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Assessing the spatial variability of raising public risk awareness for the intervention performance of COVID-19 voluntary screening: A spatial simulation approach

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ABSTRACT
The rapid spread of a (re)emerging pandemic (e.g., COVID-19) is usually attributed to the invisible transmission caused by asymptomatic cases. Health authorities rely on large-scale voluntary screening to identify and isolate invisible spreaders as well as symptomatic people as early as possible to control disease spread. Raising public awareness is beneficial for improving the effectiveness of epidemic prevention because it could increase the usage and demand for testing kits. However, the effectiveness of testing could be influenced by the spatial demand for medical resources in different periods. Spatial demand could also be triggered by public awareness in areas with two geographical factors, including spatial proximity to resources and attractiveness of human mobility. Therefore, it is necessary to explore the spatial variations in raising public awareness on the effectiveness of COVID-19 screening. We implemented spatial simulation models to integrate various levels of public awareness and pandemic dynamics in time and space. Moreover, we also assessed the effects of the spatial proximity of testing kits and the ease of human mobility on COVID-19 testing at various levels of public awareness. Our results indicated that high public awareness promotes high willingness to be tested. This causes the demand to not be fully satisfied at the peak times during a pandemic, yet the shortage of tests does not significantly increase pandemic severity. We also found that when public awareness is low, concentrating on unattractive areas (such as residential or urban fringe areas) could promote a higher benefit of testing. On the other hand, when awareness is high, the factor of distances to testing stations is more important for promoting the benefit of testing; allocating additional testing resources in areas distant from stations could have a higher benefit of testing. This study aims to provide insights for health authorities into the allocation of testing resources against disease outbreaks with respect to various levels of public awareness.

1. Introduction
The rapid spread of a (re)emerging pandemic is usually attributed to the invisible transmission caused by asymptomatic cases (Fielding, Kelly, & Glass, 2015); for example, the global threat of the COVID-19 pandemic could be caused by ineffective detection of positive cases in early stages (Nikolai, Meyer, Kremsner, & Velavan, 2020). Therefore, identifying and isolating invisible spreaders as well as severely symptomatic people as early as possible could control disease spread (Peirlinck et al., 2020), and encouraging the public to voluntarily test is an important measure for tracking invisible spreaders, especially in high-risk regions. Nonetheless, the effectiveness of screening may not be significant because low public awareness on the epidemic or pandemic may lead to an ineffective quarantine or isolation of individuals who have been exposed and unknowingly infected. For example, in Bangladesh, low public awareness of COVID-19 infection risk had resulted in the majority of the population seldom being in compliance with governmental guidelines or using prevention resources such as masks or testing kits. Local prevention approaches, thus, cannot achieve their expected effectiveness for controlling disease diffusion (Islam, Talukder, Siddiqui, & Islam, 2020). On the other hand, the public in South Korea possessed a relatively high awareness of voluntary test in the early stages of the COVID-19 outbreak, so the local epidemic could be mitigated effectively (Lee & You, 2020). Therefore, raising public awareness is beneficial for improving the effectiveness of epidemic prevention (Agaba, Kyrychko, & Blyuss, 2017; Hu et al., 2020).

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Awareness could be conceptualized as the extent to which the public possesses knowledge of infections in social environments (Li, Feng, Liao, & Pan, 2020); this knowledge would influence human behaviors (Janz & Becker, 1984). Therefore, the mechanism behind raising awareness does not directly improve the effectiveness of preventive measures; instead, it affects the engagement of preventive behaviors in a society. Recent studies have also suggested raising public awareness to increase the willingness to use medical resources to confront the COVID-19 pandemic (Hu et al., 2020; Sun et al., 2020). However, this strategy seldom considers the influence of spatial accessibility on medical resources, which causes mismatches between demand and supply. Spatial accessibility refers to the volume of a certain resource available in different places; it is a comprehensive evaluation that considers the spatial distributions of both demand and supply and the travel costs for individuals for moving between those different places (Wang, 2012). An area with low spatial accessibility could mean that residents cannot access sufficient resources to satisfy local demand (Kuo & Wen, 2021); thus, the strategy of increasing demand by raising public awareness would be useless to confront epidemics in such areas. During the COVID-19 pandemic, the issue of spatial accessibility could be a concern of the health authority allocating testing kits (Tao, Downs, Beckie, Chen, & McNelley, 2020). As a result, although raising public awareness could increase usage willingness and demand for testing kits, its effectiveness on screening would be limited by spatial accessibility to testing kits. Thus, it is necessary to explore the spatial variations in raising public awareness on the effectiveness of COVID-19 screening.

In addition to spatial accessibility, epidemic progression also influences the spatial distribution of demand for medical resources because the threat of emerging epidemics in neighborhoods drives local residents to request resources more aggressively (SteelFisher, Blendon, Bekheit, & Lubell, 2010); thus, the effectiveness of screening is also influenced. Epidemic progression usually contains different exposure risks to disease over space and time because of its spatiotemporally varying severities, such as different epidemic peak times or incidences in different regions (Thomas et al., 2020). These variations could be attributed to intensive human mobility or frequent interpersonal contacts, especially for acute infectious diseases such as COVID-19 (Hou et al., 2021). In other words, human mobility would dominate spatiotemporally varying exposure risks and trigger corresponding changes in the demand for medical resources. As a result, human mobility should also be considered when investigating the spatial variations in raising public awareness on the effectiveness of COVID-19 screening.

The effectiveness of screening could be influenced by the spatial demand for medical resources in different periods. Spatial demand could also be triggered to different extents by public awareness in areas with geographical factors, including spatial proximity to resources and human mobility. Therefore, to clarify the spatially varying effect of raised public awareness on the effectiveness of COVID-19 screening, the objectives of this study are as follows: first, we implemented spatial simulation models to integrate different levels of public awareness and epidemic dynamics in time and space; second, we investigated the effects of the spatial proximity of testing kits and the attractiveness of human mobility on COVID-19 screening at different levels of public awareness. The Taipei metropolitan area, one of the most densely populated cities in East Asia, was used as a case study to demonstrate the feasibility of our integrated model framework. This study could provide insights for health authorities designing testing strategies against disease outbreaks with respect to various levels of public awareness.

2. Methods

2.1. Data materials

The Taipei metropolitan area, a major socioeconomic center in Taiwan, was used as a case study to demonstrate the feasibility of the proposed integration model. This area is approximately 1362.57 square kilometers, and the population is approximately 6.34 million, which is 27.5% of the total population of Taiwan. The spatial analysis units in this study comprise 543 traffic analysis zones (TAZs), which are the basic unit for transportation planning. The average size of a TAZ is approximately 2.52 square kilometers with an average population of approximately 12,500 (Fig. 1A). Thirty hospital-based COVID-19 testing stations established by the Central Epidemic Command Center (CECC) in Taiwan were used to represent supply facilities (Fig. 1A). All of these stations provide real-time polymerase chain reaction (RT–PCR) testing, which is more accurate than rapid testing. The daily average volume of human movement among the TAZs (Fig. 1B) were estimated by the revised fourth version of the Taipei Rapid Transit Systems Demand Model (TRTS-IV) based on survey data. The estimation was conducted by the Department of Rapid Transit Systems (DORTS) of the Taipei City Government in 2015. Estimation errors between any two TAZs are generally less than 10%; only a few pairs contain larger errors, none of which is over 20% (Chou, Ko, Lee, Chen, & Lee, 2018).

2.2. Integration model

Our integration model consisted of three components (Fig. 2), the first of which uses a compartmental model modified from the SEPIA model (Gatto et al., 2020) to simulate the spatiotemporal progression of an epidemic. Among the ten compartments, people being hospitalized (H), quarantined at home (Q), and false-isolated (F) constitute confirmed cases because their testing results are positive. However, only the people in H and Q stages are truly infected; the people in F stage are not infected and mistakenly isolated due to a false-positive testing result. Moreover, we assumed that recovered (R) people always possessed effective antibodies; thus, excluding dead (D) people and exposed (E) people who are already infected, susceptible (S) people are the only group that can be infected by the three infectious groups, including presymptomatic (P), severely symptomatic (I), mildly symptomatic or asymptomatic (A).

The second component processes the dynamic demand for testing resources by integrating two quantities: potential requester and testing willingness. First, epidemic progression distinguishes people who may need testing resources. Except for dead (D) people, recovered (R) people who were assumed to possess antibodies, and already isolated people (i.e., people in the H, Q, and F stages), only people in the other five stages (S, E, P, I, and A) may request testing resources. Therefore, they are assumed to be potential requesters. Second, as mentioned above, the willingness to test is dominated by public awareness and epidemic progression simultaneously. We used the hyperbolic tangent function to measure testing willingness at various levels of public awareness based on epidemic severity at each moment; the detected infections (the number of people in H, Q, and F stages) were adopted as the measure of perceivable severity to reflect human collective behaviors responding to an epidemic (details in section 2.2.2). The measured willingness to test finally transforms the potential into dynamic demand.

The third component, based on the assessed amount of dynamic demand, uses the two-step floating catchment area (2SFCA) model to evaluate the spatial accessibility to testing resources at every location. The accessibility of a location could reflect the amount of testing resources allocated to that location; thus, this amount could determine how many people would be identified as confirmed cases. In other words, it affects the rate of people being transferred to the three isolation stages (H, Q, and F). Since isolation reduces the frequency of human contact and disease transmission, the accessibility influences succeeding epidemic progression. Throughout this cycle, all three components interact with each other repeatedly, and the coevolution of these components over time reflects the impact of testing behavior against an epidemic.

2.2.1. Simulation of epidemic progression

In the first component of the epidemic progression model, disease
transmission could occur by contact between susceptible people (S) and individuals from the three infectious groups, including presymptomatic (P), severely symptomatic (I), and mildly symptomatic or asymptomatic (A). The transmission is dominated by a spatiotemporal force of infection, that is, it is assumed to vary in space and time (Eq. (1)): 

\[ \lambda_i(t) = \sum_j \beta_s \cdot P_j(t) + \beta_r \cdot I_j(t) + \beta_A \cdot A_j(t) \cdot \omega(j, i) \]

where \( \beta_s, \beta_r, \) and \( \beta_A \) respectively denote transmission rates originating from the three infectious groups; \( \omega(j, i) \) is daily average volume of residents’ movements from location \( j \) to location \( i \); \( N_j \) represents the population number in location \( j \). The fraction, \( \omega(j, i)/N_j \), represents the influence of the epidemic in location \( j \) on the epidemic in location \( i \) through residents’ movements. Additionally, to reflect local transmission occurring within a certain place, \( i \) and \( j \) can be the same.

Eq. (2) further describes the details of our epidemic progression:

\[ \frac{dS_i(t)}{dt} = \gamma_f \cdot F_i(t) - \{ \lambda_i(t) \cdot \left[ 1 - g_i^S(t) \right] + g_i^R(t) \} \cdot S_i(t) \]

\[ \frac{dE_i(t)}{dt} = \lambda_i(t) \cdot \left[ 1 - g_i^E(t) \right] \cdot S_i(t) - \{ \theta \cdot \left[ 1 - g_i^E(t) \right] + g_i^R(t) \} \cdot E_i(t) \]

\[ \frac{dP_i(t)}{dt} = \theta \cdot \left[ 1 - g_i^P(t) \right] \cdot E_i(t) - \{ \delta \cdot \left[ 1 - g_i^P(t) \right] + g_i^R(t) \} \cdot P_i(t) \]

\[ \frac{dA_i(t)}{dt} = \delta \cdot \left[ 1 - g_i^A(t) \right] \cdot \rho \cdot P_i(t) - \{ \gamma_f + \gamma_a \} \cdot \left[ 1 - g_i^A(t) \right] + g_i^R(t) \} \cdot A_i(t) \]

\[ \frac{dI_i(t)}{dt} = \delta \cdot \left[ 1 - g_i^I(t) \right] \cdot (1 - \rho) \cdot P_i(t) - \{ \gamma_f \cdot \left[ 1 - g_i^I(t) \right] + g_i^R(t) \} \cdot I_i(t) \]

\[ \frac{dR_i(t)}{dt} = \delta \cdot \left[ 1 - g_i^R(t) \right] \cdot \left( 1 - \rho \right) \cdot P_i(t) - \{ \gamma_f \cdot \left[ 1 - g_i^R(t) \right] + g_i^R(t) \} \cdot R_i(t) \]

where \( g_i^S \), \( g_i^E \), \( g_i^P \), and \( g_i^A \) respectively denote the daily average volume of residents’ movements from location \( i \) to the testing stations; \( \gamma_f \) and \( \delta \) denote the probability of testing; \( \gamma_a \) represents the daily average volume of residents’ movements from location \( i \) to the Rubal (H) if identified by testing; otherwise, he or she will progress to recovery (at rate \( \gamma_f \) or die (at rate \( \gamma_a \)). Similarly, a mildly symptomatic or asymptomatic person would be isolated at home (Q) if confirmed as a patient or finally recover.

Fig. 1. (A) The locations of RT-PCR testing stations and the spatial distribution of population density and (B) the amount of human movement on different flows.
from illness (at rate $\gamma_F$). We assumed that home-quarantined (Q) people will recover absolutely (at rate $\gamma_Q$), yet hospitalized (H) people, despite recovering at rate $\gamma_H$, may also die at rate $\delta_H$. Finally, a susceptible person may be identified as a patient in mistake due to a false-positive test, so such a person in our model belongs to the false-positive iso-
ated stage (F). Moreover, people in this stage will “recover” (at rate $\gamma_F$) and then return to the susceptible stage.

### 2.2.2. Estimation of dynamic demand for screening

This component addresses dynamic demand for testing resources, which is composed of testing willingness and potential requester, and Eq. (3)–(6) demonstrates the way we formulated it:

**M**$_i$(t) = w(t) • q$_i$(t)  

$q_i$(t) = $[v_X • S_i(t) + v_E • E_i(t) + v_P • P_i(t) + v_I • I_i(t) + v_A • A_i(t)]$  

$w(t) = \min\left(1, \tanh\left(\frac{2 • c(t)}{N} + 0.001\right)\right)$  

$c(t) = \sum_{i=1}^{5} H_i(t) + Q_i(t) + F_i(t)$  

In Eq. (3), M$_i$(t) denotes the demand at location i at time t; it is the product of the local potential requester at that moment (q$_i$(t)) and the overall testing willingness from the public (w(t)). First, q$_i$(t) is a combination of people from five different stages at that time. We assumed that people from different stages possess different potential toward testing resources; for example, a severely symptomatic person may be more eager to accept testing than a mildly symptomatic or asymptomatic person. Thus, $v_X$, $v_E$, $v_P$, $v_I$, and $v_A$ in Eq. (4) were used to differentiate the potential by setting their values differently. These five parameters range from zero to one, meaning that all people in the corresponding stage request testing resources. The exact values of these five parameters are listed in Table 1. Eq. (5) represents that the overall testing willingness at each time step (w(t)) is influenced by the level of public awareness (k) and the aforementioned perceivable severity of an epidemic at that moment (c(t)). We consider that the people may perceive the severity of an epidemic through the number of confirmed cases daily announced by the health authorities. As mentioned earlier, confirmed cases in our model are composed of people in H, Q, and F stages. Thus, their summation at time t represents this perceivable part at each moment (Eq. (6)). H(t), Q(t), and F(t) in Eq. (6) denote the three corresponding epidemic compartments (hospitalized, quarantine at home, and false-isolated) at time t at location i; Z denotes the total number of locations. With N denoting the total population number in the study area, c(t)/N in Eq. (5) further reflects the relative severity of an epidemic, and the testing willingness it induces was evaluated by a hyperbolic tangent function coupled with public awareness (k). Here, k is a weight to denote the level of the public awareness in each simulation scenario; in other words, we use the value of k to reflect distinct levels of public awareness. As our input value for the hyperbolic tangent function is never less than zero, the pattern of the evaluated testing willingness monotonically increases from zero to one.
third component used the generalized 2SFCA model for evaluating explicitly change the pattern. Thus, we considered that the current range of higher (Fig. 3). This nonlinear property helps reflect the diminishing – phenomenon becomes clearer when the awareness is even when the epidemic is not very severe.

### Table 1

| Parameters | Descriptions | Values | References Cited |
|------------|--------------|--------|------------------|
| $\beta_p$  | Transmission rate from pre-symptomatic (P) to susceptible (S) | 0.15 $\text{day}^{-1}$ | Worby and Chang (2020) |
| $\beta_i$  | Transmission rate from severe symptomatic (P) to susceptible (S) | 0.075 $\text{day}^{-1}$ | Worby and Chang (2020) |
| $\beta_b$  | Transmission rate from mild/no symptomatic (P) to susceptible (S) | 0.075 $\text{day}^{-1}$ | Worby and Chang (2020) |
| $1/\theta$ | Time from exposed (E) to pre-symptomatic (P) | 1 $\text{day}$ | Worby and Chang (2020) |
| $1/\delta$ | Time from pre-symptomatic (P) to severe symptomatic (I) or mild/no symptomatic (A) | 5 $\text{days}$ | Worby and Chang (2020) |
| $\rho$     | Probability to be severe symptomatic (I) | 0.25 | Gatto et al. (2020) |
| $\gamma_1$ | Recovery rate of I | 0.0714 $\text{day}^{-1}$ | Worby and Chang (2020) |
| $\gamma_2$ | Recovery rate of A | 0.1428 $\text{day}^{-1}$ | Based on the assumptions in Gatto et al. (2020) |
| $\gamma_3$ | Recovery rate of H | 0.0714 $\text{day}^{-1}$ | Based on the assumptions in Gatto et al. (2020) |
| $\gamma_4$ | Recovery rate of Q | 0.1428 $\text{day}^{-1}$ | Based on the assumptions in Gatto et al. (2020) |
| $\sigma_1$ | Death rate of I | 0.0413 $\text{day}^{-1}$ | Worby and Chang (2020) |
| $\sigma_2$ | Death rate of H | 0.0207 $\text{day}^{-1}$ | Based on the assumptions in Gatto et al. (2020) |
| $\nu_s$    | Demand proportion of S | 0.01 | Scenario setting in this study |
| $\nu_e$    | Demand proportion of E | 0.25 | Scenario setting in this study |
| $\nu_p$    | Demand proportion of P | 0.25 | Scenario setting in this study |
| $\nu_i$    | Demand proportion of I | 0.99 | Scenario setting in this study |
| $\nu_2$    | Demand proportion of A | 0.5 | Scenario setting in this study |
| $U_j$      | Supply amount of testing kit of one station per day | 1000 $\text{dose}$ | Scenario setting in this study |
| $x$        | Sensitivity of testing kit | 0.9 | Bastos et al. (2020) |
| $y$        | Specificity of testing kit | 0.9 | Bastos et al. (2020) |

Table 1: Descriptions and values of model parameters.

Fig. 3. The relationships between testing willingness, $w(t)$, based on different levels of public awareness ($k$) and the detected epidemic severity, $c(t)/N$.

Spatial accessibility (SA) for each location at each time step:

$$SA_i(t) = \frac{\sum_{j=1}^{J} U_j \cdot f(d_{ij})}{\sum_{j=1}^{J} \frac{1}{ML_i(t) \cdot f(d_{ij})}}$$

where $U_j$ denotes the resource amount that facility $j$ can supply; in this study, the supply amount of every facility was assumed to be stationary, so it did not vary over time. $d_{ij}$ denotes the distance between the geographical centroid of place $i$ and the location of facility $j$. $f(d_{ij})$ further transforms this distance into a weight formation to represent the strength of one-to-one interaction between demand place $i$ and supply facility $j$. Specifically, a negative-power transformation ($d_{ij}^{-2}$) was utilized due to its general adoption in the literature (Kwan, 1998).

The evaluated value of spatial accessibility represents the average amount of resources that an individual can acquire at a certain place. This value may be larger than one; however, an individual seldom consumes over one testing reagent within one day. Thus, we used Eq. (8) to transform the accessibility into a proportion representing the demand/supply match level (ML), which equals 100% if all the demand for testing at place $i$ at time $t$ can be fully satisfied:

$$ML_i(t) = \min (1, SA_i(t))$$

Finally, Eq. (9) demonstrates the way that spatial accessibility (or demand/supply match level, specifically) affects succeeding epidemic progression.

$$g^f_i(t) = w(t) \cdot \nu_s \cdot ML_i(t) \cdot (1 - y)$$

$$g^e_i(t) = w(t) \cdot \nu_e \cdot ML_i(t) \cdot x$$

$$g^p_i(t) = w(t) \cdot \nu_p \cdot ML_i(t) \cdot x$$

$$g^a_i(t) = w(t) \cdot \nu_i \cdot ML_i(t) \cdot x$$

$$g^a_i(t) = w(t) \cdot \nu_a \cdot ML_i(t) \cdot x$$

where $x$ and $y$ denote the sensitivity and specificity of the testing reagent, respectively. The meaning of $w(t)$ and the five $\nu$ notations equal to
their meaning in Eq. (4). Therefore, the first line in Eq. (9) measures the rate at which susceptible people are isolated due to a false-positive testing result, while the other four lines measure the rates at which truly infected people in different disease stages are isolated.

2.2.4. Parameter setting

Table 1 presents the descriptions and values of all parameters in our model; most of their values were derived from two previous studies, Gatto et al. (2020) and Worthy and Chang (2020). For the other parameters, we adopted logics of parameter settings similar to Gatto et al. (2020) to assume their values. Severely symptomatic (I) people and hospitalized (H) people share the same recovery rate, yet the death rate of the latter (α_H) is half the rate of the former (α_I). Mildly symptomatic and asymptomatic (A, Q), quarantined (Q), and false-positive isolation (F) people were assumed to share the same recovery rate, which is twice the rate of severely symptomatic (I) or hospitalized (H) people. Moreover, the values of the potential demand proportions for testing resources from five different stages (i.e. V_s, V_y, V_p, V_t, and V_h) are assumed to reflect that people having more risk or severer symptoms would have higher potential demand. Finally, we assumed that each station could test 1000 people per day at most, and this volume does not change over time or at different levels of public awareness. Both the sensitivity (true positive rate) and specificity (true negative rate) of testing kit are set as 0.9, which is close to the values reported in Bastos et al. (2020).

2.3. Performance of screening

We used the integrated model framework for implementing experiments to test different levels of public awareness to understand the influence of raised public awareness on the effectiveness of screening testing. The level of public risk awareness (k) is measured from zero to seven to form different scenarios for comparison. In each scenario, four time-series indicators were used to summarize the overall situation during an epidemic. The first is testing willingness, which is actually the value evaluated by Eq. (5). This indicator can reveal the proportion of potential requesters that actually request testing resources at every time step. The proportion of resource usage, the second indicator, measures what proportion of testing kits used is at every time step to reflect an overall pattern of resource usage. The third indicator is satisfaction level, which measures the proportion of testing kits used against the total demand at every time step; this indicator represents how much of the demand can be satisfied. Finally, the proportion of severely symptomatic people compared to the total population was used to represent epidemic severity over time.

We also implemented two location-based measures to compare the effect of raising risk awareness on the effectiveness of interventions: resource usage and epidemic reduction. First, the improvement in resource usage implies that more people could be tested and more infected cases could be confirmed through testing; this property helps formulate the first measure: increase in capture rate (ICR). This indicator measures the increase in the proportion of confirmed cases to total infected people at a specific place as public awareness rises. More specifically, ICR is the difference between two capture rates (or the proportion of confirmed cases) from two distinct levels of public awareness.

\[ ICR_k^i = CR_k^i - CR_k^0 \]  

where \( CR_k^i \) denotes the capture rate (CR) at place \( i \) with \( k \)-level public awareness:

\[ CR_k^i = \int_0^T \frac{[H(t)dt + Q(t)dt]}{N_i - S_i^k(T) - F_i^k(T)} \]  

where \( N_i \) denotes the local population number at place \( i \); \( T \) denotes the last time step in the simulation, and \( S_i^k(T) \) and \( F_i^k(T) \) are the local numbers of susceptible and false-isolated people at the last time step with \( k \)-level public awareness. Thus, the capture rate measures the proportion of the total number of confirmed cases to the total number of infected people. Moreover, \( CR_k^0 \) measures the capture rate in the base scenario (\( k = 0 \)). Since high public awareness brings high testing willingness and could capture more infected people, \( CR_k^1 \) is never smaller than \( CR_k^0 \); in other words, \( ICR_k^1 \) is never less than zero. As a result, a higher ICR value reflects a better improvement in resource usage.

Improvement in epidemic reduction could be represented by a decreasing number of infected people; thus, the other measure, decrease of infection proportion (DIP), was created to measure the decrease in the proportion of infected people compared to the local population at a specific place as public awareness rises. Similarly, it is the difference between two infection proportions from two distinct levels of public awareness:

\[ DIP_k^i = IP_k^i - IP_k^0 \]  

where \( IP_k^i \) denotes the infection proportion (IP) at place \( i \) with \( k \)-level public awareness:

\[ IP_k^i = \frac{N_i - S_i^k(T) - F_i^k(T)}{N_i} \]  

where the numerator in Eq. (12) is the same as the denominator in Eq. (10): a total number of infected people; \( IP_k^0 \) measure the infection proportion in the base scenario (\( k = 0 \)). Since high public awareness consumes more testing resources to reduce the number of infected people, \( IP_k^i \) is never larger than \( IP_k^0 \); in other words, \( DIP_k^i \) is never less than zero. As a result, a higher DIP value can reflect a better improvement in epidemic reduction.

To check whether the improvement in resource usage effectively promotes epidemic reduction, we formulate two indices composed of ICR and DIP: overall benefit and local benefit. The overall benefit aims to measure the spatial consistency between resource usage and epidemic reduction to reflect whether high-ICR places usually contain high DIP values. The value of overall benefit is represented by Pearson’s correlation coefficient between ICR and DIP from all places:

\[ OBR = \frac{\sum_{k} (ICR_k^i - \bar{ICR})(DIP_k^i - \bar{DIP})}{\sqrt{\sum_{k} (ICR_k^i - \bar{ICR})^2} \sqrt{\sum_{k} (DIP_k^i - \bar{DIP})^2}} \]  

where \( Z \) denotes the number of places and \( \bar{ICR} \) and \( \bar{DIP} \) are the means of \( ICR_k^i \) and \( DIP_k^i \) among all places, respectively. A high correlation value means that the improvements in resource usage and epidemic reduction are consistent in most places; in contrast, a low correlation value means that no clear consistency exists. On the other hand, the local benefit represents the localized effect of a one-unit increase in the capture rate on the decrease in the infection proportion at each place. It was formulated by dividing DIP by ICR:

\[ LB_k^i = \frac{DIP_k^i}{ICR_k^i} \]  

A high LB value implies an efficient usage of resources because an epidemic could be dramatically reduced by capturing a small proportion of infected people with a small amount of testing resources.

2.4. Influence of geographic factors

To further investigate the influence of geographic factors on the local benefit index, we measured the proximity and attractiveness of every place. The proximity of a place is the inverse of its distance to the nearest testing station. The higher the proximity value, the closer to the testing resource. Thus, a place with a high proximity value may be safer than places with a low proximity value. Moreover, the attractiveness of each place is represented by its PageRank value calculated from the
population flow network. The PageRank value at one place (one node in a network) means the probability visited by a random walker after movement reaches steady status (Brin & Page, 1998). A place with a high PageRank value means that people tend to move toward that place, thereby making it attractive and a source high frequency of disease transmission (Huang, Chin, Wen, Fu, & Tsai, 2019). Furthermore, with the criteria of whether the proximity of a place is larger than the average proximity and whether its attractiveness is larger than the average attractiveness, we categorized all TAZ areas into four different types:

- **CA**: close to resource (high proximity), and attractive areas
- **CU**: close to resource (high proximity), but unattractive areas
- **FA**: far from resource (low proximity), but attractive areas
- **FU**: far from resource (low proximity), and unattractive areas

We then performed 2-way analysis of variance (ANOVA) to investigate the effect of raising public awareness on the local benefit of testing in these types of areas.

### 3. Results

With different levels of public awareness, Fig. 4 shows the temporal trends of four important aspects: testing willingness, proportion of resource usage, satisfaction level, and proportion of severely symptomatic people. Testing willingness contains similar temporal patterns when public risk awareness is low \((k < 3)\). However, as public awareness reaches high levels, testing willingness grows earlier during an epidemic, and it also becomes higher at peak times. The proportion of resource usage shows a temporal pattern similar to testing willingness, yet it contains an upper bound at epidemic peak times when the risk awareness is relatively high \((k > 5)\). This upper bound reflects that the rise of public awareness or willingness cannot bring a notable increase in resource usage after usage has already reached a high level. The increased demand triggered by rising testing willingness, thus, cannot be fully satisfied in the scenarios of high-level awareness. Consequently, there is a mismatch between demand and actual usage of testing resources. Finally, the peak value of the proportion of severely symptomatic people drops dramatically, although the epidemic peak time appears earlier when awareness rises.

The boxplots in Fig. 5 show the distributions of ICR and DIP with different levels of public awareness. Each boxplot, which is composed of measurement values from all TAZs, can reflect the spatial heterogeneity of the corresponding measure. The ICR and DIP of most TAZs gradually increase as awareness rises. However, their values at some TAZs still remain low even in scenarios of high awareness, which means that resource usage and epidemic reduction are difficult to improve in these places. Moreover, the range of ICR is usually wider than the range of DIP, and the difference between these two ranges becomes larger as awareness rises. This pattern indicates that ICR is more spatially heterogeneous than DIP and that high public risk awareness enforces their differences.

Compared to Figs. 5 and 6 displays the relationship between ICR and DIP at every TAZ across the study area. The overall benefit of screening is high when public risk awareness is low, but its value gradually decreases as the awareness rises; in other words, ICR and DIP are not correlated with each other. This pattern reveals that the relationship between ICR and DIP is not consistent across all TAZs in the scenarios of high awareness; local benefit could help further reflect these variations. According to the boxplots of local benefit shown in Fig. 6, both the median and interquartile range (IQR) of the boxplots do not dramatically vary among distinct levels of awareness, but the values of upper fences and outliers gradually increase as awareness rises to the next level. Those places with a high local benefit reflect that local DIP is disproportionately larger than local ICR, thereby decreasing the correlation between these two measures discovered in the scenarios of low awareness. This finding thus reveals the spatially varying effect of public risk awareness on the effectiveness of screening.

Fig. 7 demonstrates the spatial distribution of the four categories of TAZs. Most of the TAZs in the downtown area where testing stations are concentrated belong to either CA or CU. Thus, attractiveness, not proximity, dominates the major difference resulting from geographical features in this area. On the other hand, almost all the TAZs in the outskirts area belong to FU, so the influence of geographical features is more consistent here compared to their influence in the downtown area.

The results of 2-way ANOVA (Fig. 8) show the influences of raising public risk awareness on the local benefit of screening testing in different TAZ types. When awareness is low \((k < 2)\), the local benefit shows significant differences between the areas with attractiveness (CA and FA) and unattractiveness (CU and FU). The unattractive areas show higher local benefit of screening. This indicates that the attractiveness of a location is a more dominant factor for consideration when awareness is low. However, as awareness increases, local benefits in areas distant from testing stations (FA and FU) have significantly higher benefits than those near stations (CA and CU). This indicates that the geographic factor of distance to stations becomes more influential than the factor of attractiveness when the awareness is high.

### 4. Discussion

In this post-pandemic era, effective screening is still crucial for preventing the public from being exposed to infection because the protection of current vaccines might decay or disappear due to breakthrough infections or variants of SARS-CoV-2 (Mendoza, dela Cruz, Gozum, & Galang, 2021; Novazzi, Taborelli, Baj, Focosi, & Maggi, 2021). In this study, we developed an integrated model framework to investigate the
spatial variations in raising public risk awareness and their impact on the effectiveness of screening. By integrating different levels of public awareness and epidemic severity, our model captures the dynamic demand for testing resources originating from human behaviors. Our results indicated that high public awareness promotes high testing willingness and triggers considerable demand. However, the usage of testing resources cannot clearly increase after it reaches a certain level, which usually happens at epidemic peaks in scenarios of high public awareness. Thus, the demand cannot be fully satisfied under such conditions. The shortage of screening does not increase epidemic severity; thus, raising public awareness is essential despite the unsatisfactory demand. Moreover, the overall benefit of screening may not be significant when risk awareness is high; this finding reveals the spatially varying effect of public awareness on screening. To clarify the spatial effects, we compared the locations with different geographical factors, proximity to testing stations and attraction of population flow. Our results found that when public awareness is low, concentrating on unattractive areas (such as residential or urban fringe areas) could promote a higher benefit of testing. On the other hand, when awareness is high, the factor of distance to testing stations is more important for promoting the benefit of testing. Allocating more testing resources in areas distant from stations could have a higher benefit of testing.

The shortage between demand and usage of testing resources highlights an ineffective allocation of resources due to spatial accessibility. In other words, even though the demand is unsatisfactory, surplus resources still exist because the locations of the residents may be far from the testing stations. The possible mechanisms are elaborated in Fig. 8. When awareness is low, attractive locations such as central business districts or transportation hubs where people from different origins tend to gather may have a lower benefit of testing. Such locations are usually characterized by frequent human contact, which easily facilitates disease transmission and aggravates epidemic diffusion (Leung, Jit, Lau, & Wu, 2017). Low awareness, undermining the ability to drive the public to obtain sufficient testing, makes it difficult to identify a large enough proportion of infected people to local population through screening and results in a low benefit of testing. Therefore, arranging additional testing stations at those locations is not recommended. In contrast, unattractive places such as the urban fringe or residential areas may not see rapid epidemic diffusion due to a low intensity of human mobility (Liu, 2020); thus, it would be easier to identify a sufficient proportion of infected people to prevent local outbreaks even though few local residents are willing to be tested. We conclude that arranging testing resources in unattractive areas could be more beneficial when awareness is low. On the other hand, when awareness is high, it would be better to provide additional testing resources at places far from existing testing stations. Supplying testing resources at the existing stations could not satisfy the considerable demand triggered by high awareness. However, additional supply may be easily accessed by those who are distant from existing stations, thereby making the additional resources more beneficial.
To capture the level of public awareness toward a pandemic, Google Trend has similar concept of profiling the public’s attitude toward governmental intervention policies against COVID-19 pandemic (Broddeur, Clark, Fleche, & Powdthavee, 2021; Pullan & Dey, 2021). Based on a given location, a time period, and keywords, Google Trend reports a proportion of people searching related news to the total volume on the internet at that location during the given period. Thus the proportion always ranges between zero and one. It could help health authorities realize the extent of change of public awareness when different level of Google Trend is observed during a pandemic. Therefore, scenarios with different k values in our study could also be regarded as different levels of public awareness; the aforementioned strategies could be further evaluated based on the simulation results.

The index of local benefit of screening in this study reflects the marginal effect of the one-unit resource used (Eq. (13)). When the supply of resources is limited, maximizing its marginal effect could make resource usage more efficient (Al, Feenstra, & Van Hout, 2005). Moreover, the strategies of resource allocation should consider different geographic factors; this strategy emphasizes the importance of area-based preventions highlighted by Das, Li, Allston, and Kharfen (2019). During the COVID-19 outbreak, health authorities in many regions or cities established drive-through testing sites or temporary testing stations to upgrade testing capacity (Flynn et al., 2020). Thus, based on the level of public awareness at different times, our modeling results reflect the significance of geographic factors on the marginal effect of testing and provide greater understanding of the need to appropriately arrange testing resources in areas where a higher benefit could be achieved.
levels of public awareness and different TAZ types. F.-Y. Kuo and T.-H. Wen 

Our model may further consider its spatiotemporal nature in reality. Thirdly, the number of testing kits that one station could supply per day is assumed to be fixed; however, it should also vary spatiotemporally. During the COVID-19 outbreak, health authorities dynamically allocated resources from well-supplied areas to under-resourced areas or established new facilities to upgrade testing capacity, such as the aforementioned example of drive-through testing sites (Flynn et al., 2020; Ranney, Griffith, & Jha, 2020); in other words, the supply amount is usually dynamically distributed in both space and time dimensions. This dynamic supply could influence the evaluation of spatial accessibility and the succeeding pandemic progression in our model, and it warrants consideration for further studies on modeling the usage of testing resources. Last but not least, reinfection or variants of SARS-CoV-2 may generate several waves of epidemic and influence our modeling results through infecting a part of recovered people again. However, previous studies indicated that the rate of COVID-19 reinfection is not very high and it is not associate with severe symptoms or fatal outcomes (Arslan, Isık Goren, Baysal, & Vahaboglu, 2022; Crawford, 2022). Moreover, considering multiple waves due to the variants of virus may dilute the focus of this study. Previous studies also utilized similar study designs to simplify the simulation frameworks for concentrating on the issues they concerned (Mwalili, Kimathi, Ojiambo, Gathungu, & Mbogo, 2020; Worby & Chang, 2020). Therefore, we considered that these issues would not dramatically influence our findings regarding the effect of distinct levels of public awareness.

Author statement
T.H.W. conceived of the main conceptual ideas. F.Y.K. and T.H.W. developed the theory, analyzed the results, and wrote the manuscript. F.Y.K. performed the experiments in discussions with T.H.W.

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