important events and control interventions and where \( n_g \) is the number of time intervals for the estimation in the geographical area \( g \). Fig. 3 and S1 Figure show event timelines related to CII and sporadic outbreaks for the time intervals from July 16, 2020, to March 4, 2021, for the eight geographical areas.

2.3. SEIHR transmission model

SIR-type models, also known as Kermack–McKendrick models [34], consist of a set of differential equations and have been applied to a variety of infectious diseases in various studies [35–37]. The COVID-19 infection transmission model, however, is a deterministic SEIHR model and has also been analyzed in previous studies [11,38,39]. This model is divided into five human compartments—susceptible (S), exposed (E), infectious (I), hospitalized (H), and recovered (or removed, R). The differential equations are expressed as follows:

\[
\begin{align*}
\frac{dS}{dt} &= -b(t)S \frac{I}{N} \\
\frac{dE}{dt} &= b(t)S \frac{I}{N} - \alpha E \\
\frac{dI}{dt} &= \alpha E - q I \\
\frac{dH}{dt} &= q I - \gamma H \\
\frac{dR}{dt} &= \gamma H 
\end{align*}
\]

(1)
Table 2 lists the model parameters. Specifically, \( b(t)SI/N \) describes the rate at which susceptible individuals are infected by infectious individuals, with \( b(t) \) and \( N \) representing the transmission rate and total population, respectively. Latent individuals become infected at a rate \( a \). A fraction \( q \) of the infectious individuals is hospitalized, and the hospitalized individuals recover or are removed at rate \( \gamma \). The newly confirmed cases were calculated as \( c(t) = qI(t) \). The initial values are described in S3 Table. The main code of R programming and data are available on Github (https://github.com/model-fitting/forecasting-COVID-19-cases.git).

### Table 1

| Control-intervention intensity (CII)* | Three-tier system | Five-tier system |
|-------------------------------------|------------------|------------------|
| Low                                 | Level 1          | Level 1          |
| Intermediate                        | Level 2          | Level 1.5        |
| High                                | Level 2.5        | Level 2.5        |
|                                     | Special act for prevention during Korean Thanksgiving and Lunar New Year public holiday | Level 2 is implemented, restricting gatherings to no more than 4 peoples |

* The social distancing level classified as high, intermediate, or low intensity.

2.4. Transmission rate estimation

The effective reproduction number \( R_t \) is the expected number of new infections caused by an infectious individual in a population where some individuals may no longer be susceptible. The effective reproduction number is an important epidemic parameter to assess the effect of control-intervention if active disease transmission continues \( (R_t > 1) \) or ceases \( (R_t < 1) \), thus, the researchers try to satisfy \( R_t < 1 \) to prevent the outbreak [42]. Here, the time-dependent reproduction number, also called the effective reproduction number from SEIHR model, was estimated.

The SEIHR model was fitted to the number of confirmed cases on day \( t \) and in the area \( g \), denoted by \( c(t) \) and thus, the transmission rates were estimated, \( b(t) = \bigcup_{i=1}^{n_t} b_{x_i} \), where \( b_{x_i} \) is the transmission rate for each time interval \( P_i \) for \( i = \{1, 2, \ldots, n_t\} \). Hence, the average effective reproduction number corresponding to each \( P_i \) in model (1) was defined as \( R_{x_i} = b_{x_i}/q \), and the effective reproduction number was defined as \( R_t = \bigcup_{i=1}^{n_t} \{ R_{x_i} \} \), where the susceptible depletions was not involved [43].

Fig. 2 COVID-19 pandemic curves for eight geographical areas between July 2020 and March 2021 in the Republic of Korea. The (A, B) newly confirmed and (C, D) cumulative case numbers are reported by geographical area.
Most studies investigating the amount of heterogeneity in disease transmission have assumed a Poisson process with rate given by the individual reproduction numbers [44–46]. We assumed that the daily counts follow a Poisson distribution [47,48] and the likelihood function during the time interval, $P_i$ in the geographical area $g$, was defined as

$$ L(b_i; c_g(t)) = \prod_{i \in P_i} \frac{e^{-b_i c_g(t)^{x_i(t)}}}{c_g(t)!}. $$

A total of 1000 samples were selected from a normal distribution with $\sigma^2 = \frac{U + L}{2}$, where $U$ and $L$ denote the upper and lower bounds of the profiled-likelihood confidence intervals (CIs) of the estimated transmission rates, respectively. The 50% CIs were obtained from the 25th and 75th percentile, and the 95% CIs were obtained from the 2.5th and 97.5th percentile, which were calculated daily by model (1).

2.5. Distribution of $R_t$ according to CII

This study used a statistical model to estimate the instantaneous reproduction number, representing the average number

Fig. 3 Epidemiologically important events with respect to control interventions in Korea, including both capital and non-capital areas. $P_i$ indicates the time intervals corresponding to the implemented control interventions and epidemiologically important events for the SEIHR model estimation.

| Date       | Korea | Capital area | Non-capital area |
|------------|-------|--------------|------------------|
|            | Event | Event        | Event            |
| 2020       |       |              |                  |
| 07.16      |       |              |                  |
| 08.06      |       |              |                  |
| 08.16      |       |              |                  |
| 08.23      |       |              |                  |
| 09.14      |       |              |                  |
| 09.28      |       |              |                  |
| 10.12      |       |              |                  |
| 11.05      |       |              |                  |
| 11.10      |       |              |                  |
| 11.19      |       |              |                  |
| 11.27      |       |              |                  |
| 12.19      |       |              |                  |
| 12.08      |       |              |                  |
| 12.15      |       |              |                  |
| 12.23      |       |              |                  |
| 2021       |       |              |                  |
| 02.01      |       |              |                  |
| 02.15      |       |              |                  |
| 03.04      |       |              |                  |

| Parameter | Description                                           | Value | Source |
|-----------|-------------------------------------------------------|-------|--------|
| $b(t)$    | Time-dependent transmission rate from susceptible to infectious individuals | Estimation |        |
| $1/\alpha$| Latent period (day)                                   | 5     | [40]   |
| $1/q$     | Period between infectiousness and hospitalization (day) | 4     | [41]   |
| $\gamma$  | Recovered or removed rate (day$^{-1}$)                | 1/14  | [39,41]|

Table 2 Description of SEIHR model parameters.
of secondary cases generated by a single case at time \( t \) in a given \( g \), i.e., \( r_{g,t} \). The renewal equation for the COVID-19 local transmission dynamics is defined as follows \cite{27,28,49,50}:

\[
E(c_g(t)) = r_{g,t} \sum_{\tau=1}^{T} c_g(t-\tau)h_\tau,
\]

where \( h_\tau \) is the probability distribution of the serial interval in \( \tau \) and \( T \) indicates the final time (March 4, 2021). A serial interval is the time interval from illness onset in a primary case (infector) to that in a second case (infectee) \cite{42}. This study assumed the serial interval according to a gamma distribution with mean of 4.8 days and a standard deviation of 2.3 days \cite{51}. The researchers estimated \( r_{g,t} \), based on the ratio of new cases generated at time \( t \) to the total infectiousness of infected individuals at time \( t \) in a given \( g \). In particular, the \( r_{g,t} \) values were calibrated by substituting \( r_{g,t} = c_g(t)/c_g(t-1), \) when the \( r_{g,t} \) values increased abruptly because of a previous period of continued zero cases.

Zhao et al. \cite{52} compared the differences between the effective reproduction number and instantaneous reproduction number. The effective reproduction number can describe the changing dynamics of susceptibility and the effective reproduction number, based the number of cases time series. The instantaneous reproduction number achieved through the statistical model gives descriptive statistics straightforwardly using serial interval and the number of disease cases time series. Moreover, the reproduction number can track abrupt changes \cite{52,53}.

The control-intervention delay effect was incorporated into the instantaneous reproduction number (\( r_{g,t} \)). The delay indicates the time lag until the control interventions implementation (e.g. social distancing) influences the transmission dynamics of COVID-19 \cite{30,54}. The delayed reproduction number (\( r_{d,t}^g \)) can be expressed as the convolution of the probability distribution for the time delay and the reproduction number \cite{29}. The delayed reproduction number was simply defined as \( r_{d,t}^g = r_{g,t+d} \), where \( d \) is the delay with \( d \in D = \{3, 7, 10, 14\} \) in a given \( g \). Adhering to \( d \) days, the probability distribution of \( r_{d,t}^g \) was estimated, assuming a gamma distribution. Finally, the probability distribution of \( r_{d,t}^g \) was obtained, denoted by \( f_{g,t}^{d,r} \), for a given \( x \) CII. That is, \( x \) indicates low, intermediate, or high excluding extreme outliers, which are values more extreme than \( Q_1 - 3 \times IQR \) or \( Q_3 + 3 \times IQR \), where IQR indicates the interquartile range and \( Q_1 \) is the lower quantile and \( Q_3 \) is the upper quantile.

### 2.6. COVID-19 case forecasting according to CII

The number of new COVID-19 cases (i.e., \( c_g(t) \)) in a given \( g \) from March 5 to April 1, 2021, were forecasted according to the CII and 1000 samples of instantaneous reproduction numbers from \( f_{g,t}^{d,r} \), with \( d \) delay days and CII \( x \) (i.e., \( \rho \sim f_{g,t}^{d,r} \)) were randomly chosen. The SEIHR model was simulated by randomly selecting the daily transmission rates, \( \beta(t) = \rho t \) for the next four weeks. Again, the 95% confidence intervals (95% CI) were obtained from the 2.5th and 97.5th quantiles, using 1000 random samples from a normal distribution with \( \sigma^2 = \frac{\hat{\omega}^2}{\hat{\theta}} \).

Furthermore, the root mean square error (RMSE) and mean absolute percentage error (MAPE) were used to evaluate the forecasting accuracy for the new COVID-19 case numbers according to the CII. RMSE and MAPE are calculated by

\[
RMSE = \frac{1}{m} \sqrt{\sum_{\tau=0}^{T} \left( \frac{c_g(\tau)^{\text{actual}} - c_g(\tau)^{\text{forecasted}}}{c_g(\tau)^{\text{actual}}} \right)^2}
\]

and

\[
MAPE = \frac{1}{m} \sum_{\tau=0}^{T} \left| \frac{c_g(\tau)^{\text{actual}} - c_g(\tau)^{\text{forecasted}}}{c_g(\tau)^{\text{actual}}} \right| \times 100.
\]

Here, \( c_g(\tau)^{\text{actual}} \) and \( c_g(\tau)^{\text{forecasted}} \) represent the estimated and newly observed COVID-19 case numbers on day \( \tau \). The times \( t_0 \) and \( t_f \) indicate the first (May 5, 2021) and last (April 1, 2021) days of the forecasting time interval, and \( m \) is the total number of days (i.e., \( m = 28 \)).

### 3. Results

#### 3.1. Transmission rate estimation using the SEIHR model

For each time interval, a given \( g \), \( P_i \in T_g \) was estimated using the maximum likelihood estimation. Fig. 4 compares the observed and estimated (using model (1)) COVID-19 case numbers corresponding to \( T = \{ T_g \} \). S2 Figure shows a comparison of the observed and estimated cumulative COVID-19 cases. The estimated values obtained from the model mostly conformed to the observed cases within the 95% CI, however, occasional failures occurred, such as the abrupt increases in new cases in the Chungeon, Gyeongnam, Honam, and Gangwon areas. In detail, 176 and 147 cases of cluster infection were observed at the International School in Daejeon city, Chungeon area, and in Gwangju city, Honam area, respectively, at the end of January 2021 \cite{55}. Moreover, the nursing hospital in Gyeongnam area reported fifty-three cases on October 15, 2020 \cite{56}, and the military unit in Gangwon area reported 44 cases on November 24, 2020 \cite{57}.

Fig. 5 shows the average \( R_t \) obtained using model (1) for each area, along with the pandemic curve, clearly showing that the control interventions effectively reduced \( R_t \). There are several important points regarding the CII. First, \( R_t \) increased, if a low CII (green area) was maintained, showing that the number of cases increased due to the relaxed control interventions. Second, during the second wave from August 13 to September 18, 2020, control interventions are changed from the intermediate CII to high CII, as implementation of intermediate CII reduced \( R_t \) to less than 1. Third, comparing the effect of control interventions between second wave and third wave since November 4, 2020, in case of the second wave, the average \( R_t \) for the time interval \( P_3 \) (intermediate CII) and \( P_4 \) (high CII) were estimated to be 3.50 and 0.31, respectively in Korea. However, for the third wave, the reproduction number \( R_t \) was maintained to be larger than one even though a strict control intervention was implemented (a high CII), except for late December 2020 when stricter interventions were implemented. At that time, the average \( R_t \) for time intervals \( P_9 \) and \( P_{10} \) were estimated to be 1.22 and 0.76, respectively. The S4 Table also summarizes the estimated values corresponding to Fig. 5.
3.2. Estimation \( r_{g,t} \) using a renewal equation

The probability distributions of the instantaneous reproduction number, \( r_{g,t} \), for the eight geographical areas were estimated using model (1), as shown in the S3 Figure. The reproduction number peaked on August 15, 2020, with an estimated \( r_{g,t} \) of 5.36; which coincided with a rally for Korea’s National Liberation Day in Gwanghwamum, Seoul. Subsequently, 176 cases related to the Gwanghwamum rally were confirmed up to August 24, 2020 [58]. The \( r_{g,t} \) declined thereafter and reached 0.98 on August 29, 2020. From December 1, 2020 to March 11, 2021, the \( r_{g,t} \) for Korea fluctuated between 0.56 and 1.65. In non-capital areas—such as the Chungcheon, Honam, and Gangwon areas—several sporadic outbreaks, predominantly cluster infections, occurred between January 1, 2021, and February 28, 2021. The infections in January 2021 were linked to the International English Mission (IEM) School [55], in Daejeon city, Chungcheon area. The increase in February may have been due to Lunar New Year celebrations on February 12, 2021.

Fig. 4  Comparison of newly observed and estimated COVID-19 cases using SEIHR model. The blue dots and red solid lines represent the observed and estimated COVID-19 cases, respectively. The 50% and 95% CIs are shaded in yellow and red, respectively. The vertical red dotted lines represent the period dates corresponding to the time intervals \( (P) \) used in the SEIHR model estimation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
The S5 Table details the Spearman’s correlations between the CII and the delayed reproduction number, $r_d$. Here, when $d > 7$ days, the three areas of Korea, the capital area, and non-capital area present a significantly negative correlation. In other words, delayed reproduction number, $r_d$, decreases as the CII becomes stricter or stronger. In addition, a slightly higher correlation was obtained for $d = 10$ days, as the Spearman’s correlation coefficient was calculated at $-0.298$ for Korea. Thus, $d = 10$ days was assumed as the baseline of the control intervention effect.

Adhering to $d = 10$ as the effect of control interventions, the estimated $R_t$ from the SEIHR model were closely approximated to $r_d$. Most fell within the 95% CI, as shown in the S4 Figure, however, for Korea and the capital area, $R_t$ did not fall within the 95% CI of $r_d$ when the former abruptly decreased between August 23, 2020, and September 13, 2020 (i.e., the $P_4$ time interval; see the S4 Figure A, B).

Fig. 5  Average $R_t$ obtained using the SEIHR model. The gray bar indicates the number of observed cases over the left y-axis, the red solid lines represent the estimated average reproduction number ($R_{g,t}$) over the right y-axis and the vertical red dotted lines indicate the estimation-period dates. The shaded areas indicate low (green), intermediate (yellow), and high (red) CII, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
3.3. Probability distribution of $r_{gj}^d$, according to CII

The probability distribution of the reproduction number $r_{gj}^d$ was estimated with respect to the CII and area $g$, adhering to the delay, $d = 10$ days (S5 Figure and S6 Figure). Table 3 reports the probability of observing $r_{gj}^d > 1$ (i.e., $\text{Prob}(r_{gj}^d > 1)$), which is simply interpreted as the probability of an outbreak. The mean of the $r_{gj}^d$ distribution is denoted by $\mu_R$ for $d = 10$ days. Overall, as the CII was enhanced, $\text{Prob}(r_{gj}^d > 1)$ and $\mu_R$ reduced. Here, three main points were noted: First, a change from low to intermediate CII induced a far greater decrease in $\text{Prob}(r_{gj}^d > 1)$ than a change from intermediate to high CII. For example, $\text{Prob}(r_{gj}^d > 1)$ was estimated as 66.67%, 65.57%, and 33.02% for low, intermediate, and high CII, respectively. For low CII, $\text{Prob}(r_{gj}^d > 1)$ and $\mu_R$ decreased abruptly to less than one under high CII (see Fig. 6). For example, the $\mu_R$ values for Korea were computed as 1.31, 1.12, and 0.93 for low, intermediate, and high CII, respectively. For low CII, $\mu_R$ was estimated as 1.31 – 2.43 for all geographic areas, whereas high CII was shown to be 0.89 - 0.95.

Third, greater reduction of $\mu_R$ was observed for the non-capital area than the capital area as the reduction rates exceeded 50% in the Chungcheong area, Gyeongbuk area, and Gangwon area. For different $d$ values of three, seven, 10, and 14 days, $\text{Prob}(r_{gj}^d > 1)$ and $\mu_R$ are summarized in the S6 Table for all geographic areas. The results indicate similar social distancing effects for $d$ exceeding seven days, while it is difficult to observe a reduction effect for $d = 3$ days.

#### 3.4. COVID-19 case forecasting according to CII

The number of new COVID-19 cases were forecasted according to CII. It was assumed that various control interventions, such as face mask use and contact tracing, were maintained with a similar effect regardless of CII differences. Fig. 7 shows the estimated confirmed cases in Korea, the capital area, and the non-capital area from March 5, 2021 to April 1, 2021, with 50% and 95% CIs. The forecasted counts for the other five geographic areas are shown in the S7 Figure. As detailed in the S7 Table, the averages of the newly confirmed cases in the Korea geographic area were predicted as 918 (95% CI: 432, 2,029), 529 (95% CI: 348, 822), and 299 (95% CI: 224, 402) on April 1, 2021, for low, intermediate, and high CII, respectively. Fig. 8 compares the newly confirmed cases for April 1, 2021 for each geographic region, by CII. These results indicate that highly effective control intervention can reduce case numbers.

As detailed in Table 4, the RMSE and MAPE between the observed newly confirmed and forecasted cases from March 5, 2021, to April 1, 2021, were computed to evaluate the forecasting accuracy. For Korea and the capital and non-capital areas, minimum MAPE values of 11.2%, 13.62%, and 20.19%, respectively, were obtained for intermediate CII; these results were interpreted as indicating good forecasting accuracy. In addition, reasonably accurate forecasting was achieved for the Chungcheong area, with 42.92% for high CII; the Gyeongbuk area, with 27.65% for intermediate CII; and the Gyeongnam area, with 38.32% for low CII, as MAPE < 50% for these areas.

#### 4. Discussion

This study examined the 2020–2021 COVID-19 pandemic in the Korea geographical area using mathematical models, with the aim of improving the forecasting framework to reflect the effect of control interventions based on previous studies [27,54]. The time delay, $d = 10$ days, was assumed as the time lag until the control intervention affected the transmission dynamics. Persson et.al considered the time lag as seven – 13 days for the effectiveness of policy measures to reduce human mobility, including the incubation time combined with reporting delay [30]. The probability distribution of $r_{gj}^d$, was incorporated into the SEIHR compartment model to forecast the COVID-19 outbreak in the Republic of Korea after which, the $R_{gj}$ during the corresponding period was estimated. The lower estimates of the reproduction number could clearly be

| Table 3 | Outbreak probability. |
|----------|-----------------------|
| CII      | Korea Capital area | Non-capital area | Chungcheong area | Gyeongbuk area | Gyeongnam area | Honam area | Gangwon area |
| Low      | 66.67               | 67.53             | 64.71             | 58.82           | 59.68           | 62.3        | 79.66         | 68.29         |
| Intermediate | 65.57            | 48.94             | 51.19             | 43.9            | 43.55           | 47.83       | 34.48         | 38.89         |
| High     | 33.02               | 33.96             | 33.33             | 23.61           | 30.91           | 35.14       | 34.33         | 39.39         |
| $\mu_R$  |                     |                   |                   | 23.23           | 30.91           | 35.14       | 34.33         | 39.39         |
| Low      | 1.31                | 1.36              | 1.52              | 1.88            | 2.11            | 1.65        | 2.43          | 2.22          |
| Intermediate | 1.12              | 1.03              | 1.05              | 1.04            | 0.95            | 0.97        | 0.98          | 1.06          |
| High     | 0.93                | 0.93              | 0.92              | 0.89            | 0.89            | 0.89        | 0.95          | 0.95          |
| $\nu_R$  |                     |                   |                   | 28.89           | 31.36           | 39.28       | 52.51         | 54.77         | 45.85         | 60.78         | 57.06         |

$\text{Prob}(r_{gj}^d > 1)$ indicates the outbreak probability and $\mu_R$ is the mean of the probability distribution of $r_{gj}^d$. $\text{Prob}(r_{gj}^d > 1)$ and $\mu_R$ were compared according to CII. The numbers in parentheses indicate the increase and decrease rates compared to the baseline values for low CII. Here, $d = 10$ days corresponds to the delay for the control-intervention effect.
interpreted as the control-intervention effects and overall, both intermediate and high CII decreased the number of new infections. In addition, forecasting was successfully implemented, with most future observed cases being predicted within the 95% CI; however, there were occasional failures corresponding to abrupt increases in new cases. In particular, the forecast for Gangwon area had low accuracy due to the daily confirmed cases exhibiting large variations over time, ranging from three – 38 cases. These variations were caused by continuous cluster infections at churches, schools, and athletic facilities, etc [59].

As there has been no change in CII since March 4, 2020, for the period of March 5 to April 1, 2021, high CII was assumed for the Korea and capital areas, whereas intermediate CII was assumed for the other areas. However, the actual implemented CII may have differed from the chosen CII, as apparent for instances where the forecasting exhibited best fits with the MAPE minimum. This was because different control-intervention effects were observed for different geographical areas, as detailed in Table 4 and Fig. 7. For instance, the capital area implemented a high CII, but the forecasted cases were fitted when intermediate CII was implemented. This outcome is interpreted as being due to lower sensitivity to changes in control interventions, as the enhanced control interventions against COVID-19 persisted for a long time. Likewise, because most of the confirmed cases in Korea were reported in the capital area (70.56%), a similar conclusion was drawn for the forecasting results for Korea. Moreover, intermediate CII was considered to have been implemented in the non-capital area. However, similar results to the forecasting were obtained for the Chungcheong and Gyeongnam areas under high and low CII, respectively. It is, thus, evident that the control interventions had different effects in different geographic areas and therefore, it is concluded that enhanced control interventions are necessary in the Korea, capital, and Gyeongnam areas to reduce COVID-19 case numbers.

Future cases are estimated using the mathematical models by assuming the several values of the parameters such as transmission rates or reproduction numbers in the previous studies [13, 60]. Rather than assuming the constant values for the important parameter, the distribution of the reproduction number was applied to the model to estimate the number of cases in the future according to the different control interventions. To the best of the researchers’ knowledge, the present study is the first to explicitly incorporate the effects of control interventions in forecasting analysis, using epidemiological data from July 2020 to April 2021. It was found that control interventions with high CII are necessary to reduce $\mathcal{R}_t$ to less than one. The proposed model can forecast the COVID-19 transmission dynamics trend successfully, in terms of both the forecasting accuracy and interpretability, even though high accuracy could not be achieved for all geographic areas. Mathematical modeling allowed not only for the capturing of transmission dynamics, but also for the exploration of epidemiological effectiveness of control interventions on COVID-19 case forecasting.

This study had several limitations: First, it did not consider the number of cases by symptom onset date, due to a lack of information; however, analysis of case number over symptom onset date is ideal [27]. Instead, an adjustment was made in terms of the delay for which the control intervention effect on $\mathcal{R}_t$ was reflected when forecasting the COVID-19 cases.

Second, very mild or no symptoms are exhibited for a substantial number of COVID-19 infections, which may not be reflected in the data, however, most COVID-19 infections are symptomatic. For example, in Santiago, only 3% of COVID-19 cases were identified as being asymptomatic [27]. Buitrago et al. estimated the proportion of asymptomatic cases as 20% in [61]. In Korea, 4% asymptomatic cases were reported among 97 confirmed cases for a call center cluster [62].

Third, the data were analyzed for locally transmitted cases only, with imported cases excluded. Secondary cases due to imported COVID-19 cases were dramatically reduced, following a mandatory 14-day self-quarantine requirement for anyone entering Korea from other countries [63]. In detail, the secondary infection rate due to imported cases decreased from 1% between January 20 and April 1, 2020, to 0.3% up until

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**Fig. 6** Values of $\mathcal{R}_t$ according to CII by geographical area. The black, dark-gray, and grey bars correspond to low, intermediate, and high CII, respectively.
Forecasting COVID-19 cases by assessing control-intervention

Fig. 7  Forecasts new COVID-19 case numbers according to CII. COVID-19 cases from March 5 to April 1, 2021 were forecasted for (A) Korea, (B) the capital area, and (C) the non-capital area. The black dots and gray solid lines represent the observed and estimated COVID-19 cases to March 4, 2021, respectively. The future cases were forecasted for low-, intermediate-, and high-CII and represented by the red, blue, and green solid lines, respectively. The shaded areas indicate 50% and 95% CI intervals from March 5 to April 1, 2021. The gray shaded areas to March 4, 2021 indicate the observed time interval before forecasting. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
March 31, 2021 [5]. Thus, this study only focused on locally transmitted cases with respect to the control-intervention effects.

Fourth, the effects of various control interventions, including contact tracing and face mask usage, were not individually analyzed as these control interventions were assumed to have consistent effects regardless of CII. In Korea, face masks are mandatory [33], and contact-tracing capacity has not changed considerably because an intensive investigation system—including CCTV data, card transaction records, and GPS mobile data—was implemented early [64]. Thus, in the proposed model, combined control interventions are used to forecast the COVID-19 pandemic. Moreover, mathematical modeling including the control interventions have been analyzed to make a decision which situation of social distancing is appropriated in the absence of the vaccination described in [65,66].

Despite these limitations, the present study successfully estimated future confirmed cases by geographical area in Korea, along with more explicit estimations, compared to current methods. These findings will hopefully encourage public health decision makers, those in the public health sector, and policymakers addressing COVID-19 case elimination to take significant steps to recognize the impact of control interventions.

5. Conclusions

This study analyzed the effect of control interventions against COVID-19 in Korea using the statistical model. Findings showed that the high-intensity control measures significantly reduced $R$ to be less than one. The mathematical model forecasted COVID-19 transmission dynamics with good accuracy and interpretability according to the different intensities of control interventions. Therefore, the high-intensity control intervention, active case detection, and isolation efforts should be maintained to control the pandemic.

**Declaration of Competing Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
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Ethical Considerations

This study analyzed data that are publicly available through previous reports [5]. The datasets used in this study were summarized and anonymized. The data and code are available at https://github.com/modellingsimulation/forecasting-COVID-19-cases.git. Ethical approval is not required for analysis of publicly available data with no identifying information.

Authors' contributions

H. Lee, G. Jang, and G. Cho retrieved and analyzed data; H. Lee and G. Cho developed the model structure and simulated the models using the data. All authors contributed to writing and revising subsequent versions of the manuscript. All authors read and approved the final manuscript.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jaej.2022.02.037.

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