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Data Analysis and Prediction for Emergency Supplies Demand Through Improved Dynamics Model: A Reflection on the Post Epidemic Era

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Abstract: Throughout history, humanity has grappled with infectious diseases that pose serious risks to health and life. The COVID-19 pandemic has profoundly impacted society, prompting significant reflection on preparedness and response strategies. In the future, humans may face unexpected disasters or crises, making it essential to learn from the COVID-19 experience, especially in ensuring adequate emergency supplies and mobilizing resources effectively in times of need. Efficient emergency medical management is crucial during sudden outbreaks, and the preparation and allocation of medical supplies are vital to safeguarding lives, health, and safety. However, the unpredictable nature of epidemics, coupled with population dynamics, means that infection rates and supply needs within affected areas are uncertain. By studying the factors and mechanisms influencing emergency supply demand during such events, materials can be distributed more efficiently to minimize harm. This study enhances the existing dynamics model of infectious disease outbreaks by establishing a demand forecasting model for emergency supplies, using Hubei Province in China as a case example. This model predicts the demand for items such as masks, respirators, and food in affected regions. Experimental results confirm the model's effectiveness and reliability, providing support for the development of comprehensive emergency material management systems. Ultimately, this study offers a framework for emergency supply distribution and a valuable guideline for relief efforts.

Keywords: emergency materials; supply scheduling; dynamics model

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1. Introduction

Major epidemic diseases, often highly contagious and widespread, pose significant threats to public health, safety, and overall societal stability. The COVID-19 pandemic highlighted the urgency of addressing infectious diseases due to their sudden onset, complex impact, and severe consequences. Throughout history, various infectious diseases have repeatedly affected humanity, yet our capabilities to combat them remain limited. Therefore, early intervention and accurate forecasting of both case numbers and material needs are essential for controlling epidemics effectively. In response to COVID-19, the World Health Organization (WHO, 2020 [1]) developed the COVID-19 Essential Supplies Forecasting Tool (ESFT) to assist governments and stakeholders in estimating the necessary supplies and health workforce to combat the pandemic.

Beyond public health emergencies, natural disasters can also trigger outbreaks of infectious diseases, further intensifying the demand for emergency medical supplies, such as protective gear, biomedical equipment, diagnostic tools, essential medications, and consumables. The rapid rise in demand during the pandemic revealed severe shortages in key areas, necessitating additional external resources to meet supply needs. To address this issue, this study proposes an improved SEIR (Susceptible-Exposed-Infected-Removed) model (Bjørnstad et al., 2020 [2]; He et al., 2020 [3]) combined with a safety stock model, utilizing COVID-19 case data to forecast supply requirements in affected areas over time. This modified model integrates the actual transmission characteristics of infectious diseases and accounts for both quarantined and hospitalized patients requiring emergency supplies. It also distinguishes between quarantined and unquarantined incubating patients and considers potential cases of rebound positivity among recovered individuals, ultimately validating its predictions using safety stock theory.

The ongoing waves of COVID-19 infections and global crises, such as the Ukraine-Russia conflict, have further strained healthcare supply chains (Gleeson, 2022 [4]; Partida [5], 2022; Das et al., 2023 [6]), underscoring the need for robust, adaptable models to manage demand. In this study, the SEIR model is enhanced to reflect real-world epidemic transmission characteristics, especially for high-transmission outbreaks. Existing forecasting methods using stochastic or dynamic planning or assuming fixed demand distributions often lead to inaccuracies. This article introduces a refined model that better accounts for COVID-19 prevention and treatment dynamics, offering improved accuracy in predicting demand for various patient categories, closely matching real data.

While the model specifically forecasts demand for COVID-19, it can be adapted to predict emergency supply needs in response to other infectious disease outbreaks, particularly those following natural disasters or extreme weather events. This model provides a more accurate, adaptable tool for epidemic preparedness and response.

2. Literature Review

Epidemics and natural disasters—such as earthquakes, floods, and typhoons—frequently impact people's lives and disrupt economic development (Wallemacq and House, 2018 [7]; Meng et al., 2023 [8]). Research on emergency supply chains for these events highlights consistent theories and methods, especially around managing the inherent randomness in emergency material supply. Taskin and Lodree (2010) [9] introduced a stochastic inventory model to address multi-period randomness in emergency supplies, which manifests in uncertain demand and challenging transportation conditions. To improve emergency supply readiness, Ma (2025) [10] proposed a two-stage robust model to locate emergency supply points and pre-position stock amounts. Emergency medical supplies, however, present unique challenges, as the complexity of medical devices and variability in drug requirements underscore the critical role of logistics. To address supply shortages, Mangla et al. (2023) [11] developed a multi-supplier emergency order allocation strategy to ensure sufficient and timely supply during pandemic peaks. Zhang et al. (2023a) [12] combined safety stock and capital reserve policies for optimal emergency medical supply planning, while Zhang et al. (2023b) [13] further incorporated time-space networks for resource allocation, adapting to evolving needs in emergencies. Luo et al. (2022) [14] addressed these demands through a multi-period location-allocation model for emergency medical supplies and patient management.

Advances in information technology and artificial intelligence (AI) bring new opportunities for emergency preparedness. Machine learning algorithms and predictive models are increasingly used to forecast emergency supply needs. For instance, AI-driven case inference helps anticipate supply demands (Fang and Wang, 2021 [15]). Hu et al. (2019) [16] applied gray system models, enhancing them with a dynamic GM(1,1) prediction model, while Barrett et al. (2020) [17] used statistical models to forecast ventilator and ICU bed needs. Li and Su (2021) [18] categorized epidemics into four phases—generation, outbreak, peak, and recession—and developed time-varying and Bayesian decision models for supply demands, comparing model accuracy. Wan et al. (2023) [19] introduced a hybrid multi-objective optimization algorithm to minimize unmet demand, distribution costs, and routing risks. AI and Big Data Analytics (BDA) applications have further bolstered supply chain resilience, as noted by Shah et al. (2023) [20]. Despite the growing role of AI, BDA, blockchain, and simulation in emergency supply management, practical applications for enhancing resilience in these chains are still limited (Arji et al., 2023 [21]). Thus, exploring real-time forecasting approaches using intelligent information processing, beyond traditional ARIMA and CBR models, is essential for effective dynamic demand prediction in emergencies (Zhu et al., 2019 [22]).

In summary, effective emergency medical supply management requires timely, accurate manufacturing and delivery. BDA and AI-based collaborative platforms are emerging as mainstream solutions (Bag et al., 2023 [23]). Given the unpredictable nature of new infectious diseases, traditional case-based reasoning is less suitable for demand forecasting. Additionally, sudden public health crises exhibit distinct phase characteristics with varying transmission rates, making phased demand forecasting methods, as explored in this study, a more effective approach.

3. Data and Methods

3.1. Data Sources and Case Context

In this study, significant challenges arose in obtaining the necessary data. The improved model categorized patients into inpatients and confirmed cases who were not isolated, further dividing latent infections into isolated and non-isolated groups. This level of classification detail was not reflected in the data published by the Hubei Provincial Health Commission, as certain categories ceased to be reported after some time. Despite extensive searches on multiple data sources, including national, Hubei, and Wuhan Health Commissions, as well as lists of emergency material demand released by 26 hospitals in Wuhan from 22 February to 8 March 2020, relevant data remained unavailable. Consequently, the study relied on complex calculations based on other available data.

3.2. Research Methodology

This study develops an enhanced predictive model based on the SEIR model (Hethcote, 2000 [24]), a classical infectious disease dynamic model that accounts for the incubation period to examine its effects on the epidemiology of infectious diseases. Additionally, incorporating artificial intelligence algorithms (Ma et al., 2024 [25]; Ma et al., 2025 [10]), the improved SEIR model is validated using data from Hubei province during the COVID-19 outbreak. Of course, there is a great deal of uncertainty in this model. Even during the peak period of the epidemic outbreak, the predictions released by various research institutions have good accuracy and reference value. However, with changes in uncertainty factors and policies, accurate predictions may become difficult.

3.3. Model Description

The infectious disease transmission dynamic model is a fundamental mathematical framework used to analyze the transmission speed, spatial spread, pathways, and dynamics of infectious diseases, thereby supporting effective prevention and control measures.

Infectious disease models are typically classified into types based on disease progression: SI (Susceptible-Infected), SIS (Susceptible-Infected-Susceptible), SIR (Susceptible-Infected-Removed), SIRS (Susceptible-Infected-Removed-Susceptible), and SEIR (Susceptible-Exposed-Infected-Removed). According to their transmission mechanisms, they are further divided into various forms, including those based on ordinary differential equations, partial differential equations, and network dynamics. The SEIR model, due to its complexity and closer alignment with machine-learning algorithms and real transmission patterns of infectious diseases, is particularly effective for predicting demand and optimizing emergency supply models.

As illustrated in Figure 1, the SEIR model (Zhang et al., 2023b [13]; Luo et al., 2022 [14]; Wang & Nie, 2023 [26]; Liu, 2022 [27]) categorizes the population into four compartments: susceptible (S), representing the number of individuals at risk of infection; exposed (E), representing individuals in the incubation phase; infected (I), representing those actively infected; and recovered (R), representing those who have recovered. Here, represents the infection probability, represents the transmission rate, i.e., the likelihood of transmission from an infected individual, and represents the recovery rate. The total population (N) is expressed as N = S + E + I + R. The differential equations governing the SEIR model are as follows:

$$dS/dt = -\beta SI/N \quad (1)$$

$$dE/dt = \beta SI/N - \sigma E \quad (2)$$

$$dI/dt = \sigma E - \gamma I \quad (3)$$

$$dR/dt = \gamma I \quad (4)$$

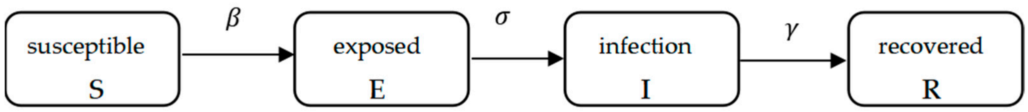

Figure 1. Schematic diagram of SEIR model.

Modeling studies in infectious diseases have contributed to the development of generalized infectious disease dynamics models. These models serve as essential tools for quantitative theoretical research, capturing the dynamics of infectious diseases by incorporating various relevant factors. They enable analysis of disease progression, reveal epidemic patterns, predict trends, and identify key factors contributing to outbreaks.

4. Infectious Disease Dynamics Modeling

4.1. Existing Models and Shortcomings

Existing models are generally adaptations of the classical SEIR infectious disease dynamics model, modified using data from specific outbreak transmission cases (Zhou et al., 2020 [28]). Many of these classical models used in China were developed during the 2003 SARS epidemic, utilizing data from that period. However, the classical SEIR model is inadequate for modeling the third stage of COVID-19 due to the following limitations:

1. COVID-19, like many other infectious diseases, is transmissible during the incubation period, meaning individuals in this stage can spread the infection.
2. The model lacks an isolation mechanism, which is essential as exposed or latent individuals are often isolated. Isolated latent individuals do not transmit the disease, and susceptible individuals in isolation eventually either become susceptible again or latent individuals are sent for treatment.
3. Asymptomatic infected individuals are not accounted for; they are similar to unisolated latent infections but have a higher transmission capacity.
4. Re-infection or return of positivity in recovered patients is not considered.

To address these limitations, the model has been enhanced to reflect the unique characteristics of COVID-19's third stage.

4.2. Improved SEIR Model

Based on the actual epidemic situation, susceptible individuals are categorized into two non-infectious groups: those quarantined due to contact history and those not quarantined who can move freely. Similarly, there are two types of latent infections: individuals infected after contact who are isolated during the incubation period and do not transmit the virus, and undetected individuals who remain infectious. Infected individuals are divided into two categories:

1. Non-infectious individuals: those hospitalized with a confirmed diagnosis, who are considered non-infectious due to isolation, including asymptomatic individuals in quarantine.
2. Undetected infectious individuals: primarily asymptomatic individuals with a high transmission potential who go unnoticed and represent a risk category.

Recovered individuals are also divided into two categories: those who have completely recovered and those who experience re-infection after recovery. The relationship diagram is shown in Figure 2 (Zhuang and Wu, 2022 [29]).

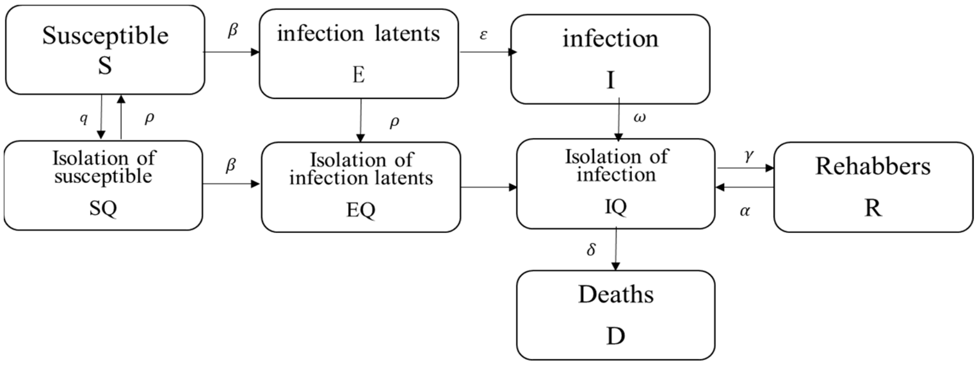

Figure 2. Schematic diagram of the improved model.

4.2.1. Subsubsection

The parameters used in the model are defined as follows:

- S: Susceptible persons, representing the general population not under quarantine.
- SQ: Isolated susceptible persons who had contact with an infected individual and are under quarantine. If asymptomatic after 14 days, they return to the non-isolated susceptible category.
- E: Infection latents, unquarantined individuals who are infected and in the incubation period.
- EQ: Isolated latent infections, individuals identified as infected during the incubation period and isolated. This includes latent patients identified after exposure to an infected person or latent patients not previously isolated.
- I: Infected persons, confirmed cases not in isolation, mainly undetected asymptomatic individuals.
- IQ: Hospitalized infected persons, those confirmed as infected and in isolation.
- D: Deaths, individuals who succumbed to COVID-19.
- R: Recovered persons, those who recovered from COVID-19. Some may be re-infected, given the cases of re-infection after recovery.
- ρ: Isolation ratio.
- σ: Exposure rate.
- ε: Probability of disease development in exposed individuals.
- β: Infection rate, the probability that a contact results in infection.
- q: De-isolation rate, with q = 1/14, as isolation typically lasts 14 days.
- θ: Rate of conversion from isolated exposure to isolated infection.
- δ: Mortality rate among infected persons.
- γ: Recovery rate among infected persons.
- ω: Probability of an infected individual being isolated.
- α: Probability of re-infection in recovered patients.
- μ: Daily emergency supply requirement per exposed person.
- K: Set of infected areas, defined as K = {1, 2, . . ., k}.
- J: Set of medical supply points, defined as J = {1, 2, . . ., j}.
- T: Duration of the COVID-19 period, defined as T = {1, 2, . . ., t}.

Time-dependent variables:

- N_k(t): Total population in infected area k at time t.
- S_k(t): Number of non-quarantined susceptible individuals in infected area k at time t.
- E_k(t): Number of unquarantined exposed individuals in infected area k at time t.
- I_k(t): Number of non-quarantined infected individuals in infected area k at time t.
- SQ_k(t): Number of quarantined susceptible individuals in infected area k at time t.
- EQ_k(t): Number of isolated exposed individuals in infected area k at time t.
- IQ_k(t): Number of isolated infected individuals in infected area k at time t.
- R_k(t): Number of recovered individuals in infected area k at time t.
- D_k(t): Number of deaths in infected area k at time t.

- d_k(t): Emergency supply demand in infected area k at time t

4.2.2. Assumptions

The assumptions for this model are as follows:

1. Natural birth and death rates were not included, as these factors typically take a long time to impact the population structure.
2. The population in each infected area is assumed to be stable. Strong government control is assumed to prevent population movement after the outbreak.
3. The available quantity of emergency medical supplies is assumed to be known.
4. Individuals in SQ who do not carry the virus after a 14-day observation period rejoin the susceptible population (S). Assuming 1/14th of SQ returns to S daily may lead to insufficient demand during rising infection periods and excess demand during declining periods. To address this, a 10% increase in demand is applied during periods of rising infections, and a 10% decrease during declining phases is incorporated in the demand forecast.
5. Recovered patients are considered non-infectious, with the exception of a small probability of re-infection.

4.2.3. Modeling

Under each of the previous assumptions, the behavior of the spread of the outbreak in infected area k at moment t, that is, the change in the number of each population, is given by the following equations:

$$\frac{dS_k(\mathrm{t})}{dt} = -[\sigma\beta + \rho\sigma(1-\beta)]\frac{S_k(\mathrm{t})(I_k(\mathrm{t}) + E_k(\mathrm{t}))}{N_k(\mathrm{t})} + q * SQ_k(\mathrm{t}) \tag{5}$$

$$\frac{dE_k(\mathrm{t})}{dt} = \sigma\beta(1-\rho)\frac{S_k(\mathrm{t})(I_k(\mathrm{t}) + E_k(\mathrm{t}))}{N_k(\mathrm{t})} - \varepsilon E_k(\mathrm{t}) \tag{6}$$

$$\frac{dI_k(\mathrm{t})}{dt} = \varepsilon E_k(\mathrm{t}) - \omega\ I_k(\mathrm{t}) \tag{7}$$

$$\frac{dSQ_k(\mathrm{t})}{dt} = \sigma\rho(1-\beta)\frac{S_k(\mathrm{t})(I_k(\mathrm{t}) + E_k(\mathrm{t}))}{N_k(\mathrm{t})} - q * SQ_k(\mathrm{t}) \tag{8}$$

$$\frac{dEQ_k(\mathrm{t})}{dt} = \sigma\beta\rho\frac{S_k(\mathrm{t})(I_k(\mathrm{t}) + E_k(\mathrm{t}))}{N_k(\mathrm{t})} - \theta * EQ_k(\mathrm{t}) \tag{9}$$

$$\frac{dIQ_k(\mathrm{t})}{dt} = \omega I_k(\mathrm{t}) + \theta * EQ_k(\mathrm{t}) - (\ \delta + \gamma) * IQ_k(\mathrm{t}) + \alpha R_k(\mathrm{t}) \tag{10}$$

$$\frac{dR_k(\mathrm{t})}{dt} = \gamma * IQ_k(\mathrm{t}) - \alpha R_k(\mathrm{t}) \tag{11}$$

Equation (5) describes the change in the number of unquarantined susceptible persons in infected area k; the number of susceptible individuals is in a constant process of reduction, and part of the exposure to infected persons is isolated into isolated susceptible persons. Undetected infected susceptible persons become non-isolated latent persons, and uninfected susceptible persons in isolation became susceptible again after 14 days of isolation. It is assumed that 1/14th of the SQ quit consuming resources every day, and reverting back to the susceptible will lead to the under-prediction of supplies in the rising infection period and the error phenomenon of rich supplies in the falling infection period; thus, the subsequent supply prediction model will be improved with respect to this point. Equation (6) describes the variation in the number of isolated undetected infection latents. Undetected infection latents come from susceptible individuals who are in contact with infected individuals with a probability ρ of being detected for isolation and becoming isolated infection latents, and a proportion of those become infected after the incubation period. Equation (7) describes the variation in the number of infected individuals who are not isolated, which comes from the fact that undetected infection latents have a ω probability of being detected and then isolated for treatment. Equation (8) describes the change in the number of isolated susceptibles, where some become isolated infection latents and some return to susceptibility at the end of the isolation period. Equation (9) describes the change in the number of isolated patients referred to the hospital for treatment. Equation (10) describes the change in the number of hospitalized patients, some of whom are cured, and some of whom die. Equation (11) describes the change in the number of recovered patients with an α probability of re-infection after recovery. Because data are usually reported daily during an epidemic, the above system of differential equations was transformed into a system of difference equations as follows:

$$S_k(\mathrm{t}+1) = S_k(\mathrm{t}) - [\sigma\beta + \rho\sigma(1-\beta)]\frac{S_k(\mathrm{t})(I_k(\mathrm{t})+E_k(\mathrm{t}))}{N_k(\mathrm{t})} + q * SQ_k(\mathrm{t}) \quad (12)$$

$$E_k(\mathrm{t}+1) = E_k(\mathrm{t}) + \sigma\beta(1-\rho)\frac{S_k(\mathrm{t})(I_k(\mathrm{t})+E_k(\mathrm{t}))}{N_k(\mathrm{t})} - \varepsilon E_k(\mathrm{t}) \quad (13)$$

$$I_k(\mathrm{t}+1) = I_k(\mathrm{t}) + \varepsilon E_k(\mathrm{t}) - \omega\, I_k(\mathrm{t}) \quad (14)$$

$$SQ_k(\mathrm{t}+1) = SQ_k(\mathrm{t}) + \sigma\rho(1-\beta)\frac{S_k(\mathrm{t})(I_k(\mathrm{t})+E_k(\mathrm{t}))}{N_k(\mathrm{t})} - q * SQ_k(\mathrm{t}) \quad (15)$$

$$EQ_k(\mathrm{t}+1) = EQ_k(\mathrm{t}) + \sigma\beta\rho\frac{S_k(\mathrm{t})(I_k(\mathrm{t})+E_k(\mathrm{t}))}{N_k(\mathrm{t})} - \theta * EQ_k(\mathrm{t}) \quad (16)$$

$$IQ_k(\mathrm{t}+1) = IQ_k(\mathrm{t}) + \omega I_k(\mathrm{t}) + \theta * EQ_k(\mathrm{t}) - (\,\delta + \gamma) * IQ_k(\mathrm{t}) + \alpha R_k(\mathrm{t}) \quad (17)$$

$$R_k(\mathrm{t}+1) = R_k(\mathrm{t}) + \gamma * IQ_k(\mathrm{t}) - \alpha R_k(\mathrm{t}) \quad (18)$$

Given the initial values of $S_k(0)$, $E_k(0)$, $I_k(0)$, $SQ_k(0)$, $EQ_k(0)$, $IQ_k(0)$, $R_k(0)$, et cetera, the number of susceptible persons, contacts, infected persons, recovered persons, and dead persons in the infected area k can be predicted by the above formula.

4.2.4. Model Elaboration

Epidemics of various scales have always coexisted with humanity. Beyond large-scale infectious diseases like smallpox and COVID-19, outbreaks of infectious diseases can also arise following natural disasters such as floods and earthquakes. While the primary focus is on preventing post-disaster infections, once outbreaks occur, accurate prediction of medical supply needs becomes critical for effective containment, prevention, and minimizing additional harm to those in affected areas.

The improved SEIR model, though originally designed for COVID-19, is broadly applicable to common infectious diseases. With adjustments, it can accommodate other types of infections; for instance, in the case of lifelong immunity diseases, the recurrent pathway from recovered (R) to re-infected (IQ) can be removed. The model enables straightforward estimation of the number of individuals requiring supplies, aiding efficient distribution and supporting infection control efforts in various scenarios.

4.3. Emergency Material Requirements Model

4.3.1. Safety Stock Model

After forecasting the number of isolated latent and infected individuals, emergency supply needs are estimated by applying inventory management principles (Guo and Zhou, 2011 [30]). Safety stock, a logistics concept, provides buffer inventory to handle uncertainties in supply and demand. Businesses maintain safety stock to prevent production disruptions due to unpredictable fluctuations. This concept closely resembles emergency supply reserves, though with a key difference: emergency supplies prioritize meeting demand fully, with less emphasis on cost control.

The safety-stock model and its applicability are detailed below. Key factors affecting safety stock include unpredictable customer demand, fluctuating production processes, variable distribution cycles, and differing service levels. The modeling approach varies based on whether demand and lead times are random.

Equation (19) is the classical model for safety stock.

$$SS = z\sqrt{\sigma_d^2\left(\overline{L}\right) + \sigma_L^2\left(\overline{d}\right)^2} \quad (19)$$

In Equation (19), SS represents safety stock, $\overline{L}$ denotes the mean lead time, $\overline{d}$ is the average daily demand, z is the service level coefficient, $\sigma_{\overline{d}}$ is the standard deviation of demand d, and σ_L is the standard deviation of lead time. Equation (19) shows that safety stock is calculated as the service-level factor multiplied by the standard deviation of demand over the replenishment cycle.

This safety stock model is designed to address uncertainties in demand, supply, and availability, aligning well with the emergency supply demand forecasting in this study. Thus, based on this safety stock concept, the following section briefly outlines the demand forecasting model applied in this study.

4.3.2. Symbol Description

Symbol used in this part is as follows:

- EQ(t): Number of isolated latent infections. Non-isolated latent infections are not immediately considered for medical supply needs.
- IQ(t): Number of inpatients.
- J = {j|j = 1, 2, . . ., J}: Types of emergency supplies.
- N(t): Number of healthcare workers in the area.
- t = 1, 2, . . ., t: Time series, with the initial point of the epidemic designated as time 1, followed by fixed intervals.
- N_j: Average demand for supply type j across all personnel.
- E_j: Demand criteria for material category j for latent infections.
- I_j: Demand criteria for material category j for inpatients.
- A_j: Current inventory level of materials in category j.
- z: Service level factor, which varies by emergency supply type. For example, critical medical supplies may have a higher z value, while non-medical supplies like food may have a lower value. A z value of 1.65 represents a desired 95% demand satisfaction rate.
- L: Average delivery time for emergency supplies, adjustable according to epidemic severity; shorter in more critical phases.
- σ'_{jd}: Standard deviation of historical demand for supply j.

4.3.3. Mathematical Models

The demand forecasting model constructed based on the above theory can be expressed by Equations (20)–(23).

$$D_j{}'(\mathrm{t}) = \begin{cases} z \times \sigma'_{jd} \times \sqrt{L} + \sigma_d,\ j \in Food\ supplies; \\ MAX\left\{z \times \sigma'_{jd} \times \sqrt{L} + \sigma_d - A_j \middle| 0\right\},\ j \in Medical\ supplies; \end{cases} \quad (20)$$

$$\sigma'_{jd} = \sqrt{\frac{\sum_t^{t-7}[\sigma_d - \overline{\sigma_d}]^2}{7}} \quad (21)$$

$$\sigma_d = \begin{cases} N_j \times (N(t) + \mathrm{EQ(t)} + \mathrm{IQ(t)}),\ j \in Food\ supplies; \\ \mathrm{EQ(t)} \times E_j + \mathrm{IQ(t)} \times I_j,\ j \in Medical\ supplies; \end{cases} \quad (22)$$

$$\overline{\sigma_d} = \frac{\sum_t^{t-7} \sigma_d}{7} \quad (23)$$

$$D_j(\mathrm{t}) = \begin{cases} D'_j(\mathrm{t}) \times (1+10\%), & M(\mathrm{t}) \le M\,(\mathrm{t}+1); \\ D'_j(\mathrm{t}) \times (1-10\%), & M(\mathrm{t}) > M\,(\mathrm{t}+1); \end{cases} \tag{24}$$

Equation (20) is the demand forecasting formula. Equations (21)–(23) are the explanatory equations for each variable. The first Equation (20) is the demand forecast for food supplies, and the second is the demand forecast for medical supplies, in which medical supplies are ventilators, belong to non-consumable medical supplies, so the past inventory is considered. Equation (24) implies that since assumption (4) will generate an error, it will lead to the under-prediction of supplies during the period of increasing infections and the over-estimation of supplies during the period of decreasing infections. A treatment of a 10% increase in demand during the period of increasing infections and a 10% decrease in demand during the period of decreasing infections is made. Because real material demand data are not available, to verify the feasibility of this model, a traditional method, that is, the number of people multiplied by the average demand, is used to predict the demand, and the two results are compared to verify the feasibility of the model.

$$D_j(\mathrm{t}) = \begin{cases} N_j \times (N(t) + \mathrm{EQ}(\mathrm{t}) + \mathrm{IQ}(\mathrm{t})), & j \in \textit{Food supplies}; \\ MAX\{(\mathrm{EQ}(\mathrm{t}) \times E_j + \mathrm{IQ}(\mathrm{t}) \times I_j) - A_j | 0\}, & j \in \textit{Medical supplies}; \end{cases} \tag{25}$$

5. Results and Discussion

5.1. Case Description and Parameter Assignment Test

Since December 2019, several cases of pneumonia of unknown origin were identified in hospitals in Wuhan, Hubei Province, which were subsequently confirmed as respiratory infections caused by COVID-19. By the end of January 2020, a large-scale outbreak had emerged, with Wuhan implementing a lockdown on 23 January amidst a rapid increase in confirmed cases and fatalities. The background information for this article draws from leading medical journals, including the Journal of the American Medical Association and Association of Public Health Interventions with the Epidemiology of the COVID-19 Outbreak in Wuhan, China (Pan et al., 2020 [31]). During the third of five epidemic phases outlined in these sources, the epidemic reached its peak, prompting the government to enforce strict preventive and control measures despite a severe shortage of medical resources.

Due to the urgency at this early stage of the epidemic, there were insufficient human and material resources for comprehensive tracking of case numbers. To obtain data for comparative analysis, infection data from Hubei Province as of 22 February 2020, served as a baseline for projecting medical supply and food demand over the next 16 days, including requirements for medical personnel. Specific material requirements are detailed in Table 1.

Table 1. Material types and demand specifications Unit: per person per day.

	Mouthpiece	**Ventilator**	**Food**
IQ	6	0.2	a
EQ	6	0	a
Medical staff	6	0	a

In the table above, the daily mask demand per person was estimated based on the guideline that masks are replaced every four hours, resulting in an estimate of six masks per person per day. According to information from a press conference by the Hubei Provincial Health and Wellness Commission, it is estimated that Hubei has 170,000 frontline medical personnel. Among inpatients, only critically ill patients required ventilators, with an estimated ratio of 0.2 used in this study. Food intake was calculated based on the assumption of a standard unit of food per person per day.

5.2. EQ and IQ Numerical Prediction and Error Analysis

This study validated the model by comparing the predicted data for a 30-day period starting from February 22 in Hubei Province with actual data collected from the 16th day onward. The demand forecasting model was then applied to predict requirements for these 16 days. Due to varying parameter conditions across different periods, key variables and parameters were selected based on the epidemic situation in Hubei at that time. Data on confirmed cases, contacts, recoveries, and deaths were sourced from the Wuhan Health and Wellness Commission, while hospitalization numbers were obtained from official bulletins. The number of isolated latent cases was calculated using Equation (24), as referenced in the literature (Zou and Liang, 2020 [32]). Initial variable values are displayed in Table 2, with parameter assignments detailed in Table 3.

$$E_n = (I_{n+5} + IQ_{n+5} + R_{n+5} + D_{n+5}) - (I_n + IQ_n + R_n + D_n) \quad (26)$$

Table 2. Initial settings of the improved SEIR infectious disease dynamic model.

Variables	**I(0)**	**IQ(0)**	**S(0)**	**SQ(0)**	**E(0)**	**EQ(0)**
value	46,439	40,127	59,170,000	61,181	1623	1346 (estimated)
description of the values	official data	official data, number of people treated in hospital	obtained from the total population minus the number of cured deaths	official data, number of people under medical observation	number of cured deaths on 26 February minus the number on 22 February	number of people under medical observation multiplied by the proportion of incubators

Note: Since the bed data were not updated after 25 February, this study assumed that the total number of beds remained unchanged after 25 February to estimate the number of hospitalizations.

Table 3. Assignment of parameters to the improved SEIR infectious disease dynamics model.

parameter	β	σ	ρ	ε
value	2.05×10^{-9}	0.448	1×10^{-6}	1/7
parameter	δ	ω	γ	α
value	0.0402	0.13	0.1769	0.122

Note: The meanings of the parameters are given in previous symbolic descriptions.

The improved infectious disease dynamic model and parameters were tested using MATLAB R2016a. The predicted values of EQ and IQ obtained after several experiments and adjustment of parameters are shown in Figures 3 and 4.

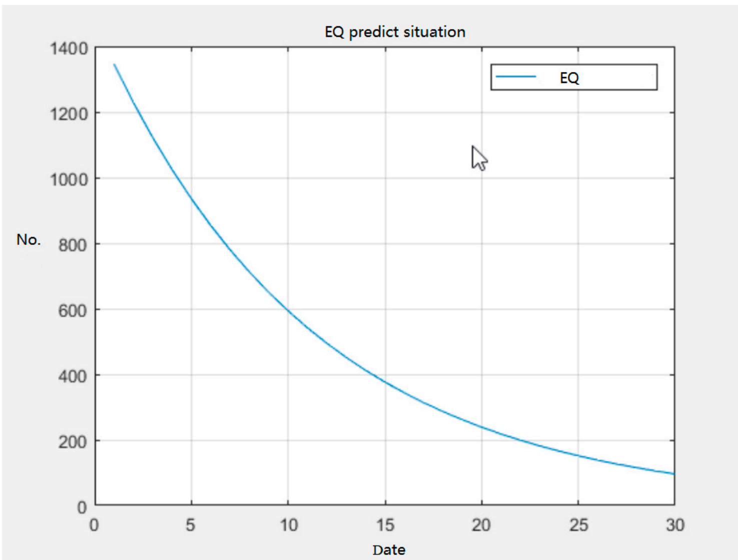

Figure 3. EQ predictor values.

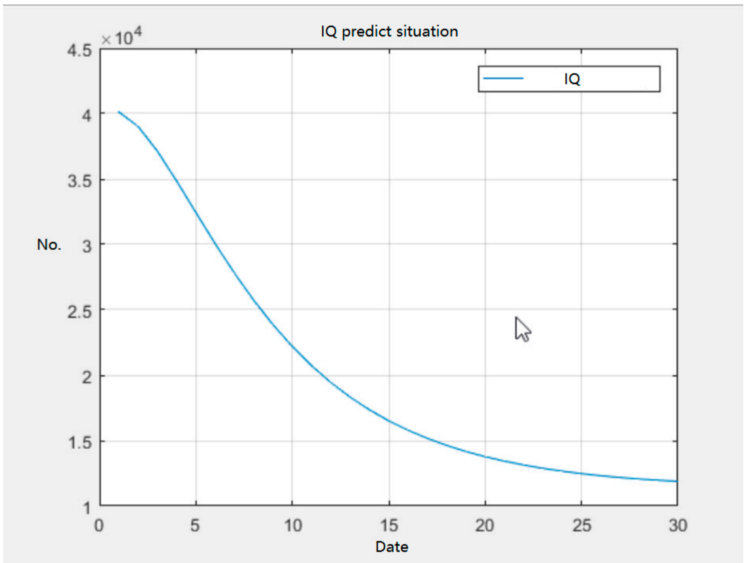

Figure 4. IQ predictor values.

The model results indicate that the predicted values of EQ and IQ were in line with the real data trend. Tables 4 and 5 show the predicted values of EQ and IQ during 22 February to 8 March. Tables 6 and 7 show the true values of EQ and IQ during this time.

Table 4. Predicted values for isolated infection latents (EQ).

date	22 February	23 February	24 February	25 February	26 February	27 February	28 February	29 February
projected number	1346	1229	1122	1025	936	854	780	712
date	1 March	2 March	3 March	4 March	5 March	6 March	7 March	8 March
projected number	650	594	542	495	452	413	377	344

Table 5. Inpatient (IQ) predictive values.

date	22 February	23 February	24 February	25 February	26 February	27 February	28 February	29 February
projected number	40,127	39,028	37,134	34,849	32,434	30,053	27,800	25,728
date	1 March	2 March	3 March	4 March	5 March	6 March	7 March	8 March
projected number	23,857	22,191	20,723	19,439	18,321	17,352	16,515	15,792

Table 6. True values of isolated infection latents (EQ).

date	22 February	23 February	24 February	25 February	26 February	27 February	28 February	29 February
number	1346	1289	1176	1088	1019	949	865	787
date	1 March	2 March	3 March	4 March	5 March	6 March	7 March	8 March
number	707	625	556	502	463	403	343	291

Table 7. Inpatient (IQ) true values.

date	22 February	23 February	24 February	25 February	26 February	27 February	28 February	29 February
number	40,127	39,073	37,896	36,242	34,978	32,878	31,064	28,912
date	1 March	2 March	3 March	4 March	5 March	6 March	7 March	8 March
number	26,901	25,050	23,039	20,765	19,758	18,518	17,078	15,826

Next, the fit and error of the predicted values were analyzed. The predicted data of the isolated latents and hospitalized patients were fitted to the real data obtained from the query information, and the results are shown in Figures 5 and 6. The goodness-of-fit value for the predicted value of EQ was 0.988013, and the goodness-of-fit value for the predicted value of IQ was 0.979685. It can be seen that the model fits well. The average relative error of the calculated EQ prediction values was 6.4%, and the average relative error value of IQ prediction values was 6.225%. The prediction accuracy was high, and the relative error distribution is shown in Figures 7 and 8.

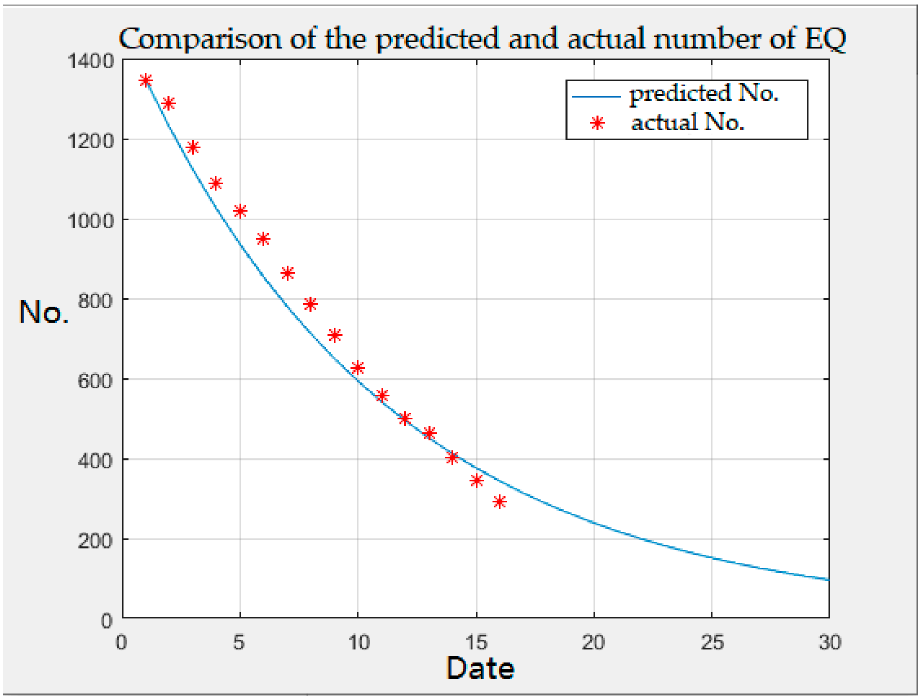

Figure 5. Comparison of the predicted and actual number of EQ.

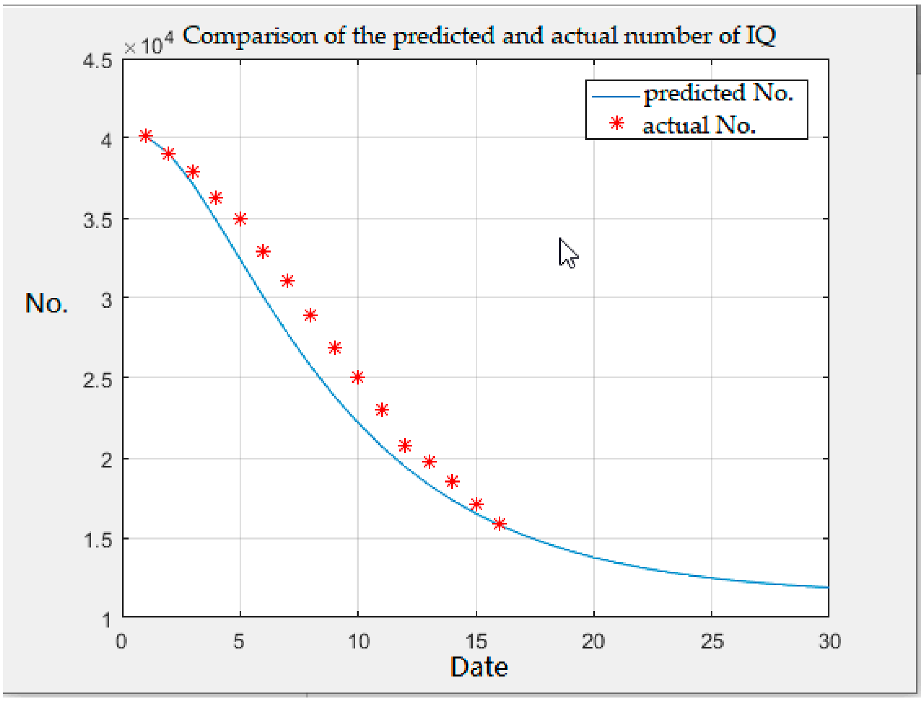

Figure 6. Comparison of the predicted and actual number of IQ.

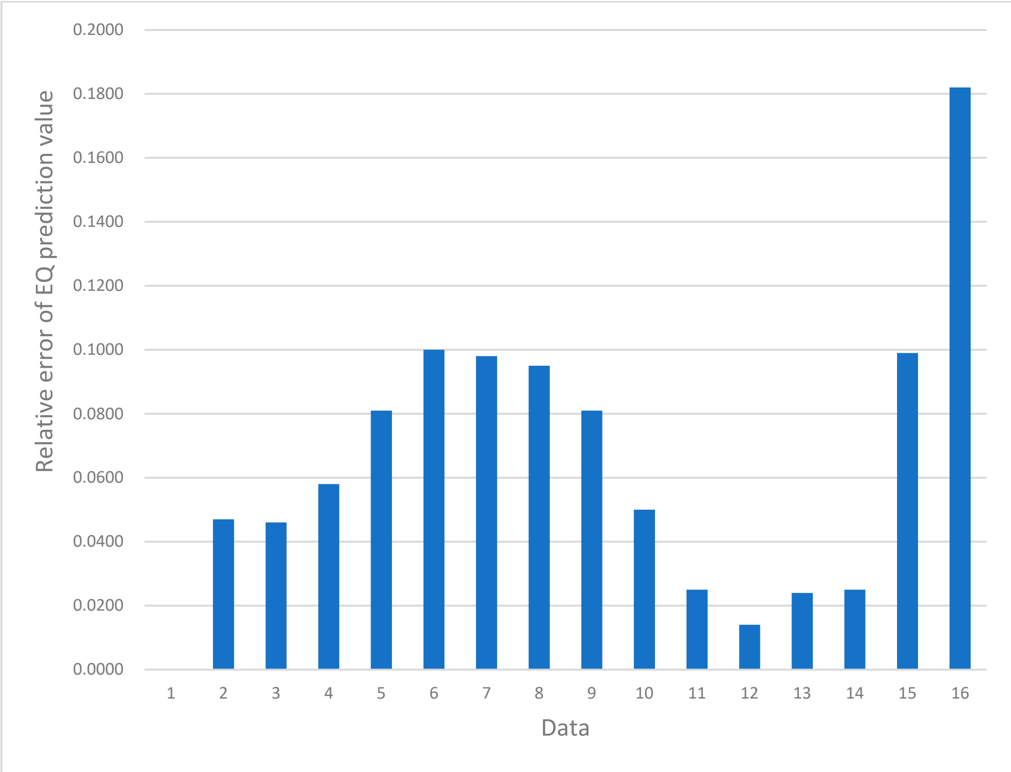

Figure 7. Relative error of the EQ prediction value.

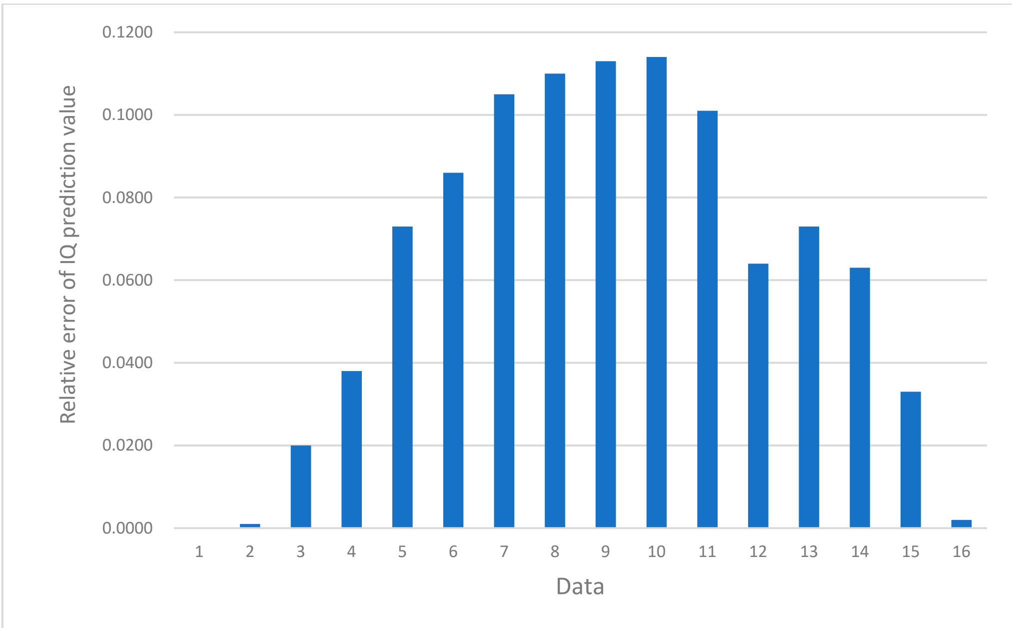

Figure 8. Relative error of the IQ prediction value.

5.3. Demand Forecast

The data was incorporated into the demand forecasting model, and the urgency of the epidemic decreased at this point, depending on the case context. The number of new confirmed cases decreased, that is, $M(t) > M(t + 1)$, and the availability factor z was set to 1.28 for food items and 1.65 for medical items. The average delivery period of the emergency supplies was assumed to be 4 d. The predicted demand obtained by solving for 1 day as a timing unit is listed in the following Table. (Since the original volume of the ventilator cannot be checked, the first day of the estimated volume was taken as the standard here).

The projected data in Table 8 shows that, the supplies demand also decreases as the number of patients decrease. The demand for respirator is listed for clarity, but the actual demand for them is declining, and the subsequent demand would become zero because the original stock would be sufficient to meet the demand with a decline in the number of patients. Next, the result data derived from the demand forecasting model is compared with the number of people times unit demand method to verify the feasibility of the model in this study.

Table 8. Projected demand for various types of emergency supplies (safety stock theory).

Data	date							
	22 February	23 February	24 February	25 February	26 February	27 February	28 February	29 February
Mask	1,166,190	1,158,081	1,154,169	1,153,250	1,150,410	1,145,338	1,143,390	1,140,342
Respirator	8056	7769	7624	7588	7495	7326	7263	7173
Food	193,459 a	192,165 a	191,255 a	190,656 a	189,783 a	188,630 a	187,909 a	187,083 a
Data	date							
	1 March	2 March	3 March	4 March	5 March	6 March	7 March	8 March
Mask	1,115,306	1,105,184	1,093,649	1,081,756	1,070,166	1,059,280	1,049,302	1,040,304
Respirator	6984	6657	6258	5832	5409	5007	4636	4300
Food	185,884 a	184,197 a	182,274 a	180,292 a	178,361 a	176,546 a	174,883 a	173,384 a

Note: "a" refers to the value N_j that is average demand for supply type j across all personnel.

The data in Tables 8 and 9 are compared and analyzed, and the difference between the two sets of data is small, indicating that the demand forecasting model of this study is in line with reality. The main difference between the two sets of data is that the number of mask ventilators in Table 8 is higher compared to Table 9, and the food is lower. This is due to the setting of availability coefficients, which can be set differently for different stage characteristics. Compared with the direct method of using the number of people multiplied by the unit demand, the demand prediction model of this study is designed to be flexible and consistent with the actual data, and can be designed according to the severity of the epidemic and different kinds of supplies.

Table 9. Forecasted values of demand for various types of emergency supplies (traditional method).

Data	date							
	22 February	23 February	24 February	25 February	26 February	27 February	28 February	29 February
Mask	1,268,838	1,261,542	1,249,536	1,235,244	1,220,220	1,205,442	1,191,480	1,178,640
Respirator	8025	7806	7427	6970	6487	6011	5560	5146
Food	211,473 a	210,257 a	208,256 a	205,874 a	203,370 a	200,907 a	198,580 a	196,440 a
Data	date							
	1 March	2 March	3 March	4 March	5 March	6 March	7 March	8 March
Mask	1,167,042	1,156,710	1,147,590	1,139,604	1,132,638	1,126,590	1,121,352	1,116,816
Respirator	4771	4438	4145	3888	3664	3470	3303	3158
Food	194,507 a	192,785 a	191,265 a	189,934 a	188,773 a	187,765 a	186,892 a	186,136 a

Note: "a" refers to the value N_j that is average demand for supply type j across all personnel.

6. Conclusions

This study addresses demand uncertainty during an epidemic by combining an improved infectious disease dynamics model with post-epidemic demand estimation, utilizing safety stock theory. This approach enables demand prediction for various epidemic regions and stages, providing a basis for the efficient dispatch and distribution of emergency supplies and offering valuable guidance for relief efforts.

However, the demand forecasting model has some limitations: (1) It focuses on the supply needs for medical sites, not the total population in the affected area. (2) The probabilities for a susceptible person becoming isolated and a latent person becoming isolated are approximated as the same, which may introduce errors. (3) The model's validation method requires further development. Future studies will classify and predict demand for the entire population in the affected area, improve parameter selection, and enhance model validation techniques.

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