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RESEARCH ARTICLE

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Adaptive pandemic management strategies for construction sites: An agent-based modeling approach

Abstract In the face of sudden pandemics, it becomes crucial for project managers to quickly adapt and make informed decisions that anticipate the consequences of their actions. This highlights the need for proactive management strategies to enhance epidemic response efforts. However, current research mainly emphasizes the negative impacts of pandemics, often neglecting the development of adaptable management approaches for construction sites. This study aims to fill this research void by developing strategies tailored to managing pandemics at construction sites. Using agent-based modeling, the study simulates the movement patterns of workers and the consequent spread of an epidemic under different risk scenarios and management tactics. The results indicate that measures such as wearing masks, managing group activities, and enforcing entry controls can significantly reduce epidemic spread on construction sites, with entry controls showing the greatest effectiveness.

Keywords epidemic transmission, agent-based modeling, safety management, management strategy

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1 Introduction

The emergence of human-to-human infectious diseases, such as SARS, Ebola virus, MERS-CoV, and COVID-19, has significantly impacted the execution of construction projects. Adverse results of these outbreaks are primarily linked to extended construction timelines, escalated expenses, and diminished quality (Luo et al., 2020). Construction laborers face a heightened risk of infection due to the labor-intensive nature of their work and the necessity for close physical proximity. A recent study analyzing the results of more than 730000 COVID-19 tests revealed that construction workers exhibited the highest rates of asymptomatic cases among nearly all occupational groups (Allan-Blitz et al., 2020). Several public health authorities have identified construction as one of the top three occupational settings where outbreaks have occurred, including those in the Washington State Department of Health (2022), Michigan government (2022), and Nashville, Tennessee Tribune (2020). Consequently, there is an urgent requirement for proactive and forward-looking management strategies to enhance epidemic response capabilities within construction activities.

Presently, research on the adverse consequences of pandemics on construction sites has predominantly relied on statistical data analysis. Alsharef et al. (2021) conducted interviews with 34 industry personnel and observed that the unfavorable effects included significant project delays, challenges in procuring materials in a timely manner, reduced productivity rates, material cost escalations, and other issues. Sierra et al. (2022) conducted a comprehensive review of the literature, identifying key challenges faced by contractors, including on-site health and safety concerns, potential legal liabilities, workforce availability, supply chain and subcontractor instability, and the uncertainty associated with the ongoing and unpredictable progression of the pandemic. However, these studies primarily adopt a postcausal inference approach (Alfadil et al., 2022), such as archival analysis, field studies, and questionnaire surveys, which may not provide scenario-specific details and responses to counterfactual questions.

Postcausal inference entails the identification of prominent variables and the quantification of their effects by examining causal relationships in historical cases (Gradu et al., 2022). However, this method can only elucidate the epidemic prevention results of past instances and lacks the capacity to offer predictive insights into pandemic responses. In contrast, agent-based modeling (ABM) represents a specialized approach that concentrates on individual behaviors and its applicability to complex systems, including human behaviors, ecosystems, and economic systems (An et al., 2021). This modeling approach offers several advantages. First, ABM can simulate interactions between diverse types of individuals or agents and their responses to the environment, thereby providing a more precise representation of the effect of management strategies. Second, ABM exhibits resilience to random scenarios by simulating a multitude of random individual behaviors and interactions using Monte Carlo methods (Naili et al., 2019). This allows for a more comprehensive consideration of the intricacies and diversity inherent within the system, circumventing an overreliance on singular cases. Last, ABM serves as a valuable complement and validation for data-driven causal inference methodologies (Casini and Manzo, 2016).

Leveraging the strengths of ABM, this study proposes an innovative simulation approach rooted in spatiotemporal intersections to deduce epidemic transmission risks within construction sites. This research places emphasis on the analysis of trajectory data, pattern recognition, and the simulation of worker trajectories. This approach holds particular relevance due to the distinctive characteristics of construction sites, characterized by partially enclosed spaces, stable personnel rosters, and high-density interactions. With this enhanced modeling capacity, project managers can receive more informed guidance for their pandemic response strategies.

Consequently, this study employed ABM to replicate the pandemic transmission dynamics within the construction site, offering scenario-specific and counterfactual insights to project managers, enabling them to undertake practical measures for the prevention of human-to-human epidemics. The subsequent sections outline the research framework. Section 2 investigates pertinent studies on epidemic analysis within the construction industry. Section 3 outlines the methodological approach utilized in this study. Section 4 expounds upon the procedures and configurations of the computational experiment devised to validate the efficacy of the proposed methodology, followed by an examination of the experiment's findings in Section 5. Ultimately, Section 6 draws the paper to a conclusion by summarizing the contributions, acknowledging limitations, and delineating potential avenues for future research in this domain.

2 Literature review

2.1 Impact of the epidemic on the construction industry

The outbreak of an epidemic engenders notable societal concerns, attributable to the substantial incidence of infections, mortality rates, and unanticipated strain on healthcare services (Dobrucali et al., 2022). One of the most immediate ramifications of human-to-human epidemics on the economy and society is the scarcity of labor resources (Wang et al., 2022). The effects of epidemics on the construction industry can be succinctly outlined as follows.

In terms of project-related challenges, epidemics introduce a high level of uncertainty into the management objectives of construction projects, resulting in project delays, supplementary expenditures, and the emergence of hazardous work environments (Briggs et al., 2022). Such unpredictability is challenging to preclude before the commencement of construction, and once it manifests, there is a pronounced risk of construction disruptions (Gan and Koh, 2021). Construction firms must earmark dedicated resources to procure and stock adequate quantities of materials necessary for epidemic mitigation, including items such as masks, protective attire, disposable gloves, alcohol, disinfectants, and intelligent temperature monitoring equipment. This inventory of materials should be established to cater to the exigencies of the construction site and personnel for the standardized prevention and control of epidemic situations. Additionally, instances of imported infections can propagate swiftly among workers in confined spaces, engendering high-risk focal points within urban areas.

Regarding management-related complexities, project managers grapple with augmented workloads, including tasks such as personnel access management, dissemination of epidemic prevention information, on-site decontamination, and sterilization (Ebekozien and Aigbavboa, 2021). Furthermore, labor shortages stemming from the epidemic necessitate the implementation of scientifically and logically structured management procedures to mitigate uncertainties pertaining to future workforce availability, including the adaptation of work schedules (Aslan and Türkakın, 2022). Disruptions to the supply chain also present a notable challenge to the timely delivery of construction projects.

Concerning individual repercussions, epidemics exert profound effects on the physical and mental well-being of construction laborers (Nnaji et al., 2022). The uncertainties surrounding personal income, job status, and individual health precipitated by epidemics contribute to substantial psychological stress and burnout among construction personnel. Apprehensions regarding their personal circumstances engender a corresponding sense of familial responsibility, compelling them to remain committed to their responsibilities.

2.2 Epidemic modeling of construction sites

Mathematical modeling assumes a pivotal role in the depiction, analysis, prognosis, and regulation of epidemic dissemination. Present research on mathematical modeling of epidemic transmission falls into two primary categories: equation-based models and agent-based models.

Equation-based models for pandemic transmission conventionally rely on a system of equations to outline the state space and interdependencies that characterize the course of pandemic transmission. Prevailing studies commonly employ the Susceptible-Infected-Removed (SIR) model and System Dynamics methodologies. The SIR model, a venerable infectious disease model originating in 1927, has found extensive utility in the analysis of epidemics associated with diverse infectious diseases (Kermack et al., 1927). Differential equations underpin the SIR model, offering an approximate representation of the trajectory from the inception to the conclusion of an infectious disease. Within the SIR framework, the total population is partitioned into categories of disease susceptibility (S), active infection (I), and immunity or recovery (R), including individuals who have recuperated, succumbed to the ailment, or received vaccination (Atkeson, 2020). Cooper et al. (2020) devised a theoretical framework rooted in the SIR model to scrutinize the propagation of epidemics within a community. The SIR method, along with its myriad adaptations, assumes a fundamental role in the assessment, projection, and comparative analysis of epidemics across diverse administrative regions (Wu et al., 2020, Liu, 2020). Additionally, system dynamics, another widely employed modeling approach, illuminates the temporal correlations between diverse variables (Wang and Flessa, 2020), accommodating crucial factors such as population size and contact rates (Salim et al., 2020). Other equation-based models include the time series model (Devarajan et al., 2021) and the integrated Intuitionistic Fuzzy Technique for Order Preference by Similarity to Ideal Solution (IF-TOPSIS) model (Karamoozian and Wu, 2022).

In contrast to equation-based models, agent-based models for pandemic transmission have received significant attention for their ability to capture intricate interaction patterns among the components of the system, specifically, the agents (Stieler et al., 2022). The explicit characteristic of a complex system is often perceived as the unforeseen results stemming from the interactions among numerous complex agents, a phenomenon referred to as emergence (Szabo et al., 2014). Multiagent simulations are frequently employed to simulate pandemic dissemination. Cuevas et al. (2020) devised an agent-based model to evaluate the risks associated with epidemic transmission within unoccupied spaces. Shamil et al. (2021) introduced an agent-based model to glean additional insights into the risk of pandemic transmission in Ford County, KS, USA. Notably, within the context of the construction industry, Araya et al. (2021a, 2022) conducted a series of studies utilizing ABM for simulating pandemic transmission. Gerami Seresht (2022) proposed a resilience assessment model for the construction sector concerning infectious diseases.

2.3 Research gaps and contributions

Present multiagent simulation models primarily emulate the dissemination of epidemics by establishing "contact lists." For example, Mukherjee et al. (2021) compiled a roster of close contacts through interviews and telephone communications, employing it to investigate the potential for disease propagation. Mahmood et al. (2022) instituted a household assembly in which residents with travel requirements traverse various households, and within these households, individuals can transmit the disease. In the domain of construction, Araya et al. (2021b) devised work shifts in construction projects, including day and night rotations, while analyzing the potential for disease transmission among workers sharing the same shift.

These models commonly assume that when agents inhabit the same enclosed space (thus belonging to the same contact list), there exists a potential for epidemic transmission between them. The crux of this approach revolves around the development of precise contact lists to scrutinize individuals who might have encountered the virus and are at risk of infection. This approach is particularly relevant in scenarios involving aerosol transmission within enclosed spaces.

However, within construction sites, in addition to enclosed areas such as cafeterias, dormitories, and offices, a majority of work zones constitute semiopen outdoor spaces. Consequently, the traditional contact list-based approach proves unsuitable for simulating epidemic dissemination within construction sites. A novel approach rooted in the movement trajectories of workers becomes crucial for spatiotemporal association analysis, addressing the challenge of epidemic transmission within the unique environment of construction sites.

The distinctive attributes characterizing construction sites include the following:

- *Outdoor Spaces*: In contrast to aerosol transmission within enclosed indoor environments, epidemic transmission in outdoor construction endeavors is chiefly attributed to close-range droplet transmission. Consequently, a transition from the prevailing contact list approach to the investigation of workers' movement trajectories becomes crucial.
- *Semiopen Spaces*: Diverging from public open areas such as streets and shopping centers, construction sites feature relatively compact and defined work zones, a stable workforce, and well-defined job roles.
- *High Concentration of Workers*: Due to the necessity for closely coordinated collaboration among diverse job categories, construction activities often involve

high-intensity teamwork within confined areas. Consequently, the concentration of workers escalates significantly, heightening the risk of epidemic transmission.

Consequently, the existing epidemic transmission simulation techniques predicated on contact lists are ill suited to accommodate these construction site characteristics. It is crucial to undertake further research on the modeling of workers' movement trajectories, particularly the mechanisms of transmission within various agent trajectories. In contrast to prevailing methodologies, trajectory-based simulation approaches necessitate a heightened focus on addressing challenges such as pattern recognition within worker movement trajectory data, the estimation of location transition probabilities, and the modeling of epidemic transmission risk attributable to spatiotemporal associations.

3 Research methods

As illustrated in Fig. 1, the creation of an agent-based model entails two interrelated and mutually influencing components: the simulation of workers' daily activities and the dynamics of epidemic transmission.

To model the daily activities of workers (as depicted in the left segment of Fig. 1), the primary steps are outlined as follows. First, upon the initiation of the workplace, the collection and examination of workers' raw trajectory data are conducted using spatiotemporal analysis techniques to glean valuable insights. This analysis includes the assessment of the location and layout of living quarters, work zones, supporting facilities, and temporary installations, facilitating the identification of frequently visited areas by workers at different times of the day. Second, conceivable daily activities are determined based on job requirements and other aspects of workers' lives. Finally, individual worker agents may exhibit common life routines and distinct work-related activities. Consequently, a range of activities incorporating spatiotemporal information markers are presented, interlinked and triggered by various mechanisms. Spatiotemporal associations assume a pivotal role in instigating changes in workers' health statuses. Data processing is executed using the Python programming language.

To model the epidemic transmission risk among workers (as exemplified in the right section of Fig. 1), the ensuing steps are undertaken. First, the project's epidemic prevention strategy is outlined, including measures such as the utilization of face masks and the implementation of movement control management protocols. Second, the potential health statuses of workers are identified, including susceptible, infectious, and recovered conditions. Finally, workers' health statuses manifest dynamic and environment-adaptive attributes, influenced by external

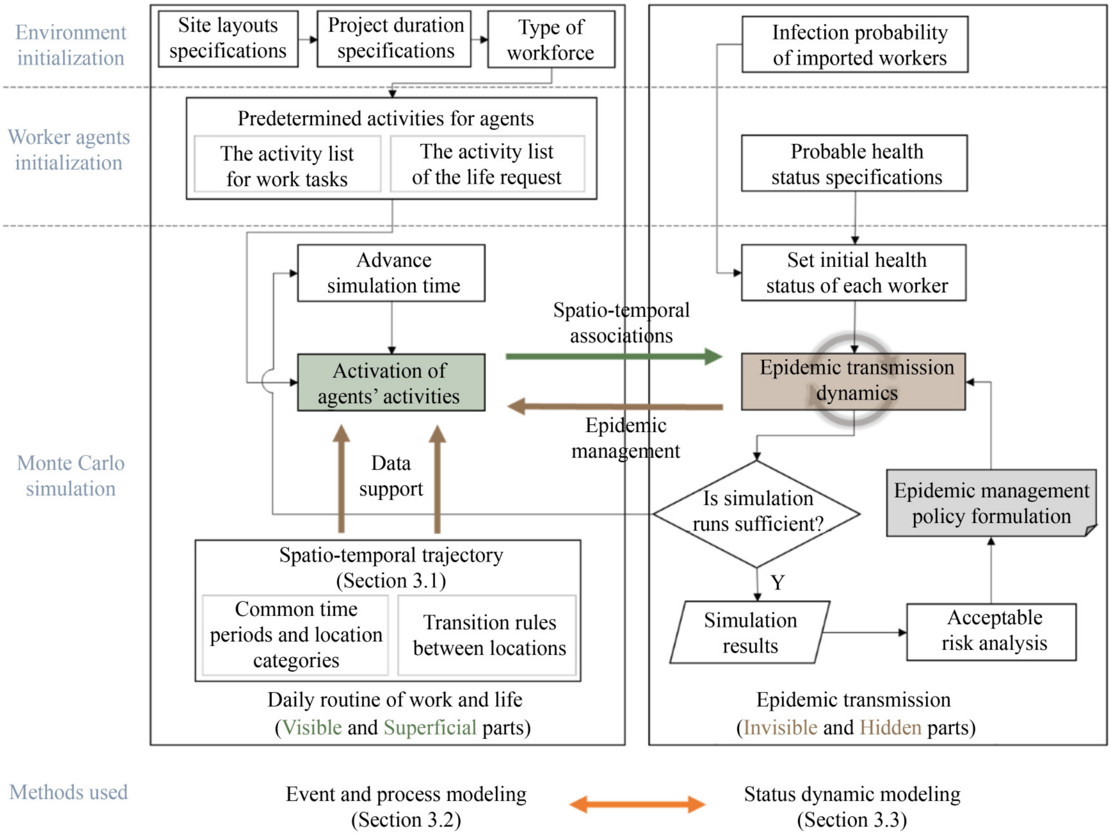


Fig. 1 The technical flowchart of this study.

factors such as spatiotemporal associations among workers' activities and predefined epidemic control strategies. Furthermore, the health condition of workers undergoes a self-evolving, multiphase progression over time. The agent-based simulation for this process is primarily implemented through the use of AnyLogic software.

These two components represent a complex process of dynamic evolution and mutual influence. The movement trajectories of workers constitute a fundamental prerequisite for epidemic transmission, and conversely, the progression of the epidemic reciprocally influences workers' movement trajectories (e.g., the isolation of infected individuals). The comprehensive modeling process for these components is elaborated upon in subsequent sections.

3.1 Spatiotemporal trajectory learning and clustering

Analyzing the movement trajectories of workers and clustering common patterns represents a pivotal phase in simulating human-to-human epidemic outbreaks. To attain this objective, a sequence of steps is initiated, commencing with data preprocessing, as depicted in Fig. 2.

In the first step, the raw trajectory data collected undergo a thorough cleaning and preprocessing procedure. Worker movement trajectory data are acquired through RFID tags carried by workers. As workers traverse various areas within the construction site, such as primary construction zones, material storage areas, the canteen, and dormitories, their RFID tags are automatically detected and logged by RFID readers positioned at these locations. During preprocessing, outliers are eliminated, duplicates are filtered, and trajectories are segmented. Subsequently, location information is extracted and labeled. These locations are mapped to predefined regions or areas, such as "office", "construction area", "material storage area", and "rebar processing area". Trajectory data are then organized based on these location labels. Additionally, time information corresponding to each location is extracted. This results in a data set that encapsulates both the spatial and temporal distribution characteristics of worker occupation or utilization for each location.

In the second step, a spatial-temporal frequency distribution table is formulated, predicated on the 'location label - occupation time' pairing. This table quantifies the distribution of time intervals during which workers occupy various construction areas. Specifically, each value in the table, denoted as area occupation intensity (*AOI*), signifies the proportion of time spent by all workers in a given area during a specific time interval. For example, an *AOI* value of 0.1 for Area D implies that 10% of all time intervals during which workers are present in Area D fall within the time interval from t_4 to t_5.

In the third step, the spatial-temporal frequency distribution table serves as the foundational element for hierarchical clustering analysis (Köhn and Hubert, 2014). Utilizing the Euclidean distance metric, the dissimilarity between different distribution vectors of time intervals associated with various construction areas is quantified.

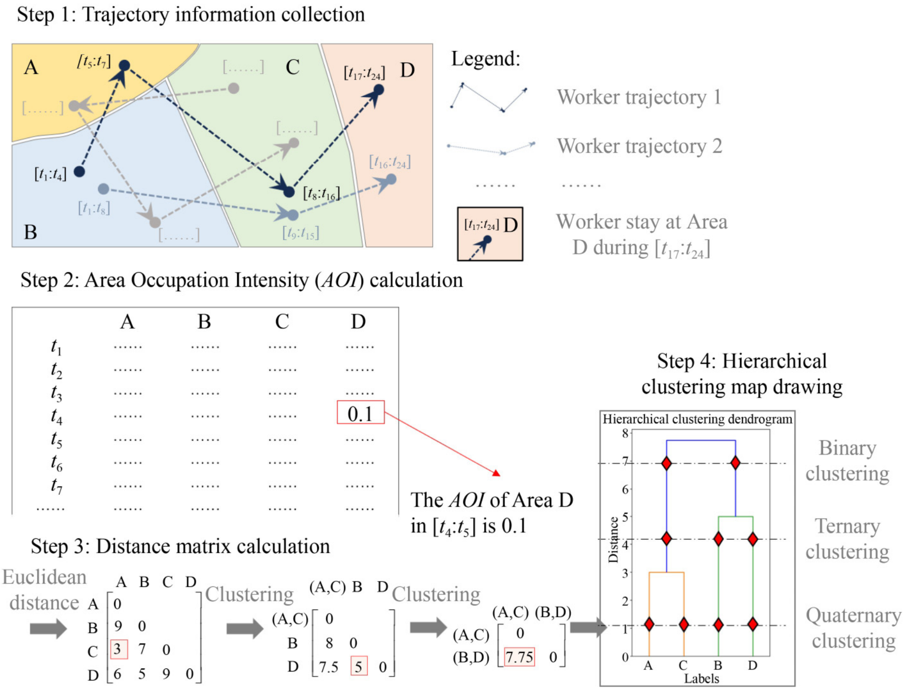


Fig. 2 Hierarchical clustering procedure for spatiotemporal trajectories.

A distance matrix is generated based on these Euclidean distances. In each iteration of the clustering algorithm, the two distribution vectors in the distance matrix with the smallest Euclidean distances are identified and amalgamated into a cluster. This amalgamation results in an updated distance matrix for the subsequent iteration. The process continues iteratively, with each iteration generating a new distance matrix by clustering the two closest distribution vectors until all the vectors are grouped into clusters.

In the fourth step, determining the optimal number of clusters for both time intervals and locations assumes significance, as it unveils common time frames and specific areas frequently occupied by workers. This not only facilitates the comprehension of worker behavior but also establishes a statistically robust framework for simulating spatiotemporal movement patterns. The within-cluster sum of squares is computed across a range of potential cluster numbers, forming an 'elbow curve' (Onumanyi et al., 2022). Subsequently, the Kneedle algorithm (Antunes et al., 2018) is employed to automatically pinpoint the elbow point on this curve. This algorithm scans the curve, identifying the point where the rate of decrease significantly changes, thus determining the optimal number of clusters. Subsequently, a hierarchical clustering algorithm, specifically agglomerative clustering (Müllner, 2011), is employed to cut the dendrogram at the corresponding level, finalizing our clusters. These clusters outline groups of trajectories sharing similar spatiotemporal patterns and provide a statistically grounded framework for comprehending worker movements across different time intervals and locations.

In summary, this method includes trajectory data preprocessing, employs hierarchical clustering for pattern identification, and utilizes transition rules to determine worker locations across distinct time intervals.

3.2 Event and process modeling

This section investigates the essential element of activity modeling, a prerequisite for establishing spatiotemporal associations in epidemic transmission. As portrayed in Fig. 3, each activity of a worker agent comprises three distinct components: triggering predefined conditions, relocating to another location, and awaiting the subsequent event. The concatenation of multiple sequential activities for a worker agent determines their daily movement trajectories (e.g., awakening in the dormitory at 6:30 am → having breakfast in the canteen at 6:45 am → commencing work at the construction site at 7:00 am → …). It is noteworthy that different categories of workers exhibit distinct behavioral patterns. For instance, the movement trajectories of carpenters will markedly contrast to that of steel workers.

a) Triggering predetermined condition.

The dissemination of the virus ensues as a consequence of dynamic alterations in workers' locations, underscoring the significance of spatial movement models in evaluating epidemic risk. Among the various available simulation models that account for the spatial movements of construction workers, diverse driving forces come into play. By scrutinizing the trajectory data gathered in the preceding section, it is feasible to discern the underlying patterns governing these movements. Typically, during a given day, workers' trajectories are influenced by several distinct factors, which can be categorized as follows:

First, we consider time-triggered drivers. Concerning the demarcation between work and personal life, workers typically adhere to fixed commuting schedules, and their spatial positions are primarily dictated by the current time. During the simulation, agents are directed to relocate to predefined general locations at specific times, predicated on the hierarchical clustering results expounded upon in Section 3.1.

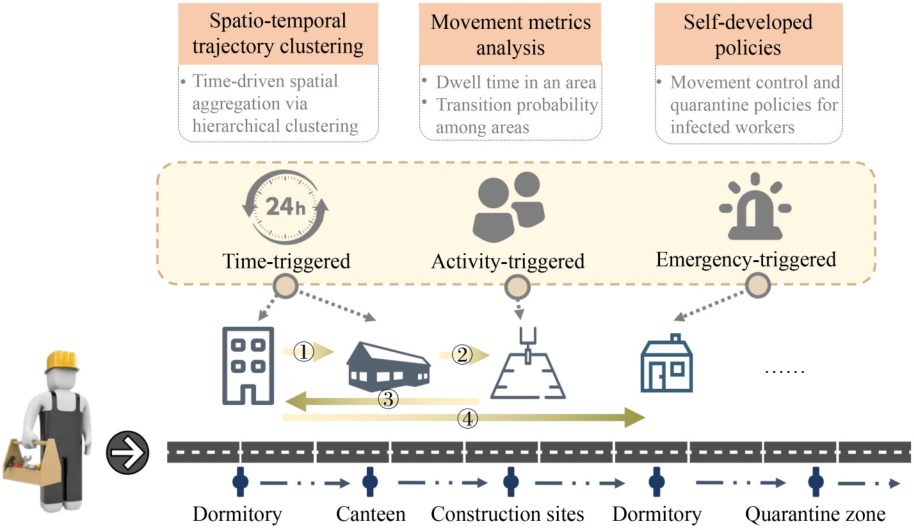


Fig. 3 The driving forces behind the movement of workers on construction sites.

Second, activity-triggered drivers. Movement patterns within construction sites exhibit marked disparities among workers of varying job categories. For example, reinforcement workers predominantly operate within material storage and processing areas, whereas office personnel typically occupy office spaces. To faithfully replicate these movement patterns, the study scrutinizes the movement metrics of workers from diverse job types. This includes an analysis of dwell times in various areas and the probabilities of transitioning from one area to another. The distribution of dwell times in each area, employing triangular fuzzy numbers, is elucidated in Section 3.1. To simulate the transition probabilities between working areas, we collated daily data on transition probabilities among different job categories and departure areas, with the objective of identifying consistent transition patterns. We employed the ANOVA method (Ross and Willson, 2017) to quantitatively assess and pinpoint the controlling factors influencing transitions. This analysis investigates the effects of variables, such as job categories and departure areas, on these transitions. Subsequently, statistically stable spatial transition probabilities are established, considering the dominant attributes of these controlling factors.

Last, there are emergency-triggered drivers. In the event of a worker being suspected of harboring infectious diseases, an emergency protocol is activated, necessitating the transfer of the worker's close contacts to a designated quarantine facility.

b) Moving to another location.

When the above predetermined conditions are triggered, the worker agent will obtain the information of a designated destination. To simulate the movement trajectories of a worker agent, the social force model (Lakoba et al., 2005) is used, where worker i is affected by three forces during walking, i.e., the desired force ($\overline{f_{i0}}$) repulsive force between workers i and j ($\overline{f_{ij}}$), and repulsive force between worker i and obstacle w ($\overline{f_{iw}}$). As shown in Fig. 4, the formula used in the social force model is written as

$$\overline{f_i(t)} = \overline{f_{i0}} + \sum j(\neq i)\overline{f_{ij}} + \sum w\overline{f_{iw}}, \tag{1}$$

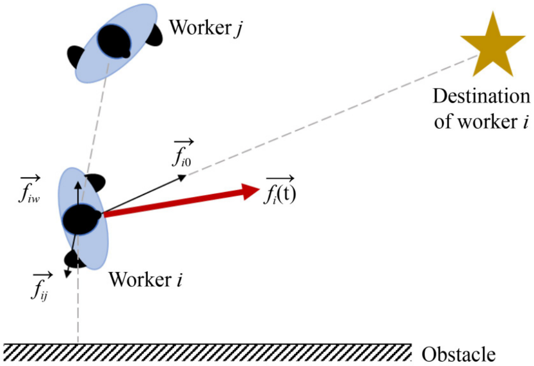


Fig. 4 Driving forces behind the movement of workers on construction sites.

where $\overline{f_i(t)}$ denotes the resultant force on worker i, which also shows the moving direction at time t.

In pedestrian dynamics, the desired force $\overline{f_{i0}}$ represents the intention of worker i to move toward a designated location. However, due to the presence of repulsive forces (e.g., $\overline{f_{ij}}$ and $\overline{f_{iw}}$ the actual walking velocity of worker i may not point to the destination. Consequently, worker i is continually correcting their movement direction to move toward the intended location. According to Newton's second law of motion, the desired force is calculated as

$$\overline{f_{i0}} = m_i \frac{\overline{v_i^0} - \overline{v_i(t)}}{\tau_i}, \tag{2}$$

where m_i is the mass of worker i who is moving at the actual velocity of $\overline{v_i(t)}$. Worker i will adjust the velocity to a desired velocity $\overline{v_i^0}$ toward the destination during the relaxation time τ_i. Sometimes, the destination is a line (e.g., a gate) or an area (e.g., a room) rather than a specific two-dimensional coordinate point. In this case, the point nearest to worker i on the line or in the area is chosen as the destination.

The repulsive forces $\overline{f_{ij}}$ between different workers mainly include two parts: psychological forces and actual forces. First, pedestrians typically endeavor to uphold a specific distance between themselves while walking. When the gap between two workers falls below a particular threshold, both individuals aim to widen the distance, thereby engendering an inverse correlation between psychological force and distance. Second, if the gap between two pedestrians is less than the combined radii of their bodies, it leads to a repulsive force owing to physical contact between their bodies. This force includes the physical components of pushing and friction (Lakoba et al., 2005). The repulsive forces acting upon worker i are articulated as:

$$\begin{aligned}\overrightarrow{f_{ij}} = {} & A\exp[(r_{ij}-d_{ij})/B]\overrightarrow{n_{ij}} + k\eta(r_{ij}-d_{ij})\overrightarrow{n_{ij}} \\ & + \kappa k\eta r(r_{ij}-d_{ij})\overrightarrow{t_{ij}}.\end{aligned} \tag{3}$$

Here, the first term denotes the psychological force, and the second and third denote the forces of pushing and friction, respectively. A, B, and k are constant parameters of the model, and κ is a friction coefficient. r_{ij} is the sum of the radii of workers i and j; d_{ij} is the distance between their center locations. $\overline{n_{ij}}$ and $\overline{t_{ij}}$ are the vectors pointing from i to j and in the tangential direction of the velocity of worker i. $\eta(x)$ is a function defined by

$$\eta(x) = \begin{cases} x, & x \geqslant 0, \\ 0, & x < 0. \end{cases} \tag{4}$$

Similarly, the repulsive forces $\overline{f_{iw}}$ between worker i and obstacle w are written as

$$\overrightarrow{f_{iw}} = A\exp[(r_i - d_{iw})/B]\overrightarrow{n_{iw}} + k\eta(r_i - d_{iw})\overrightarrow{n_{iw}} + \kappa k\eta(r_i - d_{iw})\overrightarrow{t_{iw}}. \quad (5)$$

The only difference between Eq. (3) and Eq. (5) is their subscript, which can be replaced by obstacles (e.g., walls or other facilities). The reference values used in the social force model are presented in Table 1.

Table 1 Social force model calibration parameters (Li et al., 2015; Sticco et al., 2021)

Parameter reference	Parameters	Value
Mass of a worker	m_i	59–89 kg
Desired speed	v_i^0	1.2–1.8 m/s
Relaxation time	τ_i	0.4–0.6 s
Diameter of a person	r_i	0.375 m
Social force parameter	A	2000 N
Social force parameter	B	0.3 m
Social force parameter	k	2.4×10^4 kg/s^2
Social force parameter	κ	1

Notes: An agent-based study on the airborne transmission risk of infectious disease in a fever clinic during the COVID-19 pandemic.

c) Awaiting the next event.

Upon reaching the destination of an activity, the worker will remain at the site for a certain duration until the prerequisites for the next activity are met, enabling them to initiate a new activity sequence.

3.3 Health state transmission simulation

a) Infection probability of imported workers.

Formulating epidemic management strategies for construction sites should be contingent upon the prevailing level of epidemic risk within the city where the site is situated. The probability of worker infection upon entering the construction site is contingent upon the city's prevailing epidemic conditions. To determine the infection prevalence, the total number of infections within the city, denoted as I, must first be computed. This entails aggregating the estimated infections across all age groups, derived from known mortality figures and age-specific infection fatality rates (Bohk-Ewald et al., 2020)

$$I = \sum x \frac{D_x}{IFR_x}, \quad (6)$$

where D_x represents the number of deaths in the age group due to COVID-19 and IFR_x is the infection fatality rate for age group x.

Given this overall number of infections, the prevalence of infections in the city in relation to its total population is then deduced

$$IP = \frac{I}{TP}, \quad (7)$$

where IP refers to the infection prevalence within the city and TP stands for the total population of the city.

b) Probable health status of workers.

This study formulates an infectious disease model grounded in the SEIAR framework (Li et al., 2021) to evaluate the potential health conditions of workers (Fig. 5).

The model includes several states, namely, susceptible, exposed latency, symptomatic infectious, asymptomatic infectious, and recovered. Workers in the susceptible state are susceptible to infection and have a probability of transitioning into incubating or asymptomatic infection upon exposure to elevated viral concentrations. Incubating individuals are asymptomatic but can transmit the virus to others and will eventually progress into symptomatic infection. Workers in the symptomatic infectious state exhibit explicit symptoms, including fever, cough, shortness of breath, and loss of sense of smell or taste. Following a period of treatment, they will either recover or face a low probability of mortality. Asymptomatic infectious workers lack overt symptoms but can transmit the virus to others and will eventually recover after treatment. Workers in the recovered state acquire immunity against viral infection for a certain duration, with some studies suggesting that this immunity may endure for 5–12 months postinfection (Milne et al., 2021). Additionally, protective immunity may persist for up to 4 months following mild or asymptomatic COVID-19 (Reynolds et al., 2020).

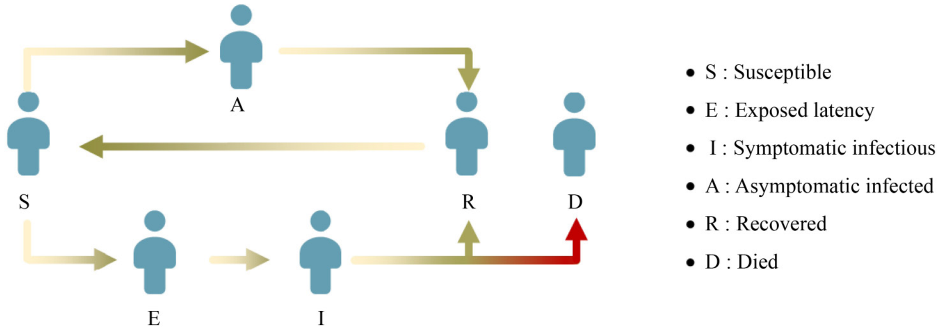


Fig. 5 SEIAR model for infectious diseases.

c) Epidemic dynamics.

In the context of infectious diseases, workers do not become ill spontaneously. The primary cause of illness is transmission from other workers through close contact. Establishing spatiotemporal associations is a prerequisite for epidemic transmission. This study considers two modes of disease transmission, which are elaborated in Step 5 of Section 4 and will not be reiterated here.

Sick workers undergo a series of status transitions based on the severity of the disease. In this study, the Markov chain model (Xu et al., 2022) is employed to depict the status transitions that occur during the self-healing or worsening process of sick workers. Assuming that worker i is in a sick state denoted by x, the probability of transitioning between states can be calculated as

$$F_i^{x\rightarrow y}(t) = 1 - \mathrm{e}^{-\lambda t}, \tag{8}$$

where $F_i^{x\rightarrow y}(t)$ denotes the probability that the transition time from status x to status y is smaller than t for sick worker i. λ is the predetermined parameter in the exponential distribution model, which can be estimated through the expected value, i.e., $E(t) = 1/\lambda \rightleftharpoons \lambda = 1/E(t)$.

Given a fixed time interval Δt (e.g., $\Delta t = 1$ day), the status transition probability within a short period of time can be calculated as

$$p_i^{x\rightarrow y,\Delta t}(t) = \mathrm{e}^{-\lambda(t+\Delta t)} - \mathrm{e}^{-\lambda t}, \tag{9}$$

where $p_i^{x\rightarrow y,\Delta t}(t)$ indicates the probability of the sick worker's health status changing from x to y within a time interval Δt at time t.

d) Risk analysis and policy formulation.

Before embarking on the risk analysis, it is crucial to determine the most troubling adverse results or the most intolerable consequences for project managers. These may include construction delays, cost overruns, and severe illness resulting from infection, among others. The estimation of construction delays can be approximated by

$$\mathit{Constructton\ Delays} = \Sigma_i \Delta T_i \cdot \sigma, \tag{10}$$

where ΔT_i denotes the total quarantine and treatment time of worker i due to infections and σ is a discount factor for noncritical process redundancy that can be proposed by expert opinions. If the corresponding data are sufficient, construction delays can also be estimated by

$$\mathit{Construction\ Delays} = \begin{cases} \Sigma_i \Delta T_i \cdot \dfrac{TCP}{TCP + TNP}, & \Sigma_i \Delta T_i \leqslant TFF, \\ \Sigma_i \Delta T_i - TFF \cdot \dfrac{TCP}{TCP + TNP}, & \Sigma_i \Delta T_i > TFF, \end{cases} \tag{11}$$

where TFF refers to the total free float time, TCP refers to the total duration of the critical path, and refers to the total duration of the noncritical path. The derivation process of Eq. (11) is detailed in Appendix A.

In light of the adverse results projected by the aforementioned model, a predefined threshold is employed to determine the acceptability of risk. In essence, a risk is considered acceptable if the projected consequences remain below the predefined threshold.

Should the analysis reveal unacceptable risks, the need arises to devise and simulate new policies. This study explores and simulates three management strategies, namely, the mandate for workers to wear masks during work, access inspections, and group balancing strategies.

4 Computational experiment procedures and settings

Step 1: Parameterizing a specific epidemic situation

The aim of this experiment is to simulate the transmission and progression of respiratory infectious diseases within an epidemic scenario occurring at a construction site and evaluate the efficacy of various strategies in averting the epidemic. Given the extensive global effect and severe consequences of COVID-19, it serves as a representative model of a severe respiratory epidemic in this experiment. Nonetheless, our approach is a versatile methodology for assessing management strategies at construction sites, and the infection parameters can be adjusted and substituted with relevant parameters to align with the specific epidemic situation confronted by project managers.

In collaboration with experts in construction management and public health, we have outlined the epidemic scenario employed in this case study. These experts include chief engineers and project managers from a housing project within a construction company (comprising 7 individuals), most of whom possess over a decade of experience and hold Bachelor's degrees or higher in their respective domains. Additionally, we consulted physicians specializing in public health and epidemiology from a reputable hospital (comprising 3 individuals), all of whom hold doctorate degrees and possess an average of 9 years of professional expertise in their respective fields. The predefined epidemic scenario utilized in this case study is outlined as follows: Workers' probability of infection upon entering the construction site is presumed to be 10%, with a recovery period spanning [5, 9, 20] d, an incubation duration of [3, 5, 7] d, and a treatment period of [3, 7, 15] d (note that [A, B, C] denotes a triangular fuzzy random number with a minimum value of A, a maximum value of C, and a mean value of B).

Step 2: Construction site initialization

Epidemic transmission is a complex process characterized by numerous variables and inherent uncertainties that defy precise prediction (Sun and Zheng, 2021). In this context, establishing appropriate model boundaries and assumptions assumes primary importance, facilitating a comprehensive grasp of the pivotal factors that influence the propagation of the epidemic. To gain deeper insights into the transmission risk associated with epidemics in authentic construction sites, we have developed a virtual digital model that faithfully replicates the layout of real-world construction sites.

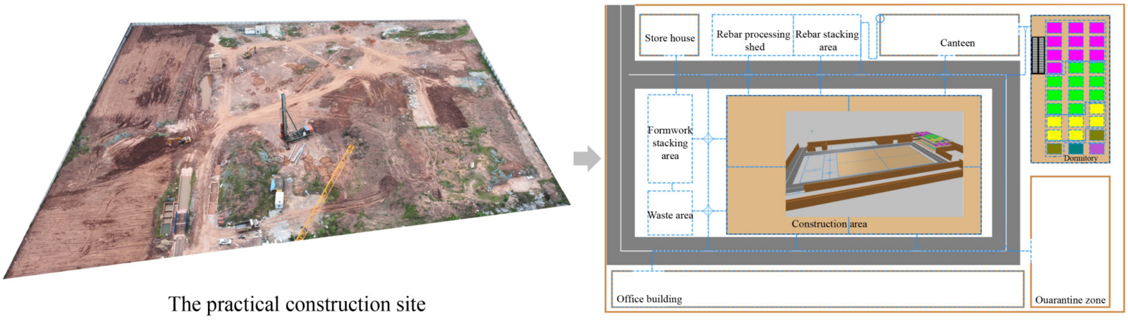
Utilizing Fig. 6 as a reference, the simulation scenario is grounded in an actual construction project situated in Changsha, China. The building under consideration is a four-story frame structure bifurcated into sections A and B, with an estimated timeline spanning approximately 100 d. A closer examination of the project schedule depicted in Fig. 6, where critical tasks are outlined by red arrows, divulges that the principal construction phases are demarcated between foundational groundwork, slated to include approximately 35 d, and the main structural phase, projected to span approximately 65 d. Upon rigorous scrutiny of the constituent tasks, they include foundation excavation (approximately 20 d), foundation backfilling (approximately 5 d), rebar processing and dying (averaging 1–2 d per floor per section), formwork installation (likewise averaging 1–2 d per floor per section), concrete pouring (similarly 1–2 d per floor per section), secondary structure (roughly 8 d), scaffolding works (approximately 60 d), masonry works (approximately 10 d), vertical transportation works (nearly 60 d), and roofing works (approximately 15 d). The primary roles associated with these processes include Carpenters, Cement Workers, Reinforcement Workers, Machine Operators, and Scaffolders. The construction of this virtual digital model aims to rigorously replicate a construction site, providing a realistic and precise platform for scrutinizing the dissemination of respiratory infectious diseases and the efficacy of diverse preventive strategies.

Table 2 rigorously catalogs the system elements and their attributes within the digital model, including a total of 90 worker agents representing eight distinct types of labor. The movement dynamics of worker agents between diverse workstations are propelled by time-triggered, activity-triggered, and emergency-triggered drivers.

Step 3: Trajectory clustering for construction workers

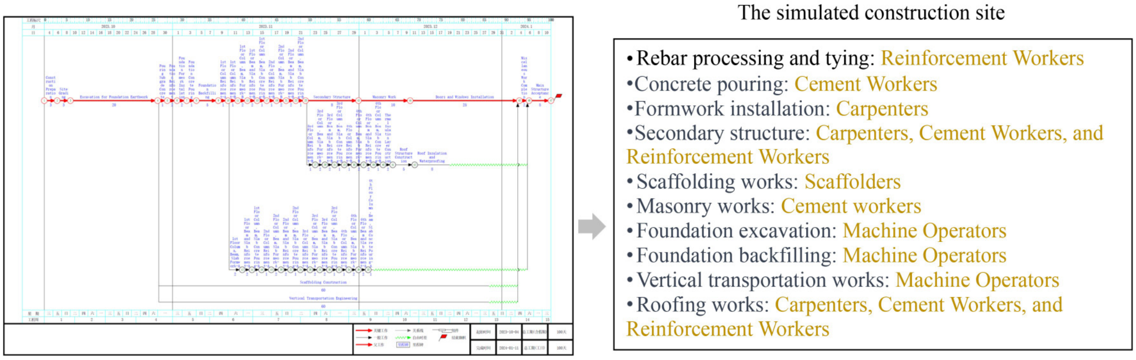
In this investigation, a location monitoring platform system (LMPS), portrayed in Fig. 7, was deployed to amass worker trajectory data. The LMPS includes electronic tags, anchors, and wireless communication devices that facilitate real-time tracking of worker positions. Workers affix electronic tags to their safety helmets, and the system rigorously records tag associations with individual workers. The LMPS leverages RFID-based positioning with an accuracy approximation of 1–2 m. Although this level of accuracy may not rank exceedingly high, it harmonizes with our requisites for spatiotemporal trajectory analysis and simulation. Our algorithm's chief objective centers on determining a worker's location within designated areas at specific times, obviating the necessity for pinpoint accuracy in coordinates. Consequently, the positioning accuracy adequately satisfies the exigencies of our research.

In the lower-left section of Fig. 8, the trajectory data undergo processing through the identification and categorization of location information, with labels such as



The practical construction site

The simulated construction site


- Rebar processing and tying: Reinforcement Workers
- Concrete pouring: Cement Workers
- Formwork installation: Carpenters
- Secondary structure: Carpenters, Cement Workers, and Reinforcement Workers
- Scaffolding works: Scaffolders
- Masonry works: Cement workers
- Foundation excavation: Machine Operators
- Foundation backfilling: Machine Operators
- Vertical transportation works: Machine Operators
- Roofing works: Carpenters, Cement Workers, and Reinforcement Workers

The project schedule

The works and job types involved

Fig. 6 Construction site layout.

Table 2 The system elements in the proposed model

System elements	Classification and quantity	General attributes	Features
Worker agents	Carpenters (32) Reinforcement workers (18) Cement workers (13) Scaffolders (9) Machine operators (8) Construction engineers (6) Office staffs (2) Quality control inspector (1) Project manager (1)	Face mask wearing indicator Health status (susceptible, exposed latency, symptomatic infectious, asymptomatic infectious, recovered)	Dynamic positions
Project size specification	The Project site	110 m × 40 m	Fixed positions
Working places	Construction area (4) Formwork stacking area (1) Rebar processing shed (1) Rebar stacking area (1) Store house (1) Waste area (1) Office building (1) Canteen (1) Dormitory (1) Quarantine area (1)	Centroid position Length Width Height	Fixed positions

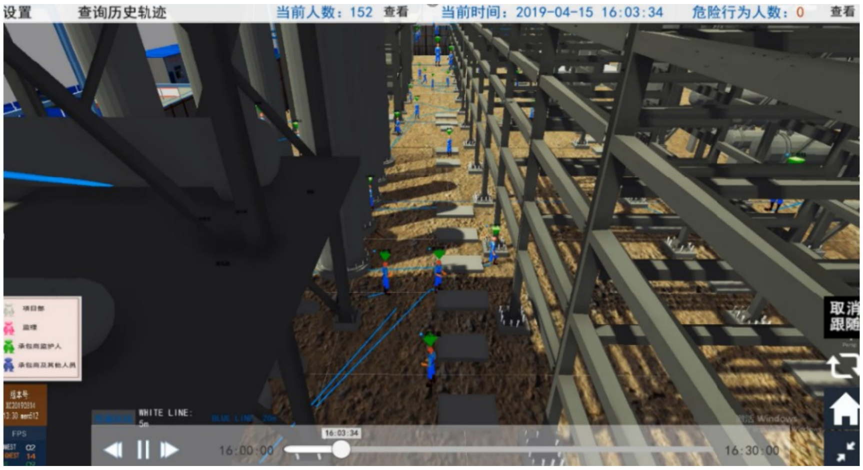


Fig. 7 Location monitoring platform for construction workers.

‘office,’ ‘construction area,’ ‘material storage area,’ and ‘reinforcement processing area.’ Subsequently, the data are aggregated based on these location labels, and the temporal data are scrutinized to discern the distribution of worker presence in each location. Employing the spatial-temporal frequency distribution, a hierarchical clustering heatmap emerges, elucidating worker behavioral patterns concerning visits to distinct locations at different times. The elbow method is enlisted to determine the optimal number of clusters for both locations and time intervals, as depicted in the right segment of Fig. 8. Notably, locations frequented by workers can be categorized into three classifications: work production areas (including the office, warehouse, material storage area, and construction area), the canteen, and the dormitory. These three location types exhibit conspicuous dissimilarities concerning the time periods during which they are utilized. The time span is further segregated into three delineations: working hours, the lunch break, and bedtime. Moreover, a pronounced mapping correlation exists between workers’ behavioral trajectories and the prevailing time, a nexus that will be harnessed in subsequent simulations of worker behavioral trajectories.

Figure 8 provides an overview of workers’ predominant location preferences during various time intervals. However, for a more granular examination of the work production area, including zones such as the office, warehouse, material storage area, and construction area, additional data preprocessing is needed to capture precise transition patterns. This preprocessing involves a comprehensive analysis of the raw data set, comprising approximately 85000 entries detailing area transitions. Specifically, the process involves quantifying the transition probabilities from an initial area to various target areas for workers of the same profession within a given day. This effort culminated in the aggregation of trajectory movement data within the work production area, organized by parameters such as collection time, profession, starting

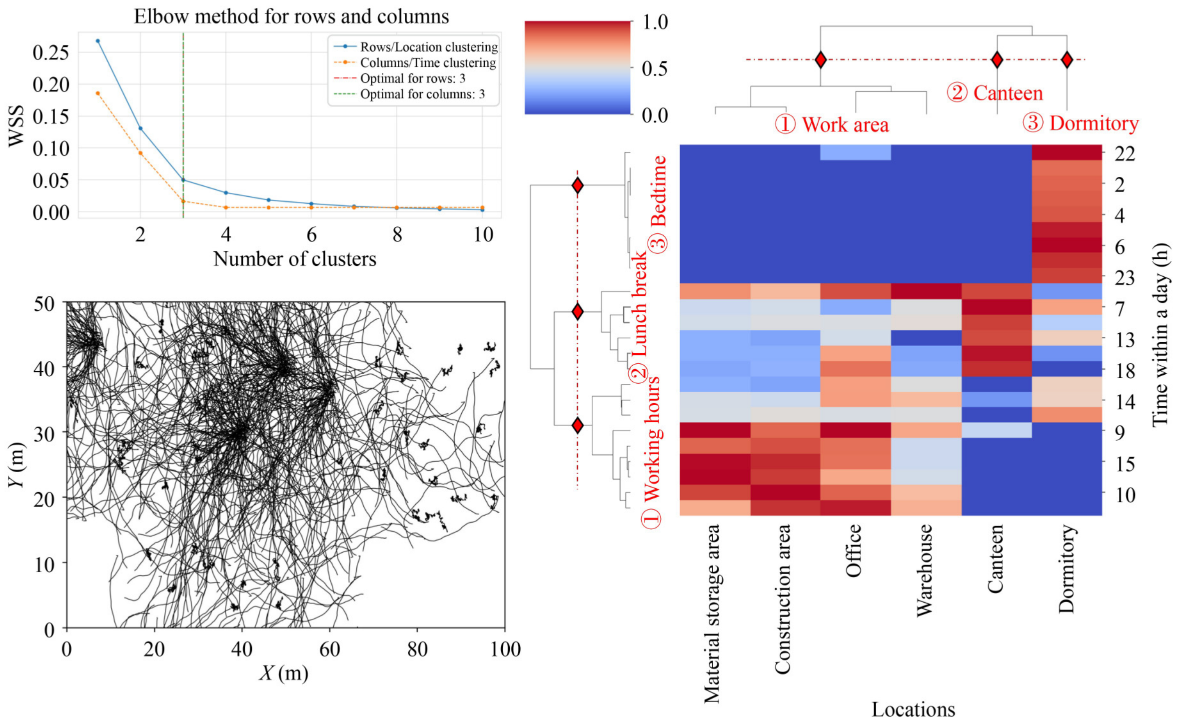


Fig. 8 Spatiotemporal pattern mining of construction workers.

area, destination zone, and transition probability. After consolidation, more than 30000 statistical entries were derived. Figure 9 visually represents these transition probabilities, categorized by the intended target area of movement. The box plots facilitate the identification of distinct influences, including starting areas, target areas, and professions, on workers' transition probabilities. Figure 9 reveals two significant insights. First, workers of the same profession exhibit varying propensities to transition to different target areas. For example, carpenters frequently move to construction and formwork stacking areas, occasionally to warehouse and waste areas, but infrequently to locations such as rebar processing sheds or office buildings. Second, different professions, such as construction engineers and office staff, manifest distinct transition probabilities, even when moving to the same area, such as the formwork stacking area.

Building upon the visualization of transition probabilities among various working areas presented in Fig. 9, we proceeded to quantify and identify the controlling factors influencing the transition probabilities to target areas through the use of ANOVA. The results, as summarized in Table 3, reveal that the variable "job type" exerts a statistically significant influence on nearly all target areas, as evidenced by the highly significant p values. In contrast, the variable "start area" seems to have a minimal effect on the transition probabilities of most target areas, with the exception of "office building", where it also demonstrates a significant influence. These findings suggest that while "job type" consistently emerges as a dominant factor, the influence of "start area" is contingent on the specific context and can vary across different target areas.

Figure 10 presents the average duration of worker stays in different work areas, categorized by their respective occupations. The graph reveals that the majority of workers, including both frontline workers and managerial staff, spend the most extended periods in the construction area. Conversely, office staff and construction engineers, who represent management and administrative personnel, exhibit the longest durations of stays within the office building.

Step 4: Workflow and policy simulations

Leveraging the recurring location data over a specific timeframe, the agent-based approach can be employed to simulate workers' activity trajectories and the ensuing dynamics of epidemic transmission.

Figure 11 illustrates the mobility trajectory of a carpenter throughout the entire construction duration under the group balancing strategy. The diagram comprises two distinct segments: the common segment and the occupation-specific segment. The common segment includes similar and relatively fixed movements shared by most workers. The mobility mechanism in this segment is consistent across different worker types, as denoted by the purple shaded area in Fig. 11. The fundamental principle of the group balancing strategy involves categorizing all workers into specific work groups to minimize the uncontrolled spread of diseases. In the simulation program, construction zones are divided and assigned to different worker groups. The objective is to ensure that workers from various groups perform their tasks in separate work areas, reducing temporal and spatial overlaps.

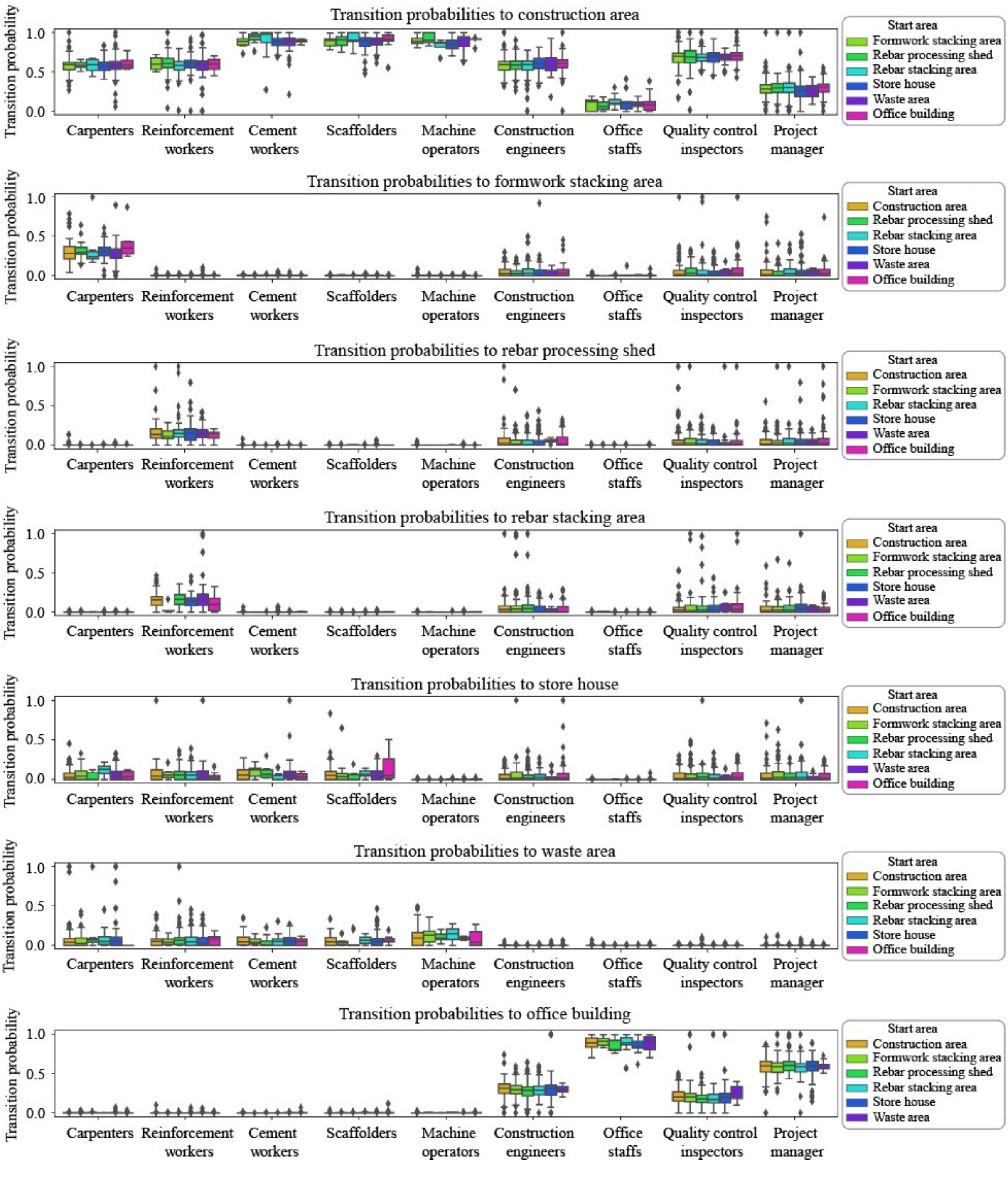


Fig. 9 Transition probabilities among different working areas.

Table 3 ANOVA summary and interpretations

Target area	Job type influence	Start area influence
Construction area	Significant (*p* = 0.00e + 00)	Not significant (*p* = 5.37e−01)
Formwork stacking area	Significant (*p* = 0.00e + 00)	Not significant (*p* = 1.25e−01)
Rebar processing shed	Significant (*p* = 1.66e−194)	Not significant (*p* = 7.44e−01)
Rebar stacking area	Significant (*p* = 2.26e−199)	Significant (*p* = 4.58e−02)
Store house	Significant (*p* = 2.39e−43)	Not significant (*p* = 5.15e−01)
Waste area	Significant (*p* = 8.03e−161)	Not significant (*p* = 2.20e−01)
Office building	Significant (*p* = 0.00e + 00)	Not significant (*p* = 5.67e−01)

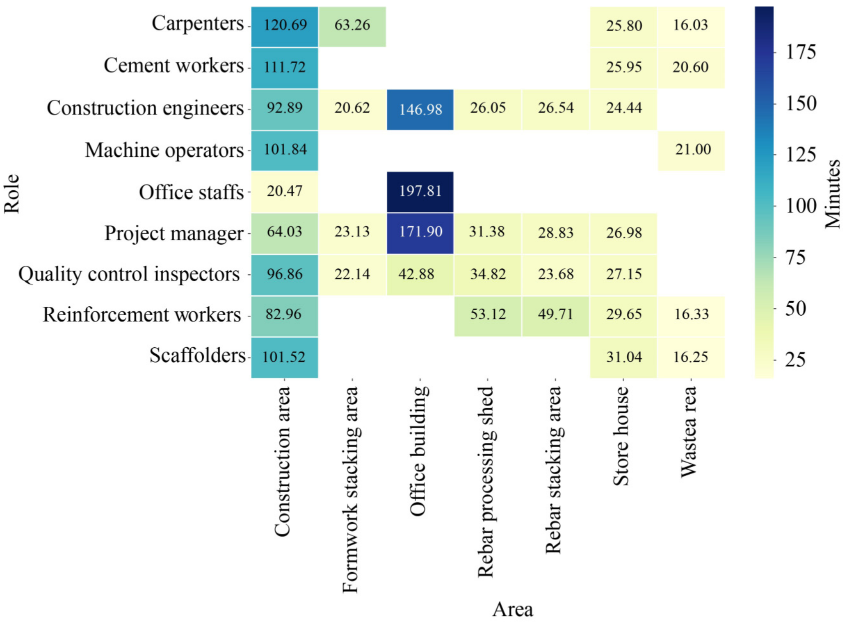


Fig. 10 Average stay time for different job types and working areas.

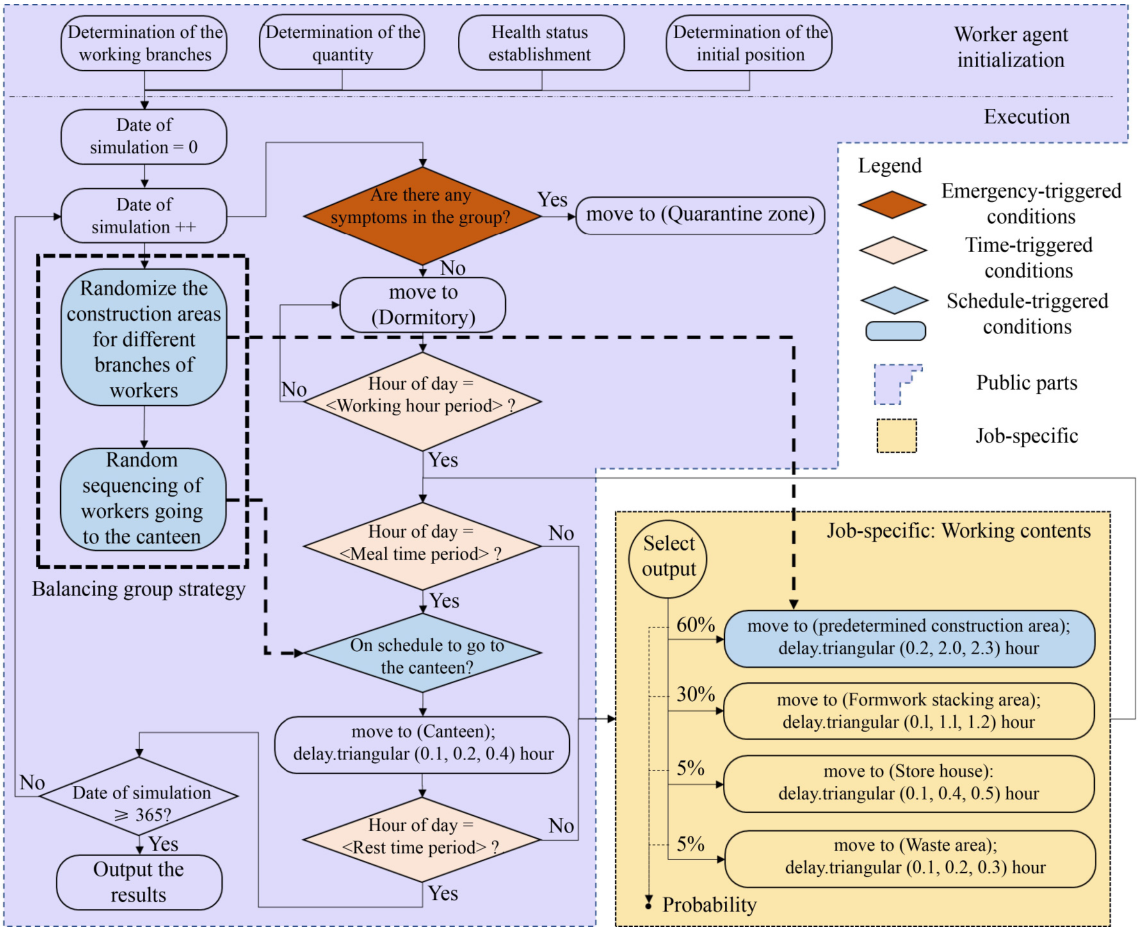


Fig. 11 Workflow diagram of carpenters under the balancing group strategy.

Additionally, as an integral part of the group balancing strategy, construction personnel adhere to staggered meal times. To mitigate the potential for disease transmission in the canteen, the program employs a random selection process to determine the order in which workers from different groups access the canteen.

Different job types exhibit distinct activity patterns, which are derived from data mining of workers' trajectory data in the previous step. The transition probabilities are summarized in Table 4, based on the findings in Fig. 9.

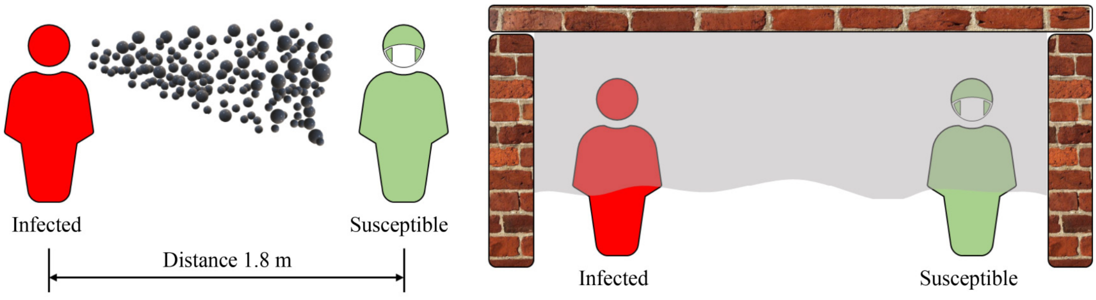
Step 5: Epidemic dynamic simulation

Construction sites, characterized by confined spaces, pose a risk for the transmission of infectious diseases through workers' movements. As depicted in Fig. 12, this study addresses two primary routes of epidemic transmission at construction sites: droplet and aerosol transmission. Information from the Centers for Disease Control and Prevention (2022) regarding COVID-19 indicates that two workers can be considered close contacts if their distance is less than 1.8 m (6 feet). Existing research suggests that approximately 80% of droplets can be captured by surgical or fabric masks (Onishi et al., 2022). However, the specific relationship between mask usage and the probability of infection within the social distancing range at the individual level is not well documented, and precise figures on this relationship are lacking. To address this knowledge gap, this study makes assumptions based on data from a Chinese government website (Taojiang County People's Government, 2021). Depending on whether two workers wear masks or not, the spread of droplets from a social distance is divided into two processes. The first process pertains to the likelihood of an infected worker transmitting the virus, while the second relates to the probability of a susceptible worker becoming infected in a contagious environment. This study assumes that the probability of virus transmission is higher when workers do not wear masks (spreading probability without A mask = 0.95, spreading probability with A mask = 0.05), and the probability of infection is also higher when workers do not wear masks (infection probability without A mask = 0.95, infection probability with A mask = 0.3).

In inadequately ventilated areas, the virus may also propagate through aerosols. This study assumes that the probability of an infected individual transmitting the virus through aerosols is a certain fraction of droplet transmission (0.2 in this case). However, the probability of a susceptible individual becoming infected remains unchanged.

Table 4 The working place distribution of various job types and their probabilities

Job types	Working places and their probabilities
Carpenters	Construction area (60%), Formwork stacking area (30%), Store house (5%), Waste area (5%)
Reinforcement workers	Construction area (60%), Rebar processing shed (15%), Rebar stacking area (15%), Store house (5%), Waste area (5%)
Cement workers	Construction area (90%), Store house (5%), Waste area (5%)
Scaffolders	Construction area (90%), Store house (5%), Waste area (5%)
Machine operators	Construction area (90%), Waste area (10%)
Construction engineers	Construction area (60%), Office building (30%), Formwork stacking area (2.5%), Rebar processing shed (2.5%), Rebar stacking area (2.5%), Store house (2.5%)
Office staffs	Construction area (10%), Office building (90%)
Quality control inspectors	Construction area (70%), Office building (20%), Formwork stacking area (2.5%), Rebar processing shed (2.5%), Rebar stacking area (2.5%), Store house (2.5%)
Project manager	Construction area (30%), Office building (60%), Formwork stacking area (2.5%), Rebar processing shed (2.5%), Rebar stacking area (2.5%), Store house (2.5%)



(a) Droplet transmission (b) Aerosol transmission

Fig. 12 Two main methods of epidemic transmission at construction sites.

5 Experiment results and discussion

5.1 Impact simulation of different epidemic situations

To gain a deeper understanding of workers' trajectories and their implications for epidemic spread, this study conducted a controlled experiment. The experiment aimed to simulate epidemic transmission through various modes of movement, specifically comparing two different modes: random walking and purpose-based movement.

While most prior research on epidemics in construction sites assumed random movement, this study underscores the importance of purpose-based movement, which better aligns with the actual movement patterns of workers. Unlike random walking, purpose-based movement involves workers moving with a specific goal in mind, such as heading to the canteen for meals or going to the construction area for their tasks. Additionally, workers are not continuously in motion; they may remain static for extended periods while working, eating, or sleeping. The controlled experimental design is outlined in Table 5.

The results, as depicted in Fig. 13, indicated notable distinctions between the two modes. In the random walking mode, the infection count exhibited a normal distribution pattern, whereas the purpose-based movement mode data displayed discrete polarized characteristics. This discrepancy can be attributed to the irregular movements of workers in the random walking mode, which facilitated the virus's spread through numerous interactions with different individuals. Conversely, workers in the purpose-based movement mode followed a more systematic movement pattern, diminishing the frequency of interactions between infected individuals and others and consequently reducing the likelihood of virus transmission.

Table 5 The experimental settings of different movement modes

	Random Walking	Purposed-based Movement
Movement mode of each agent	Be instructed to move to a random location within the construction site every 5 min	Moving based on the agent's job types and the surrounding environments, as described in Fig. 11 and Table 4
Initial infected number of agents	1	
Simulation runs	2000	
Face mask wearing ratios	0.6	
Group balance strategy	Nongroup balancing	
Other settings	Listed in Table 2	

5.2 Epidemic prevention policy management simulation

To gain a deeper understanding of the mechanisms governing epidemic transmission on construction sites, this study also investigated the effect of several commonly employed preventive and control measures, including Face Mask Wearing Ratios of Workers, Grouping Balance Strategy, and Access Inspection Strategy.

Mask-wearing requirements were considered a direct and effective means of self-protection against infectious diseases. Utilizing the previously developed model, a simulation experiment was conducted to assess the protective efficacy of masks against the virus. As depicted in Fig. 14, six distinct experimental scenarios were devised to evaluate the influence of mask-based prevention and control measures on epidemic spread. In each scenario, the simulation experiment set the ratio of workers wearing face masks at a predetermined value (e.g., 0, 0.2, 0.4, 0.6, 0.8, 1.0). Each scenario underwent 100 simulations, yielding data results such as the average, maximum, and minimum number of workers in various health conditions.

The results of the simulation experiment underscored that universal mask-wearing by all workers substantially reduced the average total number of infections by

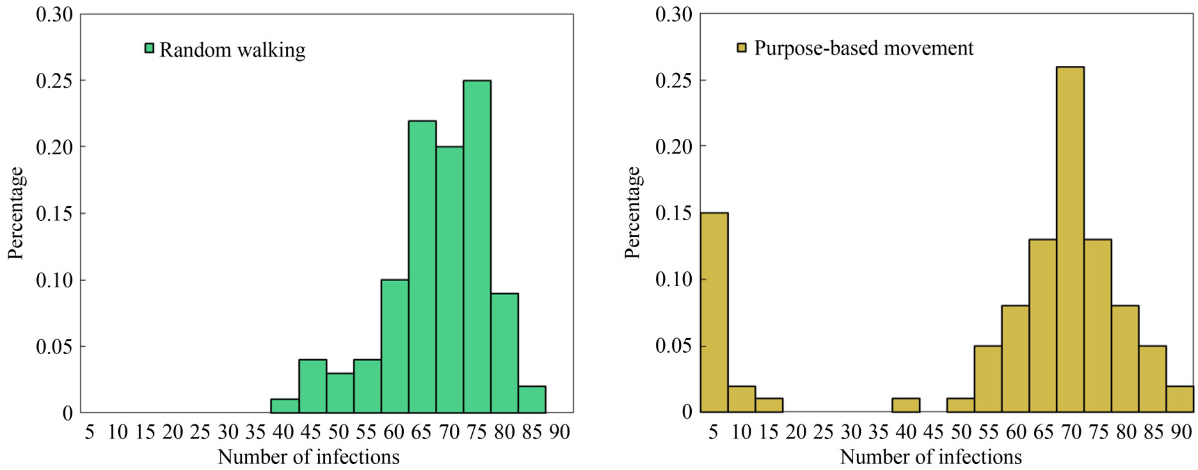
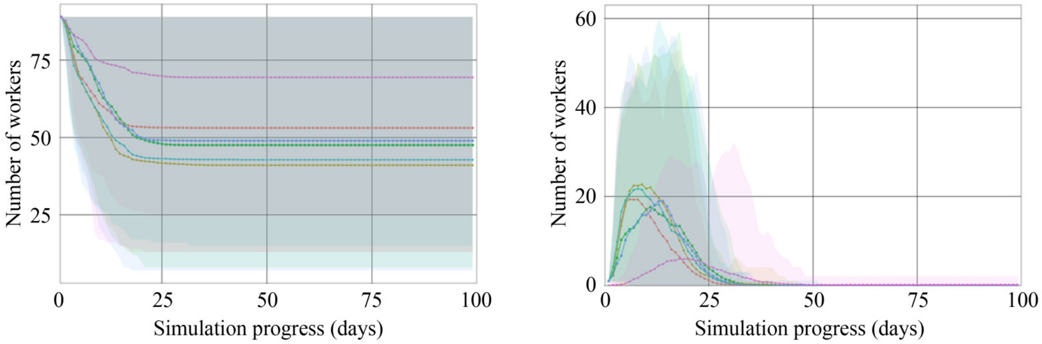
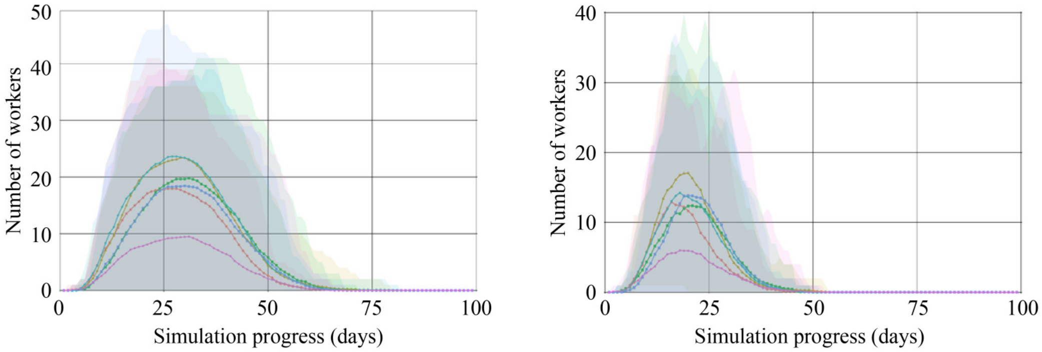


Fig. 13 Number of infections under different movement modes.



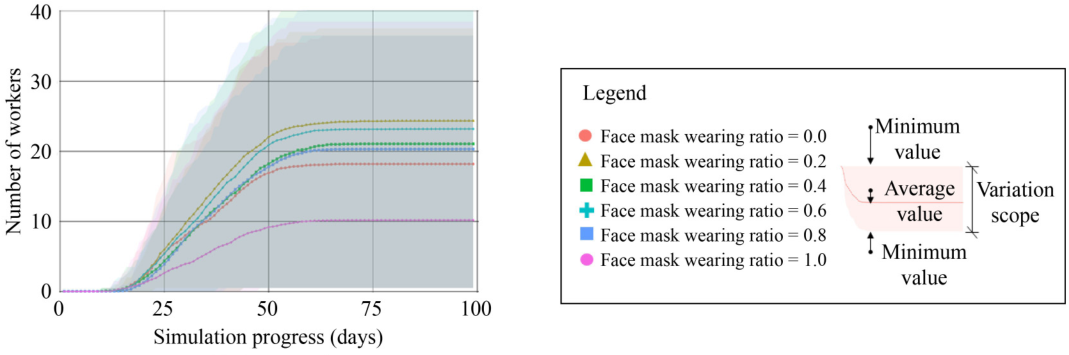
(a) Susceptible

(b) Exposed latency



(c) Symptomatic infectious

(d) Asymptomatic infected



(e) Recovered

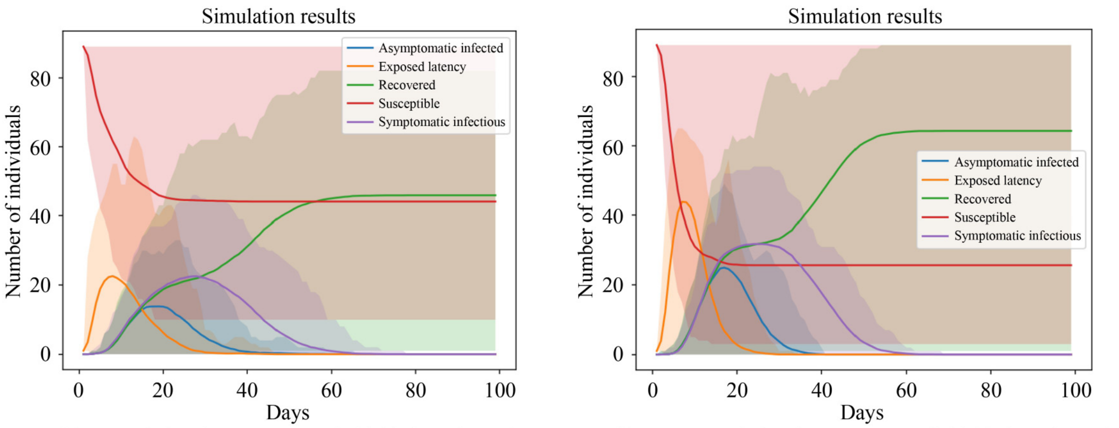
Fig. 14 Protective efficacy of face masks against the epidemic.

approximately 50% compared to other situations. However, the proportion of workers wearing masks did not yield significant improvements in epidemic prevention effects when not all workers adhered to mask-wearing practices. Specifically, variations in mask-wearing proportions had negligible effects on epidemic prevention when full compliance was not achieved among workers. These findings underscore the importance of ensuring high levels of mask-wearing compliance to effectively prevent and control the spread of infectious diseases in the workplace.

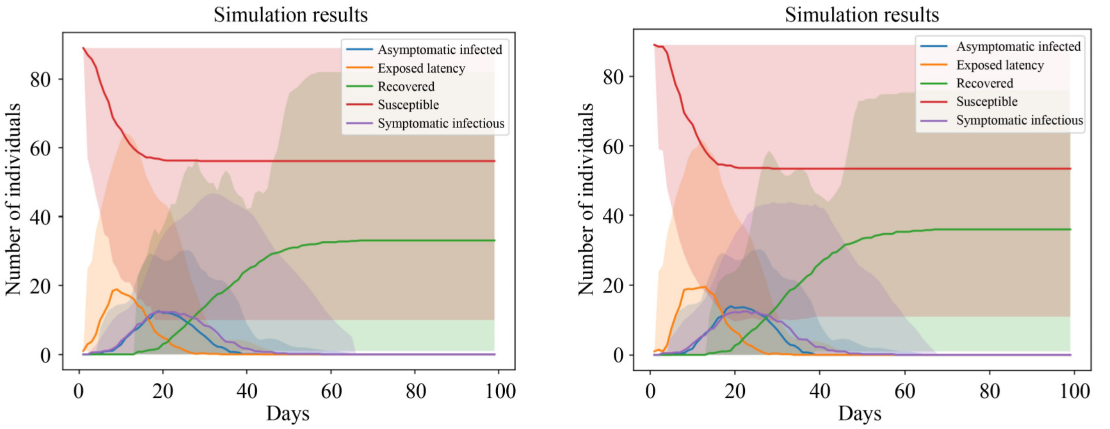
The "group balance" strategy (Centola, 2020) is an epidemic control measure that involves subdividing larger populations into smaller groups or subgroups to minimize interactions and mitigate the risk of cross-infections. This approach ensures that individuals within a particular group or subgroup predominantly interact within their designated cohort, thereby limiting the potential for the virus to spread across different groups.

When adapting this strategy to construction sites, teams can be divided into distinct subgroups based on their job types and tasks. Careful planning ensures that these subgroups operate independently, minimizing overlaps in their work schedules and work zones. Additional measures, such as staggered meal times and designated work areas, further reduce interactions between different subgroups (for a detailed illustration of the procedure, refer to Fig. 11).

In this study, the efficacy of the "group balance strategy" was assessed within the context of construction sites to determine its effectiveness in mitigating the spread of outbreaks. In the comparative experiment depicted in Fig. 15, independent simulation experiments were conducted, comparing the results of simulations



(a) Group balancing: Carpenter (initial infected agent) (b) Non-group balancing: Carpenter (initial infected agent)



(c) Group balancing: Office Staff (initial infected agent) (d) Non-group balancing: Office Staff (initial infected agent)

Fig. 15 Protective efficacy of the group balance strategy against the epidemic.

with the group balance strategy against those without it for 300 iterations. Both sets of experiments employed identical face mask wearing ratios, with the 300 experiments divided into six groups, each with a specific face mask wearing ratio ranging from 0, 0.2, 0.4, 0.6, 0.8 to 1.0. No access inspection measures were implemented in this experiment.

Comparing Figs. 15(a) and (c) with Figs. 15(b) and (d), it is evident that the group balancing strategy significantly slowed the spread of the epidemic. Under the group balancing strategy, the mean infection ratio was 51.1% (46 out of 90), whereas it reached 71.1% (64 out of 90) in the absence of group balancing. Furthermore, frontline workers (carpenters) and non-frontline workers (office staff) were selected as representatives to assess the effect of the initial infection source's job type on the simulation results. The analysis centered on the effect of different initial infection sources on the final results.

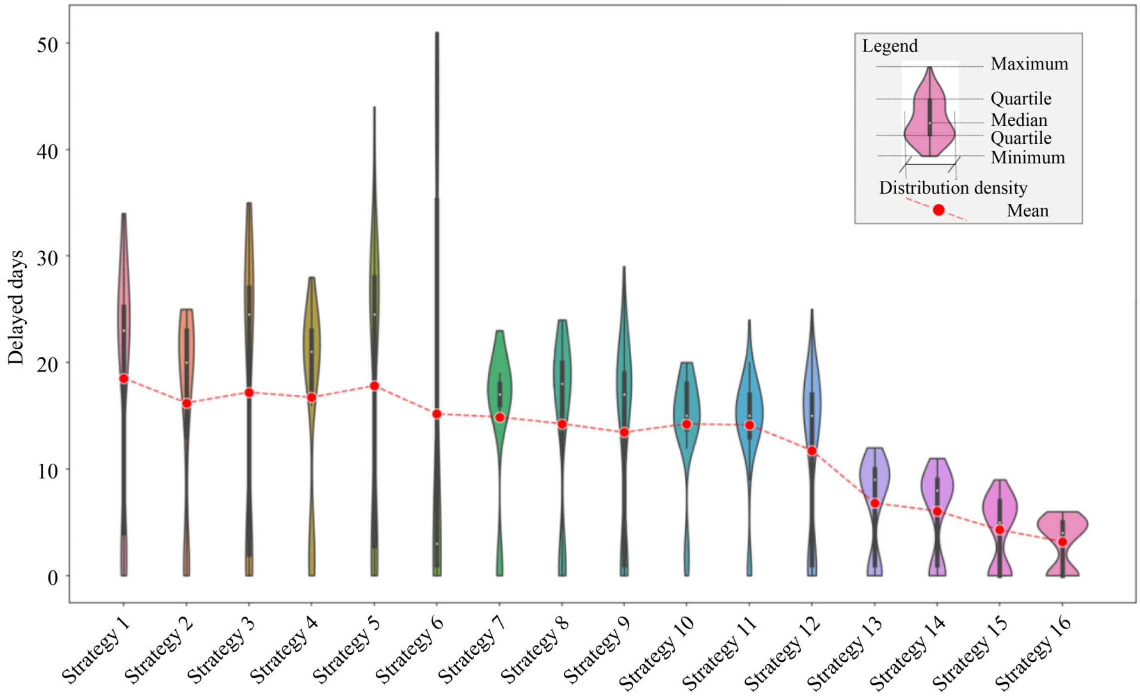
Comparing Figs. 15(a) and (c) with Figs. 15(b) and (d), it is observed that under the group balancing strategy, when the initial infection source shifted from carpenters to office staff, the number of infections decreased from 46 to 33. In contrast, under the nongroup balancing strategy, there were minimal differences in results regardless of whether the initial infection source was a carpenter or office staff. These findings suggest that the job type of the initial infection source indeed influences the spread of the epidemic. This could be attributed to distinct job types having varying movement patterns, which, in turn, affect their roles in transmitting the epidemic. For example, carpenters may have more frequent spatiotemporal associations with other job types, increasing their likelihood of transmitting the epidemic. The group balancing strategy effectively reduces excessive interactions between carpenters and other job types. Conversely, office staff primarily operate in office spaces, limiting their spatiotemporal interactions with other job types. Consequently, the group balancing strategy has a less pronounced effect on preventing the epidemic among office staff.

Access inspection is considered an effective method for outbreak management, as it involves screening and regulating the entry of potentially high-risk external individuals. Similar to the experiments testing the group balance strategy described earlier, we established comparable experimental conditions for access inspection experiments. It was assumed that 10% of the workers would leave the construction site daily and return. Upon their return to the construction site, access inspection measures were implemented. Initially, no workers were infected in the simulation. With the implementation of the access inspection policy, the infection rate among workers on the construction site significantly decreased, resulting in an 88% reduction in infection rates compared to scenarios without this policy.

The effectiveness of the three management strategies in response to the epidemic situation outlined in Section 4 (Step 1) was then evaluated. Employing Monte Carlo simulation, a controlled experiment was conducted, testing 16 scenarios (4 × 2 × 2), with each scenario simulated 1000 times. The simulation results are presented in Fig. 16, where the number of delayed days was calculated using Eqs. (10) and (11).

Our findings indicate that by strictly adhering to all three measures, construction delays caused by the epidemic can be substantially mitigated. Specifically, there was an 82.6% reduction in delays (from 18.4 d to 3.2 d) compared to scenarios without any measures. It is essential to highlight that effective minimization of construction delays is achieved when both Measure 1 (Face mask wearing ratios ⩾ 0.6) and Measure 3 (Access Inspection) are rigorously enforced. In scenarios where these measures are not strictly implemented, the anticipated construction delays exceed 10 d. The results in Fig. 16 suggest that project managers should implement tailored epidemic management measures aligned with the specific requirements of their projects.

In examining Fig. 16, which portrays the performance of various management strategies, it is evident that significant fluctuations are observed across different strategies.



Note: Strategy '*X*' corresponds to the following table.

Measure 3: Access inspection strategy	Measure 1: Face-mask wearing ratios							
	0		0.3		0.6		1.0	
	Measure 2: Group balance strategy							
	Non-group balance	Group balance	Non-group balance	Group balance	Non-group balance	Group balance	Non-group balance	Group balance
No access inspection	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8
Access inspection	Strategy 9	Strategy 10	Strategy 11	Strategy 12	Strategy 13	Strategy 14	Strategy 15	Strategy 16

Fig. 16 Performance of various management strategies.

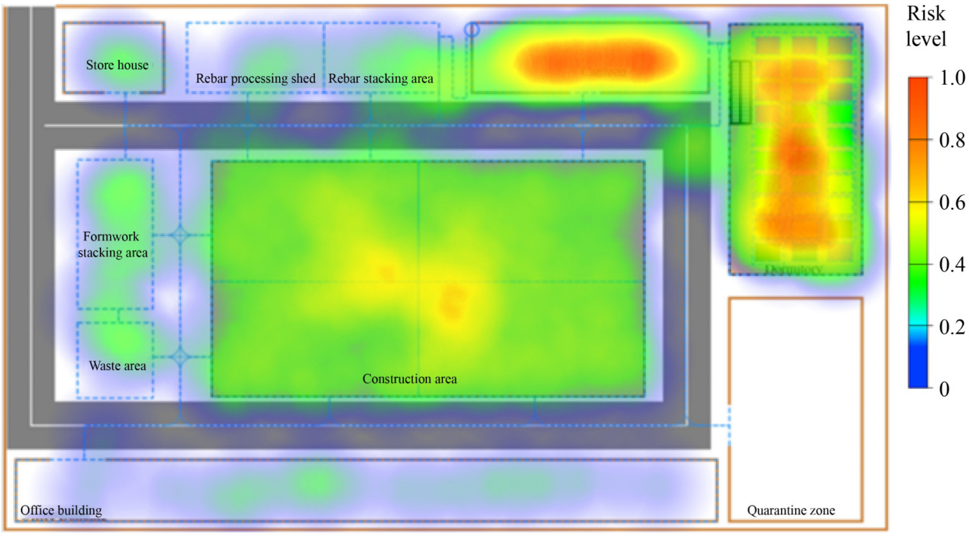


Fig. 17 Infection heatmap of workers at the construction site.

This variability underscores the inherent uncertainty associated with the results of each strategy. For example, Strategy 1 exhibited a wide range of variation, with values spanning from 0 to 34. Such patterns of data distribution were not unique to Strategy 1; similar trends were evident in other strategies as well. In Strategy 5, the results ranged from 0 to 44. Particularly notable was the polarization phenomenon in Strategy 6, where a significant concentration of results skewed toward higher values, frequently featuring values such as 51. However, it is noteworthy that lower values, such as 0 and 1, were also recorded.

Throughout the simulation, data were collected on the geographical locations where each infected worker contracted the virus. These data enabled the generation of a heatmap displaying the level of infection risk in different areas, as illustrated in Fig. 17. The visual representation of the heatmap highlights that the dormitory and canteen areas pose the highest risk of infection, followed by the construction areas. This observation can be attributed to the fact that both dormitories and canteens are indoor spaces that facilitate the transmission of the virus through two pathways: droplet and aerosol transmission.

5.3 Interpretation and analysis of simulation results

Based on the results suggested in the preceding section, our study imparts several pivotal insights and elucidations:

- *Polarization in Epidemic Spread*: The conspicuous bimodal distribution depicted in Fig. 16 does not denote inefficacy in epidemic control policies. Instead, it underscores the dominance of stochastic factors in disease dissemination. Two pivotal observations merit attention:
- As preventive measures intensify, the polarization diminishes. In the first 12 strategies, delays often exceeded 20 d, with nearly half extending beyond 30 d. However, as management strategies became more stringent, the delays notably reduced to approximately 10 d or even less in the subsequent four strategies. Despite the evident polarization, a discernible downward trend persists from Strategy 1 to 16. The average delay drops from 18.53 in Strategy 1 to 3.18 in Strategy 16, highlighting that despite uncertainties in some strategies, preventive measures remain broadly effective. *Monte Carlo Simulation in Epidemic Spread*: Our study employs Monte Carlo simulations to replicate disease spread within construction sites. Given a specific management strategy, the results can vary considerably. This variability does not reflect model instability but is an intrinsic characteristic of the Monte Carlo approach, which relies heavily on random sampling. In the context of disease transmission, the process inherently exhibits nonlinearity. Early interventions might curtail the spread, but a lack of timely measures could lead to a rapid, snowballing epidemic. Consequently, our results encapsulate this nonlinear, bimodal nature of the spread.
- *Validation of the Simulation Method*: Rigorous statistical analyses were rigorously conducted throughout the research process to ensure the validity of our conclusions, as exemplified in Fig. 9, Table 3, and Fig. 16. To calibrate our model, we juxtaposed its predictions with real-world data from construction sites during the early phases of the epidemic. Moreover, real-world construction site scenarios underpinned our initial project phase, with all raw data sourced from actual sites, thereby enhancing the model's practicality and reliability.

Furthermore, our findings align with prevailing epidemic spread theories and extant studies. The results outline the inherent uncertainties and probabilistic nature of disease dissemination (Allen et al., 2022). Even under identical management strategies, unpredictable factors, such as superspreading events, can yield varying results. This is especially conspicuous in the early spread of diseases that are highly sensitive to superspreading events (Althouse et al., 2020). The most corroborative evidence lies in the basic reproduction number, R0, of COVID-19. The literature suggests that distinctive attributes of SARS-CoV-2, particularly its elevated R0, confer upon the disease the potential for explosive growth under specific conditions (Stoddard et al., 2020). This highly nonlinear propagation mirrors the bimodal distribution observed in our simulation results, further attesting to the model's reliability and accuracy.

6 Conclusions

This paper proposes an agent-based model aimed at assessing the risk of epidemic transmission within a construction site. The simulation model employs a hybrid approach to represent the locations and activities of diverse construction workers. Agents' actions are controlled by time-triggered, activity-triggered, and emergency-triggered drivers, governing their trajectories. During instances of spatial and temporal overlap in agents' trajectories, the virus spreads among them with a specified probability, and infected workers' health conditions evolve over time.

Simulation experiments yield valuable insights into epidemic management at construction sites. The results demonstrate that epidemic progression displays considerable variability, leading to extreme results: either minimal transmission or a rapid, exponential surge in infections. Despite the significant variations observed in simulations, ranging from widespread epidemic transmission to minimal transmission, the efficacy of preventive measures should not be underestimated. Furthermore, as these measures strengthen, the extreme results diminish, and a clear downward trend in average effects becomes evident. Additionally, this research offers practical implications for the construction industry, including:

- *Answering "what-if" questions*: Our study can aid project managers and decision-makers in predicting the potential results of various epidemic prevention strategies. The proposed method can be employed to analyze the effect of management strategies in various epidemic scenarios, including different infectious diseases or site layouts. By customizing specific parameters in the model, effective management strategies can be determined for any given epidemic situation. For example, it can help evaluate the need for implementing access control and assess the associated risks of not doing so.
- *Providing information support for construction organization design*: In the process of designing construction organizations, considering the risk of epidemic transmission has become crucial. Through this study, construction teams can gain valuable insights into how to adapt workflows, allocate personnel, and configure work areas to minimize the risk of epidemic transmission.
- *Identifying priority areas for epidemic prevention*: Simulation modeling can accurately pinpoint high-risk infection areas at construction sites. This provides construction teams with targeted information to enhance the effectiveness of epidemic prevention measures.

However, it is important to acknowledge certain limitations of the proposed model. First, it primarily focuses on droplet and aerosol transmission, overlooking other transmission modes such as contact with contaminated surfaces. Additionally, it primarily emphasizes the main categories of construction workers, neglecting other personnel, such as support staff. The model also does not deeply explore how construction site layouts may influence transmission dynamics, despite the significant effect of spatial arrangements on personnel movement and interaction frequency. The potential effects of work scheduling on epidemic spread have also not been extensively explored. Factors such as task transitions, labor divisions, and team interactions can amplify transmission risks. Furthermore, several other factors may influence epidemic spread on construction sites, including ventilation conditions, the health status of personnel, and immunity levels. In future research, addressing these limitations and striving for a more comprehensive representation of epidemic spread mechanisms will be essential. Exploring effective risk mitigation strategies should also be a focus of future endeavors in this domain.

Conflicts of Interest The authors declare that they have no conflicts of interest.

Appendix A

Derivation of Eq. (11)

Based on the principles of project schedule management (Hinze, 2004), delays occurring on the critical path invariably lead to an extension of the overall project duration. Conversely, delays on noncritical paths may not result in an extension of the total project timeline, owing to the availability of free float time. Consequently, the following deductions can be made.

a) If the total delay time is no larger than the total free float time ($\Sigma_i \Delta T_i \leqslant TFF$), there is a probability of $\frac{TCP}{TCP+TNP}$.

b) that the delayed time is on the critical path, and there is a probability of $\frac{TNP}{TCP+TNP}$.

c) that the delayed time is on the noncritical path (which is assumed to cause no delays due to free float time). Thus, the expectation of the final construction delays can be roughly estimated by

$$
\begin{aligned}
& Construction\ Delays \\
& = \Sigma_i \Delta T_i \cdot \frac{TCP}{TCP+TNP} + 0 \cdot \frac{TNP}{TCP+TNP} \\
& = \Sigma_i \Delta T_i \cdot \frac{TCP}{TCP+TNP}. \qquad (12)
\end{aligned}
$$

d) If the total delay time is larger than the total free float time ($\Sigma_i \Delta T_i > TF$), the expectation of the final construction delays can be roughly estimated by

$$
\begin{aligned}
& Construction\ Delays \\
& = (\Sigma_i \Delta T_i - TFF) + TFF \cdot \frac{TCP}{TCP+TNP} \\
& \quad + 0 \cdot \frac{TNP}{TCP+TNP} \\
& = (\Sigma_i \Delta T_i - TFF) + TFF \cdot \frac{TCP}{TCP+TNP}. \qquad (13)
\end{aligned}
$$

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