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Spatial-temporal analysis of safety risks in trajectories of construction workers based on complex network theory

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ABSTRACT

Understanding the traffic patterns of construction workers on high-risk construction sites is important for implementing behaviour-based safety management. However, safety risks in worker trajectories are a complex system with high uncertainty. This resulted in few studies focusing on analysing the spatial–temporal risk in workers' trajectories from a systematic perspective. This study designs a new framework to explore the spatial–temporal patterns of safety risks in the trajectories of construction workers based on complex network theory. First, an integrated site safety risk classification method by combining hazard sources and group trajectory distribution is developed to accurately describe the spatial distribution of site risks. Second, a new complex network chronnet is used to construct complex networks containing risk information for spatial–temporal analysis. Finally, key risk areas and risk transition patterns are identified through the analysis of network measures. The study also developed a computational program that allows the network to be constructed and analysed in real-time. The feasibility and effectiveness of the method are verified through a case study. The results show that the method can reveal the risk distribution at the micro level, and explore the risk clustering and transition features in worker trajectories at the macro level. The study allows for an accurate analysis of dynamic risk patterns in construction workers' trajectories from a systematic perspective. It can also provide theoretical and practical support for personalized and adaptive behaviour-based safety management for construction workers.

1. Introduction

The construction industry is an industry with a high accident rate and difficult safety controls [41]. Due to the dynamic, random, and complex nature of construction sites, construction activities require workers to be in constant motion on high-risk sites. Thus, workers will interact with hazardous areas in an uncertain spatial and temporal manner, which makes active behaviour-based safety extremely challenging [29,43]. According to statistics, 717 construction accidents occurred in China in 2021, an increase of 3.3% compared to 2020 [34]. A large proportion of these is due to unsafe movements of workers resulting in falls from heights, traffic accidents, exposure to hazardous environments, and impacts or being struck by mobile equipment [1]. Analysing the movement of construction workers and understanding the spatial–temporal interrelationship between workers and site safety risks offer the potential for managers to formulate enhanced safety strategies [29]and improve proactive safety management from an objective level [4,11,18].

Human trajectory is rich in valuable knowledge [63], and analysing trajectory can help to achieve behaviour-based safety management [42]. The advantage of using trajectory for safety management is that the data collection is convenient, and the data is objective and real-time. These characteristics are crucial to reduce the occurrence of safety accidents [4]. Previous studies have analysed construction traffic patterns based on workers' trajectories and concluded that such analysis can help to allocate resources and improve productivity effectively [21,24,45,54]. For instance, Arslan et al. (2019c) investigated the traffic patterns of construction workers within stay regions. Unsafe movements within the stay regions were identified based on steps and turnings in trajectories. Similarly, studies have also implemented trajectory-based safety management by examining whether workers' trajectories intersect with hazard source movement trajectories [43], whether they are located within hazard zones [7], or whether there are gait anomalies in the trajectories [54]. However, there are certain limitations. First, site risks

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are not analysed from a systems perspective, only the interaction of workers with hazard sources is considered [29]. Based on field observations and related literature [3], construction workers may have to stay around risk sources for a long time during construction. Only considering interactions with hazard sources may lead to inaccurate risk judgements. Second, trajectory risks are spatial-temporally dependent as risks are widespread on construction sites and construction workers constantly interact with different risk areas. Moreover, few studies have systematically described the risk patterns in construction workers' trajectories from the perspective of temporal and spatial changes. In this study, the risk indicates the combination of exposure and likelihood of safety accidents that may occur to construction workers on-site, inferred from their movement trajectories. The spatial–temporal risk pattern here refers to the risk transition features in trajectories, including risk cluster patterns and risk frequent patterns [20]. The risk cluster pattern is the stay/transition feature of individuals/groups in different risk areas. The risk frequent pattern is the main transition feature of individuals between different risk levels.

Complex network theory can be used to uncover the spatial–temporal risk patterns of trajectory for construction workers [48]. The theory uses mathematical theory to illustrate complex walking mobility problems [36]. It has been extensively used in the study of human migration [9], traffic congestion [58], and mobility patterns [52]. Safety risks in worker trajectories are also a complex system with high uncertainty [2,30]. The movement trajectories of construction workers on-site are highly stochastic systems, and the risk in their trajectories also exhibits complex temporal and spatial variations. Traditional statistical methods and other descriptive approaches are inadequate for uncovering the dynamic changes in the complex relationships among different risk levels of worker trajectories over time and space. However, complex networks have significant advantages in describing the internal structure and connections of complex objects [31,48]. Thus, spatial–temporal patterns of trajectory risk can be realised through the complex network theory, an approach that to our knowledge has not been adopted in this topic to date.

This study aims to analyse spatial–temporal patterns of construction worker trajectory risks based on complex network theory, to uncover potential key risk areas and identify spatial–temporal risk patterns for individuals. The research first assesses the site risks from a system perspective and transforms construction workers' trajectories into complex networks. Then, network measures are calculated and spatial–temporal risk patterns are mined. Overall, this study provides a method that can analyse the movement risk pattern of workers at both temporal and spatial levels. The method is of great practical importance to describe the dynamic changes of risks in trajectory. This study can also provide theoretical support for the implementation of personalised and adaptive behaviour-based safety management from a systemic perspective.

The remainder of the study is organised as follows. Section 2 briefly reviews the research related to trajectory-based and complex network-based safety management in construction. Section 3 presents the framework of the proposed method. Section 4 provides a construction case study of an actual project to validate the feasibility of the method. Section 5 discusses the main research contributions of this study in detail and describes limitations, potential applications, and future directions. Finally, Section 6 summarises the work of the study.

2. Literature review

2.1. Trajectory-based construction safety management

The flow of construction workers will interact with different types of resource flows, limiting the physical space available to workers and causing several safety-related near misses [37]. Worker's movement trajectory can be regarded as a time series composed of position and trajectory segments [48], which contains various features, including timestamps, geographic coordinates, altitude, and speed [63]. Many researchers have conducted research for obtaining effective safety information by analysing these features. In terms of risk assessment, Golovina et al. [19] presented a visualisation solution for recording the risk of collisions between walking workers and heavy construction equipment. A quantitative model for hazard exposure assessment based on real-time location data is introduced in a more general context by Luo et al. [32]. The study provided a concept of hazard exposure to assess safety risks onsite. Arslan et al. [2] used Viterbi algorithms to classify worker movements into four states, short steps with few turns, short steps with many turns, long steps with few turns, and long steps with many turns to enable risk assessment in dynamic environments. Moreover, predicting the trajectory of workers plays an important role in the prevention of safety accidents. Using computer vision and the improved Social long short-term memory (LSTM) model, Kong et al. [25] implemented worker trajectory prediction to predict unsafe behaviours by determining whether a worker's future track point lies in a hazardous polygon region. Mei et al. [33] proposed a computer vision-based static hazardous areas intrusion detection method by combining the Yolov5 model with worker posture and intrusion direction. Cai et al. [6] believed that rich contextual information such as workgroups and tasks are underutilized in worker trajectory prediction, and proposed a context-enhanced LSTM method for predicting construction workers' trajectories. Li et al. [27] used discrete-time Markov chains to analyse the transition relationships between various daily safety statuses, and predicted site safety based on data recorded by a real-time location system.

Although previous studies have achieved satisfactory results in trajectory-based construction safety management, they have relied mainly on the analysis of the interaction between workers and hazards on site, ignoring the safety information embedded in the dynamic group trajectories [26]. In practical, workers may be continuously working around hazard sources. The trajectory safety analysis that only considers hazard sources may lead to misjudgement of safety risks. It is necessary to measure construction site risks in combination with hazard source distribution and group trajectory distribution. It will help to provide the basis for the accurate analysis of spatial–temporal risk patterns in trajectories.

2.2. Complex network and construction safety management

Complex network theory provides a new research perspective for revealing complex nonlinear relationships in risk time series. The theory abstracts each element in the system into a node and abstracts the relationship between nodes into a network edge, which can capture the macroscopic and microscopic characteristics of the system quantitatively. Thus, the complex network approach has yielded a wealth of valuable results in construction safety management, which can be broadly summarised into three components: risk monitoring, accident analysis and behavioural management.

In the field of safety risk monitoring, Gao et al. [16] used an undirected and unweighted complex network to analyse multiple settlement monitoring points and explored the spatial and temporal correlation patterns involved. The results of this study showed that the use of complex networks can identify hazard areas that are difficult to detect in conventional monitoring methods. Liu et al. [31] used a network of networks approach to measuring key risk features and hazards to improve the efficiency of safety inspectors. Yao et al. [57] used social network analysis techniques to analyse the construction safety-related Twitter network and concluded that Twitter will help to stimulate interest in construction safety. Additionally, complex networks can represent causal relationships and highlight key elements for construction accidents. For instance, Zhou et al. [67] developed a metro construction safety risk network and identified the key nodes in the network using network attacks. The results provide a reference for analysing metro construction safety accident causality. Zhou et al. [64] used the visibility graph to analyse the time series characteristics of near-miss events, and proposed management suggestions for near-miss incidents in subway construction. In terms of behavioural management, Wang et al. [48] proposed a general paradigm for analysing human movement patterns based on Global Positioning System (GPS) trajectory data using complex networks. Duan and Zhou [12] extracted unsafe behaviours of construction workers and established complex networks from accident cases. The study identified potential unsafe behaviours that were ignored in traditional safety management by analysing network cascading failures. Wang and Razavi [47] provide a safety risk analysis method for equipment collision by building a spatial–temporal network considering the interactions between different construction agents (equipment and walking workers) in construction sites. Network centrality such as degree centrality and eigenvector centrality were selected to represent the risk level of individual entities.

Understanding the complex traffic patterns of construction workers is important for the targeted control of worker safety and the rational allocation of safety resources [45]. The interaction between the worker's trajectory and risk is a complex process in time and space. However, few studies focus on analysing the spatial–temporal risk in workers' trajectories from a systematic perspective. Considering that the complex network theory has advantages in macro and micro spatial–temporal data mining. It is necessary to study how to use the complex network method to accurately mine the spatial–temporal risk patterns from a systematic perspective.

3. Method

This study provides a method to mine spatial–temporal risk patterns by representing construction workers' trajectory risk sequences with networks. The research mainly includes four parts: trajectory risk time series, complex network construction, identification of key risk areas and risk transition pattern mining, as shown in Fig. 1. First, the trajectory of construction workers during construction is collected through the smartphone GPS, and the trajectory risk time series is obtained by overlaying site risk with the trajectory. The site risk is assessed by integrating the risk level of hazard source and group trajectory distributions. Afterwards, a weighted directed spatial–temporal network with self-loops called the risk unit transition network (RUTN) is constructed based on the trajectory risk time series. The RUTN is analysed to identify potential high-risk areas and risk cluster patterns. Finally, the network nodes of the same risk level are fused to generate the risk transition network (RTN). The network measures are extracted and the risk frequent pattern of different groups is analysed based on clustering.

3.1. Construction trajectory risk time series

3.1.1. Construction site safety risk

The construction site safety risks are portrayed in the form of a heatmap by dividing the construction site into several blocks. Each block in the heatmap is a risk unit, representing a certain level of risk. The trajectory risk time series is obtained by analysing the traversal of workers between the different risk units at the construction site. Different from previous studies that divided construction sites according to the checkerboard shapes [26,56], this study uses hexagons to divide risk units. The advantage of the hexagon is that it is the closest shape to a circle [5] and is more adaptable to different shapes of risk sources.

The risk level in each risk unit is determined according to the distribution of hazard sources and group trajectories on the construction site. The measurement of on-site safety risk is obtained by combining two parts: measurement based on hazard sources and measurement based on group trajectories. The measurement based on hazard sources is determined according to the proximity between workers and various sources [32], while the measurement based on group trajectories is determined by the distribution density of the group trajectories [26].

First, there are many different types of hazards on the construction site, which can be mainly divided into two types: point hazards and surface hazards. Two types of risk areas exist around each hazard source: danger zones and buffer zones. The danger zone refers to the range directly affected by the hazard source, while the buffer zone reveals the range that may be indirectly affected. Referring to the research of Luo et al. [32] on risk exposure, the safety risk level of hazard sources is

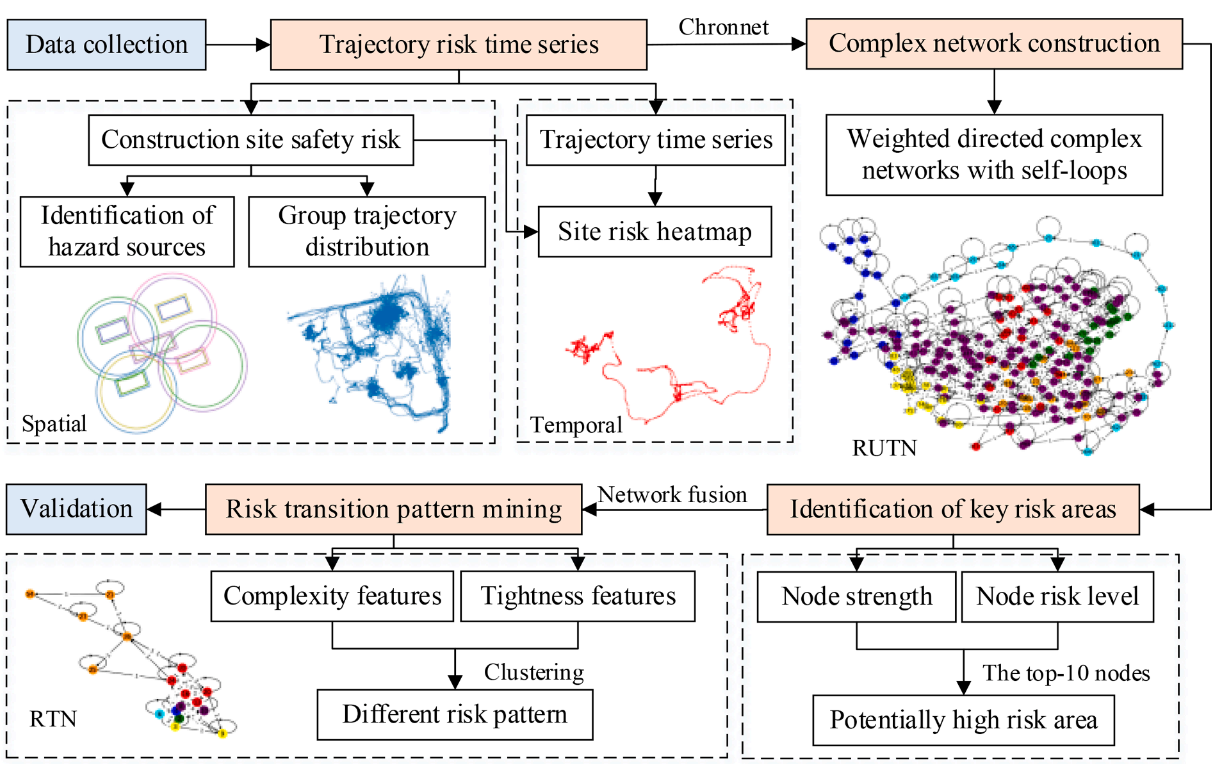


Fig. 1. Research framework.

divided based on risk exposure, and the calculation method is shown in Equation (1). The greater the risk exposure the greater the likelihood of a safety accident occurring in the area. Due to the size and shape differences between different types of hazards, the risk exposure values may vary greatly. Therefore, the risk levels are divided equidistantly according to the risk exposure, and then the sum of the risk levels of different types of hazard sources is calculated to obtain the site risk [35].

$$Exposure = \begin{cases} \frac{1}{2}\left(\frac{1}{D_{\min}} - \frac{1}{D_{\max}}\right)^2, & if\ D \leqslant D_{\min} \\ \frac{1}{2}\left(\frac{1}{D} - \frac{1}{D_{\max}}\right)^2, & if\ D_{\min} \leqslant D \leqslant D_{\max} \\ 0, & if\ D > D_{\max} \end{cases} \quad (1)$$

$$D = 2R\arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\varphi}{2}\right) + \cos\varphi_A\cos\varphi_B\sin^2\left(\frac{\Delta\gamma}{2}\right)}\right) \quad (2)$$

where D is the distance between the track point in the trajectory and the hazard sources, which can be calculated according to equation (2), R is the radius of the earth and takes the value of 6371.39 km, $\Delta\varphi$ and $\Delta\gamma$ are the difference in latitude and longitude between the two coordinates. D_{min} and D_{max} are the buffer zone and risk zone boundaries around the hazard source, which are determined according to the characteristics of the hazard sources.

Secondly, according to the field investigation, workers may be continuously located in the risk areas due to the constraints of work tasks. Considering the historical accident-free trajectories of worker groups contain information related to site safe zones [26]. The likelihood of safety accidents outside these zones is high [55]. The likelihood here reflects the possibility of construction workers experiencing safety accidents in different risk units. In this study, the distribution density of historical accident-free trajectories of multiple construction workers in risk units is used to characterize the likelihood. Generally speaking, the risk unit with more accident-free track points indicates that the likelihood of accidents occurring here is smaller compared to other units [26,55]. Therefore, according to the total number of worker trajectory points within each risk unit, the risk level is divided into different risk levels, which reveals safety likelihood within the risk unit.

Finally, this study obtains the final site risk by considering the distribution of group trajectories integrating with hazard sources, as shown in Fig. 2. Specifically, the construction site risk exposure and likelihood are combined to determine the risk level within each unit and a construction site risk heatmap (SRH) is get. The SRH is the result of a risk assessment of risk units formed by dividing the construction site. Based on Jeong and Jeong, [22], Luo et al. [32], risk is a combination of likelihood and exposure, which are two different types of measures. According to the general principles of risk assessment, the site risk within each risk unit is calculated as the product of the two types of measures. Then, the GPS coordinates of workers are compared in turn to the risk unit in the SRH, and the corresponding final risk time series are obtained.

3.2. Complex network construction

To reveal the complex spatial–temporal dynamic patterns of construction worker safety risk on sites, the chronnet is used to transform the obtained risk time series into a complex network for analysis [15]. Chronnet uses spatial grid cells as network nodes and creates a network based on the chronological order of events within each grid, the edges in the network are the events that occur in chronological order [15]. In this study, the spatial grid is the risk unit in the construction site and the events are the track points that fall into the risk unit. The process of network generation is shown in Fig. 3.

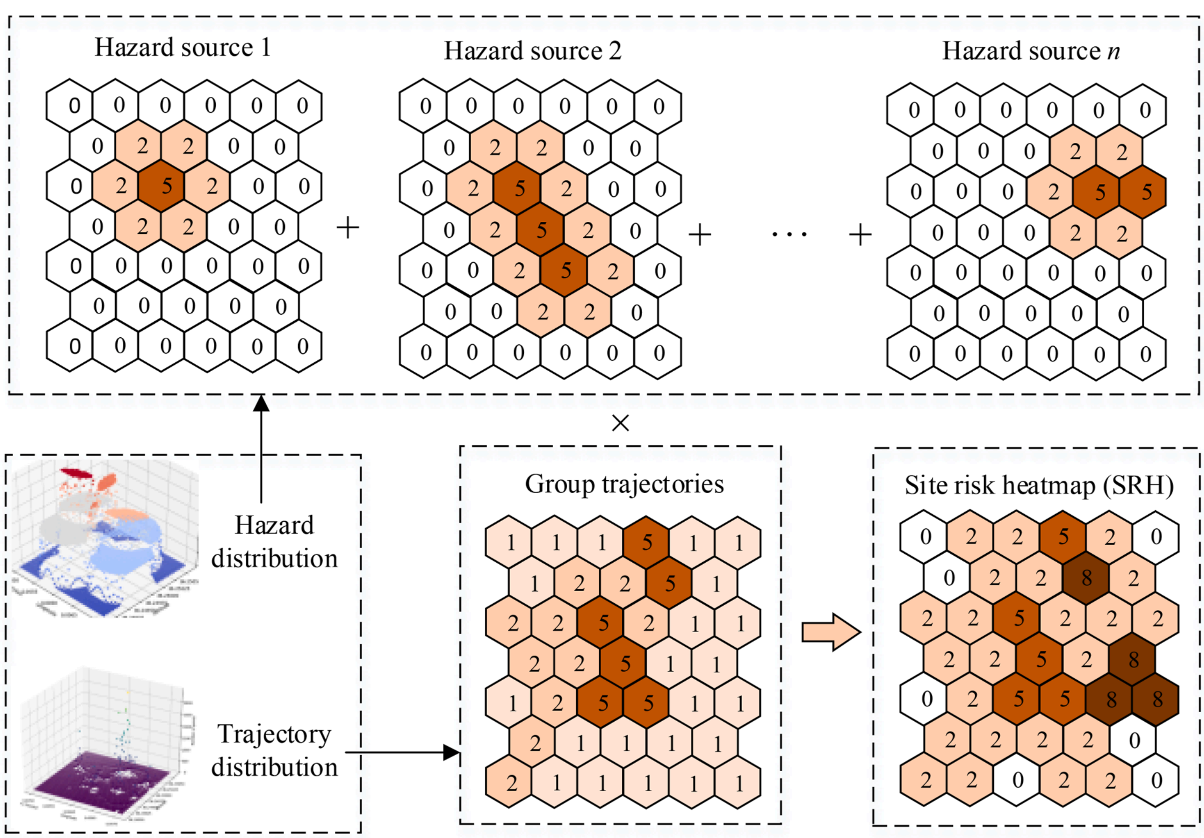


Fig. 2. Site risk heatmap generation method.

Timestamp	Latitude	Longitude	Site risk	Unit
2022-07-30 06:07:19+00:00	La_1	Lo_1	2	i, 1
2022-07-30 06:07:20+00:00	La_2	Lo_2	2	i, 1
2022-07-30 06:07:21+00:00	La_3	Lo_3	4	g, 1
2022-07-30 06:07:22+00:00	La_4	Lo_4	2	f, 2
2022-07-30 06:07:23+00:00	La_5	Lo_5	2	f, 2
2022-07-30 06:07:24+00:00	La_6	Lo_6	4	e, 3
2022-07-30 06:07:25+00:00	La_7	Lo_7	6	f, 4
2022-07-30 06:07:26+00:00	La_8	Lo_8	6	f, 4
2022-07-30 06:07:27+00:00	La_9	Lo_9	8	g, 5
2022-07-30 06:07:28+00:00	La_{10}	Lo_{10}	8	g, 5

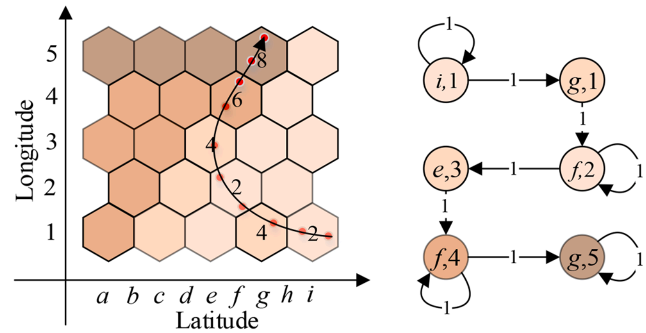


Fig. 3. The chronnet network generation process.

First, the risk time series $X = \{r_1, r_2, \ldots, r_T\}$ based on the SRH is obtained, with T being the total length of the series. The ith ($i = 1, 2, \ldots, T$) time point r_i in the sequence consists of four parts, the event timestamp t_i, the location information $L_i = \{La_i, Lo_i\}$, the site risk level d_i, and the risk unit number unit$_j$ ($j = 1, 2, \ldots, M$), M is the total number of risk units. Timestamp and location are extracted directly from the original trajectory. Site risk level and risk unit number are obtained based on the SRH, where the risk unit number characterises the location of the risk unit. After that, according to the spatial location of track points in the SRH, a directed edge of weight 1 is created from node v_i to v_j if two consecutive time points r_i (located in unit (La_i, Lo_i)) and r_{i+1} (located in unit (La_{i+1}, Lo_{i+1})) occur successively under a time window of 1 s. Nodes v_i and v_j represent the ID of units where two consecutive trajectory points are located. If the two nodes are located in the same unit, the node constitutes a self-loop. This process is repeated until the time length T. The edge weight between nodes is the number of transfers between adjacent risk units or within the risk unit itself. The node weight is the site risk d_i of the risk unit. It reflects the risk intensity at that location. Finally, a weighted directed complex network with self-loops RUTN is formed.

3.3. Identification of key risk area

The node intensity and node weights are integrated to identify potential key risk areas, where the key risk area refers to a high-risk area with long stays or frequent crossings. If a worker spends too much time in relatively high-risk units, or if there are many risk transitions in those units, the risk units are the priority safety management area. This can be calculated using modified risk intensity. In a complex network, the node strength refers to the sum of the weight of all edges adjacent to the node, reflecting the frequency of staying or crossing in this risk unit. For the jth risk unit, the modified risk intensity H_j incorporating the site safety risk is defined as the product of the node weight (risk intensity) and the node strength (risk frequency), see equation (3).

$$H_j = s_i \times d_i \tag{3}$$

where s_i is the node strength of the worker's ith track point, and d_i is the corresponding node weight. Ultimately, the risk unit with the top modified risk intensity in the SRH is the key risk area that needs to be focused on in safety management. Additionally, as the same trades usually occupy a similar work area and share similar trajectories, the key risk areas for different trades can be obtained by superimposing the modified risk intensities from the tracks of the same trade.

3.4. Risk transition pattern mining

Risk transition patterns refer to the traversal features between different risk levels over time. Mining the risk transition patterns of workers helps to accurately analyse the risk movement patterns of different workers for risk detection [10]. It also provides an important reference for adaptive behaviour correction by formulating differentiated safety correction strategies for workers with different risk movement patterns. The analysis consists of three steps in this study: network fusion, measures extraction, and clustering.

In this study, the RUTN was fused to generate the RTN to study the risk transition pattern, the network fusion process is shown in Fig. 4. In SRH, different risk units may have the same site risk level. Therefore, nodes with the same risk level in RUTN are fused to the same node to generate the RTN. In RTN, the network nodes are converted to different risk levels and the edges between the nodes represent the existence of risk transition relationships. During the network fusion, the node weight is still the risk level. The edge weight is the sum of the edge weights of the same risk transition direction in RUTN, reflecting the number of transitions between the same or different risk levels. The newly generated network is still a weighted directed complex network with self-loops.

Hidden non-linear risk patterns in trajectories can be identified by analysing the network structure and measures [16]. In this study, the risk transition features are measured in terms of complexity and tightness, relevant measures and descriptions are shown in Table 1 [40].

Complexity measures the strength and uncertainty of a construction worker's transition between different risk levels in a network. The indicators include the number of nodes, the average network strength, and the network entropy. In complex network theory, the number of nodes refers to the number of all vertices in the network. The average strength of a node is the average node strength in the network of all nodes. Staying or traversing in different risk levels is more obvious in the network with a higher average strength [48]. The network entropy is obtained by calculating the Shannon information entropy based on the node strengths [59]. It portrays the overall strength probability distribution in the network [60]. The higher the entropy value, the greater uncertainty and difficulty in predicting the risk transition of workers [65].

Tightness measures the likelihood of repeated transitions between different risk levels. The metrics include the average network clustering coefficient, network transitivity and network modularity. The average clustering coefficient of a network is the average weighted clustering coefficient of all nodes, which is a measure of the tendency of nodes to cluster together [65]. The transitivity of the network measures the closeness of the cluster in the network. It is obtained by calculating the ratio of the number of closed triplets to the maximum possible number of triplets in the network [50]. Modularity reflects the structure of the community in the network. In this study, the fast greedy algorithm is used to detect the community and calculate the modularity [8].

In the third step of pattern mining, the risk transition patterns of different workers are classified using cluster analysis based on network measures. In this study, we use the hierarchical clustering method of Euclidean distance for clustering. This clustering method has the advantage over other clustering methods of not requiring the number of clusters to be acquired in advance [46]. The specific features of each

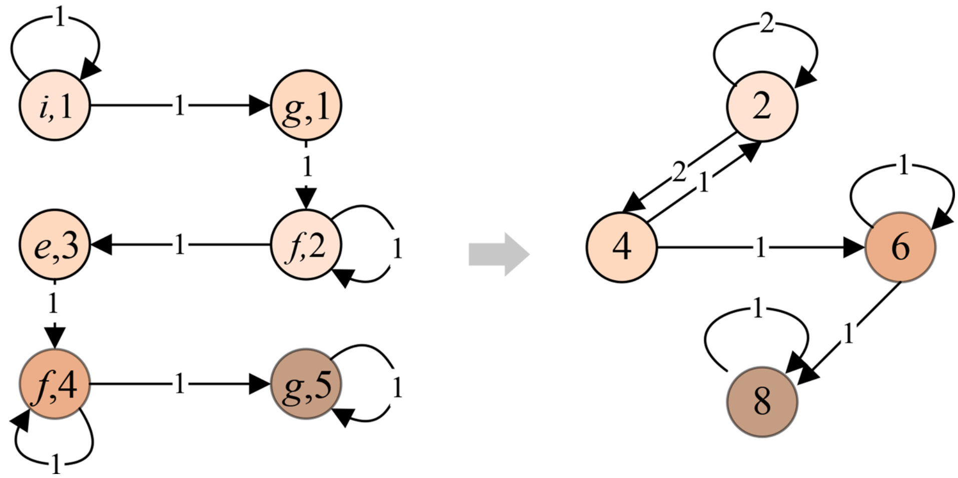


Fig. 4. Network fusion process.

Table 1
Network measures and descriptions.

Measure	Formulas	Descriptions
Number of nodes	N	Networks with a higher number of nodes indicate that workers are traversing more risk areas
Average strength	$< s > = \frac{1}{N}\sum_{i=1}^{N} s_i$	Reflects the frequency of staying or crossing in risk levels
Entropy	$H = -\frac{1}{\log_2 N}\sum_{i=1}^{N} p(s)\log_2 p(s)$	Reveals the unstable state of risk transition
Average cluster	$C = \frac{1}{N}\sum_{i=1}^{N} C_i = \frac{1}{N}\sum_{i=1}^{N} \frac{2t_i}{k_i(k_i-1)}$	Representing the ability to repeat or reinforce risks in the network
Transitivity	$T = \frac{\sum_{i=1}^{N} 2t_i}{\sum_{i=1}^{N} k_i(k_i-1)}$	Network with greater transitivity will be tighter, with a high degree of interconnectedness between different risk levels [39]
Modularity	$Q = \frac{1}{2m}\sum_{ij}^{N}\left(A_{ij} - \gamma\frac{k_i k_j}{2m}\right)\delta(c_i, c_j)$	High modularity means that risk transition in the network is faster than in a loosely connected community [66]

Note: N: the number of nodes; s_i: strength of the ith node; $p(s)$: node strength distribution; k_i: degree of the ith node; t_i: number of triangles around the ith node; m: the number of edges; A_{ij} is the adjacency matrix; γ is resolution parameter; $\delta(c_i, c_j)$ is 1 if i and j are in the same community else 0.

cluster are analysed to analyse the different spatial–temporal patterns.

4. Results and validation

A residential project construction site was selected to collect the raw data. The project includes nine 10-storey residential buildings, as shown in Fig. 5. The construction area is located in Shandong Province, East China, with a total construction site area of approximately 30,000 m^2. During the data collection, only 5 of the buildings started construction, 4 of which started the main structure construction, and 1 was still under foundation construction. Additionally, four tower cranes with two types with jib lengths of 46 m and 51 m were erected on site. Moreover, there are a number of different construction teams working on site. In addition to general safety managers, on-site construction activities also involve trades such as carpenters, steel workers, plumbers, and electricians.

4.1. Data collection and cleaning

The raw trajectory data of construction workers is collected using a smartphone GPS in this study. Numerous GPS logging software for Android, IOS and other operating systems are available on the Google Play Store and others, which provides convenience for data collection. Workers turn on the GPS before work and turn it off at the end of the day. The trajectory files (*.gpx) during working hours are transferred via WIFI to computers for processing. Data were collected at a frequency of one point per second. However, due to the interference of external factors such as the power of phones, obstacles, and metal materials, the GPS signals will drift and be interrupted. For this, the raw trajectory data needs to be pre-processed to meet the data calculation requirements before the network can be constructed.

First, according to relevant literature [53], the intermediate track point data is directly obtained by linear interpolation for the time interval between adjacent track points that is less than 10 s. For those below 60 s, the trajectory points are conditionally linearly interpolated according to their working conditions. Second, to ensure the accuracy of the results, after removing the non-working time trajectory, the longest continuously recorded trajectory segment was selected for analysis. Finally, to solve the problem of track point drift, the Kalman filter method is used to denoise the original track [23,38].

A total of 67 workers' trajectories were collected for method validation, of which 45 workers' trajectories were used to generate the SRH, and the other 22 were used to validate the proposed method. The workers' trade used for validation and their processed trajectory lengths are shown in Table 2. The rebar maker refers to those who are engaged in cutting, bending, and processing steel bars before it is delivered to the construction site. In this study, the handymen included many different trades such as site inspectors, pumpers, and welders.

4.2. Construction site safety risk

The site safety risks were assessed by integrating the distribution of site hazards and the distribution of group trajectories. First, the main construction site is divided into 2879 risk units by hexagons, covering a total construction site of about 9040 m^2. Each risk unit has a side length of about 1.1 m and an area of 3.14 m^2. Based on this, the main hazard sources of the construction site were analysed, including four tower cranes (which can be regarded as point hazards), four buildings under construction and one foundation pit (which can be regarded as surface hazards). The hazard zone and buffer zone boundaries of each source were determined based on the site survey and relevant literature [14,32]. For the tower crane on site, the danger zone is within the radius of the tower crane itself and the buffer zone is 6 m outside the radius; for the surface hazard sources such as the building under construction, the danger zone and buffer zone boundaries are 0.5 m and 3 m outside the boundary. Using equation (1)-equation (2), the risk exposure in different risk units is calculated, as shown in Fig. 6a – Fig. 6b. Each scatter point in the figure represents the risk exposure within each risk unit. The risk

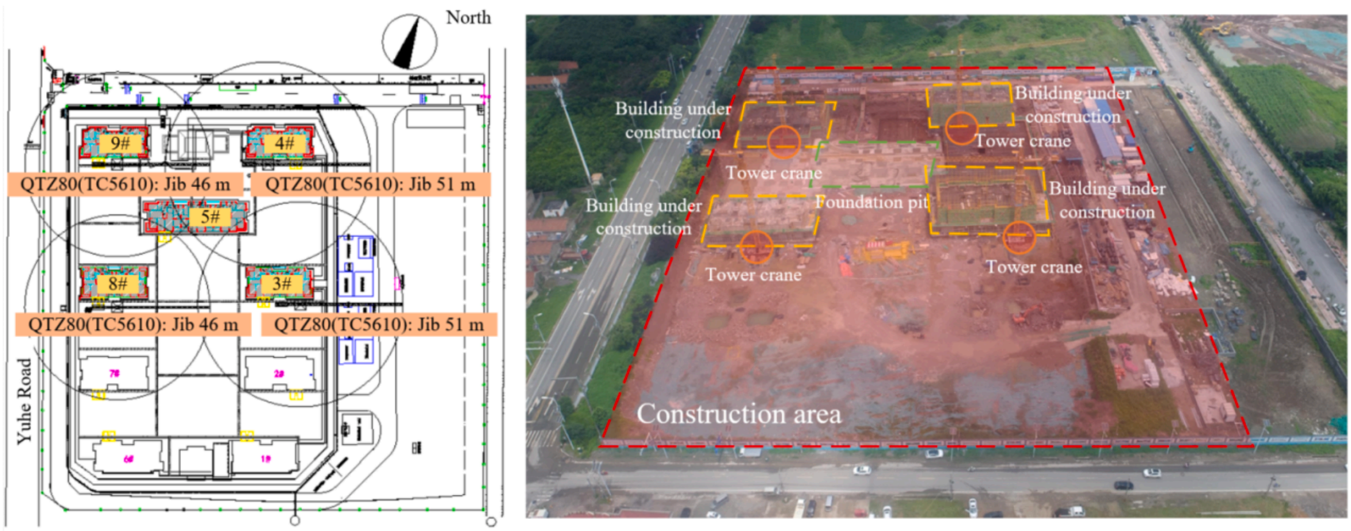


Fig. 5. Construction site layout.

Table 2
Workers' trades and trajectory lengths.

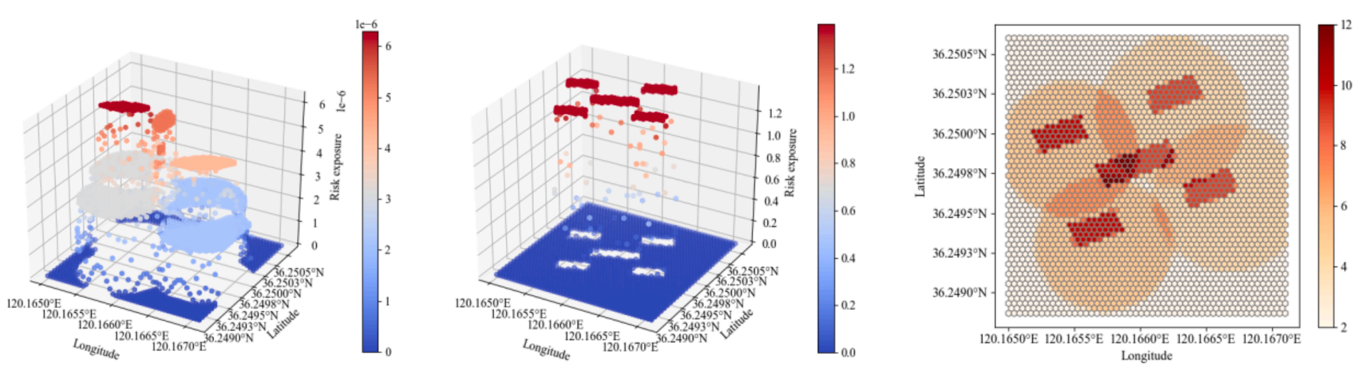
ID	Trade	Processed length	ID	Trade	Processed length
Worker 01	Carpentry	3601	Worker 12	Rebar maker	3735
Worker 02	Handyman	9169	Worker 13	Handyman	1793
Worker 03	Rebar binder	954	Worker 14	Carpentry	3798
Worker 04	Rebar maker	3250	Worker 15	Handyman	6273
Worker 05	Rebar maker	1747	Worker 16	Carpentry	5338
Worker 06	Rebar binder	15,971	Worker 17	Carpentry	8983
Worker 07	Scaffolder	1252	Worker 18	Rebar binder	9104
Worker 08	Scaffolder	13,100	Worker 19	Rebar binder	8553
Worker 09	Handyman	3460	Worker 20	Handyman	1474
Worker 10	Scaffolder	673	Worker 21	Carpentry	4310
Worker 11	Rebar binder	6052	Worker 22	Carpentry	4040

levels are determined according to the risk level classification method in Table 3, and the risk levels of all hazard sources are fused to get the final risk source distribution heatmap, as shown in Fig. 6c.

Similarly, based on the historical accident-free construction trajectories of 45 workers, a scatter plot was created by overlaying all workers' trajectories. The number of track points within each risk unit is counted, as shown in Fig. 7a. The risk level of each risk unit was determined according to the classification method in Table 3, and the results are shown in Fig. 7b. Finally, SRH was generated by fusing Fig. 6c and Fig. 7b with reference to Fig. 2, as shown in Fig. 7c. The risk unit numbers can be consulted in Appendix A and the risk levels corresponding to the risk units are shown in Appendix B.

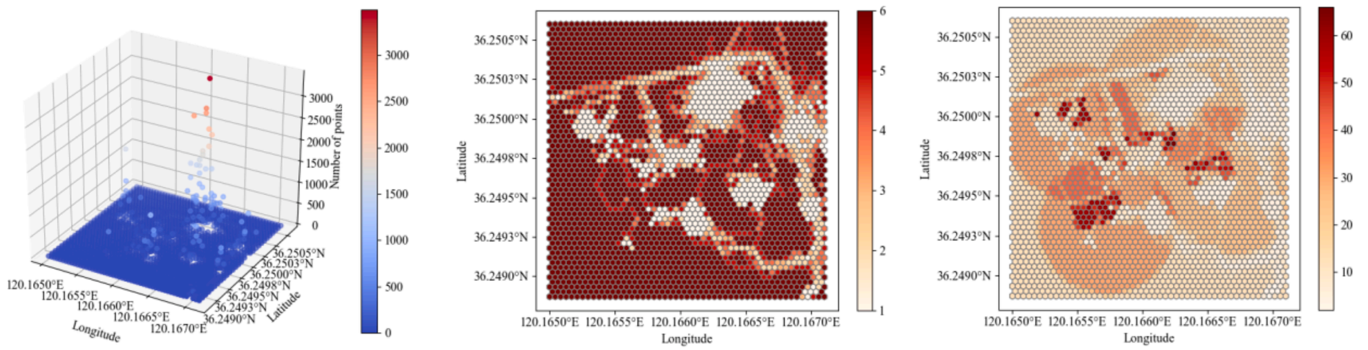
Table 3
Risk level classification method.

Risk level	Surface hazard sources	Point hazard source	Number of track points in the unit
1	Less than or equal to 0.2	Less than or equal to 1e-6	Over 30
2	0.2–0.4	1e-6 – 2e-6	15–30
3	0.4–0.6	2e-6 – 3e-6	10–15
4	0.6–0.8	3e-6 – 4e-6	5–10
5	0.8–1.0	4e-6 – 5e-6	1–5
6	Over 1.0	Over 5e-6	Less than or equal to 1



(a) (b) (c)

Fig. 6. Distribution of hazard sources.



(a) (b) (c) SRH

Fig. 7. Group trajectory distribution and SRH.

4.3. Complex network construction

Taking worker 15 as an example, after superimposing the worker trajectory and SRH, the RUTN is constructed, as shown in Fig. 8. The network includes 163 nodes, 407 edges and 147 self-loops. The number in the network node is the number of risk units, and the node size is proportional to the risk level of the risk unit.

Small-world and scale-free features are the most typical features of complex networks [49]. However, RUTN are directed networks, while the small-world feature is mainly analysed for the undirected network. Therefore, this study only analyses the scale-free feature of trajectory risk networks. The scale-free feature of network is analysed based on cumulative degree/strength distributions, which are the probabilities that the degree/strength of a node is not less than k/s [17,68]. The cumulative degree and strength distribution and power law fit curve for the RUTN were analysed and the results are shown in Fig. 9. It can be seen that the fitted curve for the cumulative degree distribution is $y = 2.5906x^{-1.1515}$. The network strength is a reflection of the frequency of transitions and the fitted curve for the cumulative strength distribution is $y = 1.5680x^{-0.4661}$. The curves are straight lines in a Log-Log coordinate system. The results indicate that the RUTN conforms to the scale-free feature, which suggests that a few individual risk units in the worker's trajectory are connected to a large number of other units. In this network, 90% of the risk units have a degree of 10 or less, with only three risk units, 249, 949, and 2080, exceeding 10. Similarly, 80% of the risk units have a strength of 900 or less, with only two risk units, 1805 and 949, having a strength of no less than 900.

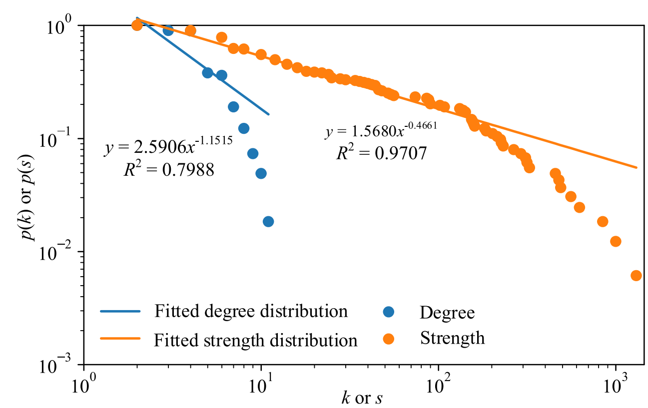


Fig. 9. Cumulative degree and strength distribution of RUTN.

4.4. Identification of key risk areas

Identifying areas where construction workers are at greater risk based on modified risk intensity. In complex networks, many methods have been proposed to identify key nodes in the network, such as closeness centrality (CC), betweenness centrality (BC), and degree centrality method (DC). However, these common methods for identifying key nodes usually lack consideration of point weights. To highlight the superiority of the key risk areas identification method proposed in this study, the identification results of CC, BC and DC were selected for comparison. Using worker 1 as an example, the top 10 high-risk areas in

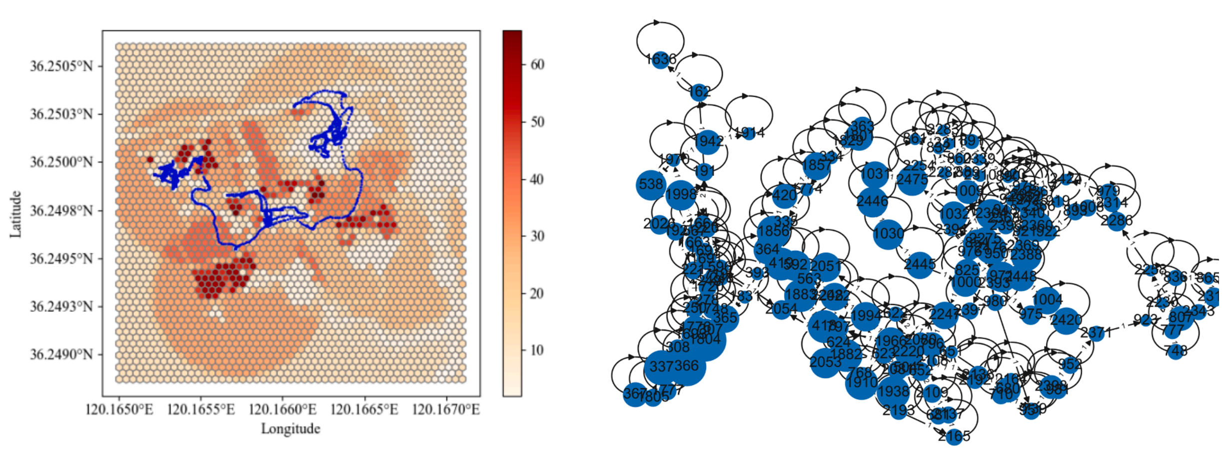


Fig. 8. RUTN of worker 15.

his trajectory are shown in Table 4 and Fig. 10.

From the results, compared with the safety risk area identification results of BC, CC, and DC, the top ten modified risk intensity of the proposed method is 7962, which is higher than the other key node identification methods. It can be seen that the key areas identified by the proposed method are more concentrated near the gathering points in the workers' trajectories. Further, according to the sum of the risk intensity of the same group of workers, the method also gives information on the key risk areas for different trades, as shown in Fig. 11. It can be seen that there are differences in the key risk distribution areas between different job types. Except for the handyman, the risk distribution areas of other types of work are relatively concentrated. Thus, these areas will therefore be the focus of personalized safety training for specific trades.

An expert was invited to identify key risk areas on the construction site to verify the feasibility and reliability of the method. The expert, aged 51 with 20 years of work experience, was the safety supervisor on site. The results showed that the critical risk areas identified by the proposed method (see Fig. 11) generally covered the areas identified by the expert. However, the risk area indicated by the expert did not include the critical risk area for the scaffolder in Fig. 11 (near 120.1660 °E, 36.2494 °N). A review of construction footage revealed that during the period of data collection for this study, this area had a large accumulation of steel pipes for scaffolding (see Fig. 11), which workers needed to access frequently. As construction workers do not normally visit this area, there is a high level of risk likelihood in the area. However, risk management in this area was overlooked by safety managers. The approach proposed in this study helps safety managers to be more proactive in identifying risk management gaps and reducing the likelihood of safety accidents.

4.5. Analysis of workers' risk transition patterns

By fusing the risk unit nodes with the same site risk level in SRH, a directed weighted network with self-loops RTN is established to identify the risk frequent pattern of different workers. The RTNs of 22 workers are shown in Fig. 12. Different node colours in the figure represent different communities obtained by using the greedy algorithm. Afterwards, the complexity and tightness measures are extracted to explore hidden nonlinear patterns.

Next, based on the elbow and the average silhouette coefficient, the optimal number of clusters is determined manually [62]. Finally, three clusters were determined with a Euclidean distance of 1.5, and the clustering results were represented in a dendrogram, as shown in Fig. 13. In this figure, each node in the same cluster contains a similar set of network measures, and different colours represent different clusters of workers.

Table 5 counts the mean values of network measures in each cluster, where categories 0, 1, and 2 account for 18.18%, 68.18%, and 13.64% of the total number of workers, respectively. Among them, the workers under category 0 have the largest number of nodes, cluster coefficient and modularity. The average transitivity of category 1 is the largest. The average strength and average entropy of category 2 are the largest. The trajectories of representative workers for each cluster can be found in Fig. 14 and Appendix C. Each cluster is analysed and explained separately as follows:

Cluster 0: From the perspective of measures, the network density of construction workers in this cluster is higher, but many lower risk levels are involved. The representative worker trajectory is shown in Fig. 14a. However, if the risk level of 50 is used as the threshold to divide the high-risk area, all workers in the cluster will interact with the high-risk area. This indicates that workers within this cluster have complex risk transition behaviour and spend most of their time crossing between different site safety risk levels. Therefore, in site safety management, extra attention needs to be paid to the key risk areas of this cluster and make targeted behavioural interventions for them.

Cluster 1: The majority of the mean values of the parameters in this cluster lie between those of cluster 0 and cluster 1. It is the cluster with the highest proportion of workers among all workers, with a representative worker trajectory as shown in Fig. 14b. Similarly, if the high-risk area is classified using a risk level of 50, only 57.14% of workers in this cluster (5,7,10,13,15,16,17 and 19) interact with the high-risk area, leaving 42.86% of workers with risk levels of 30 and below. Therefore, workers within this cluster generally transitioned into lower-risk areas, but also may venture into high-risk areas. It is recommended that focused training be provided to those workers who have high-risk area interactions.

Cluster 2: The network complexity and tightness of this cluster are lower compared to the other clusters, which can also be directly evident from the RTN, with representative worker trajectories shown in Fig. 14c. The risk level of nodes in the RTN for workers in this cluster largely lies at 20 and below. Combined with the network measures, this suggests that workers in this cluster spend most of their time with little crossing between risk levels. They are often scattered across different low-risk areas, and their behavioural patterns are simple. Regular monitoring needs to be maintained for workers in this cluster.

Finally, to facilitate the safety management of workers at the construction site, a risk monitoring program based on the complex network was designed using pyqt5, as shown in Fig. 15. The program can observe basic information in real-time based on the worker's track points, such as the current latitude and longitude coordinates, risk unit number, and site risk level. Based on the above information, the program is capable of generating RUTN and RTN concurrently at the same frequency as the GPS signal. By utilizing the key risk area and risk transformation mode calculation methods outlined in this paper, the risk cluster pattern and risk frequent pattern can be computed and recorded within the program.

Table 4
Comparison of different methods.

Top10 nodes	BC			DC			CC			Proposed method (PM)		
	Unit	Risk	Strength	Unit	Risk	Strength	Unit	Risk	Strength	Unit	Risk	Strength
1	1127	8	14	2727	4	148	1127	8	14	335	5	290
2	2427	4	12	1322	4	212	2427	4	12	1264	4	242
3	865	4	12	2699	4	182	2650	16	8	1322	4	212
4	2399	8	16	2756	4	20	1156	12	16	1292	4	196
5	515	14	12	515	14	12	2399	8	16	1775	5	152
6	1156	12	16	1293	4	62	1212	8	14	2699	4	182
7	1213	12	10	1296	2	24	1241	8	22	1803	5	144
8	1241	8	22	2703	3	24	2649	12	14	2781	4	152
9	2258	4	14	1240	8	34	2258	4	14	2727	4	148
10	2650	16	8	1295	6	34	1213	12	10	2002	28	18
Sum	–	90	136	–	53	752	–	**92**	140	–	67	**1736**
Intensity	–	–	1176	–	–	3260	–	–	1240	–	–	**7962**

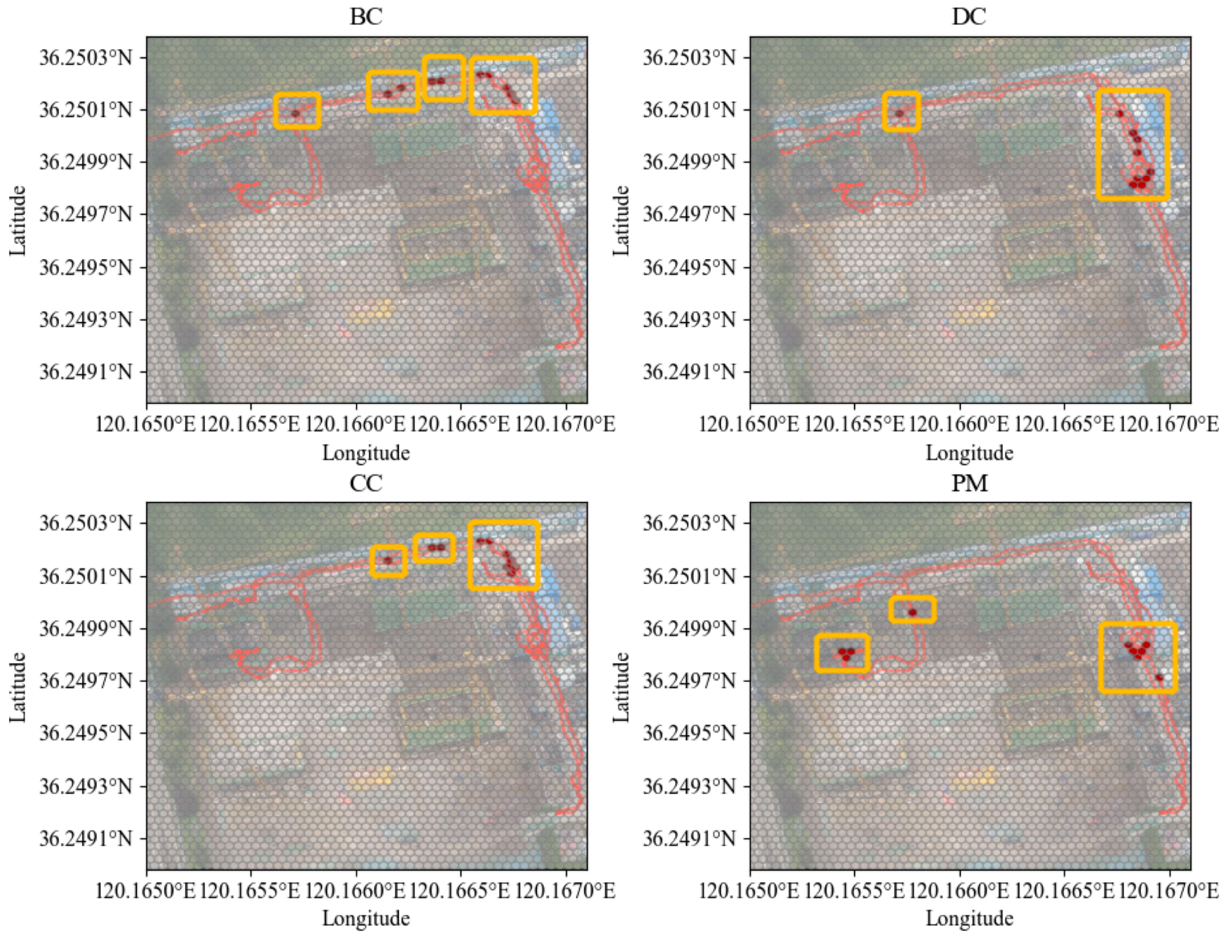


Fig. 10. Top 10 key risk areas of different methods.

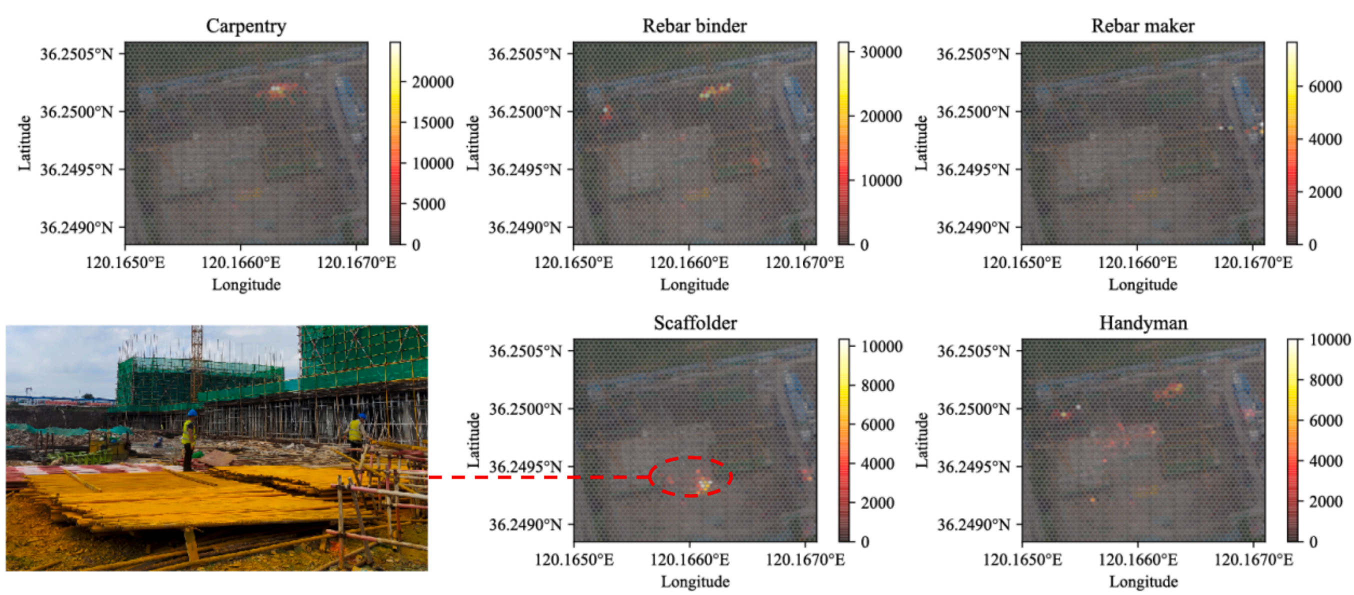


Fig. 11. Different key risk areas according to the trades.

5. Discussion

In this study, a spatial–temporal analysis method for workers' trajectory risks is proposed based on complex network theory. First, the site hazard sources and group trajectory distribution are analysed to obtain a site safety risk heatmap. With this, the worker trajectory time series are converted into a risk unit transition network and a risk transition network. Finally, risk cluster patterns and risk frequent patterns are mined based on the network measures. Key risk areas and the risk transition clusters in the workers' trajectories are analysed. The

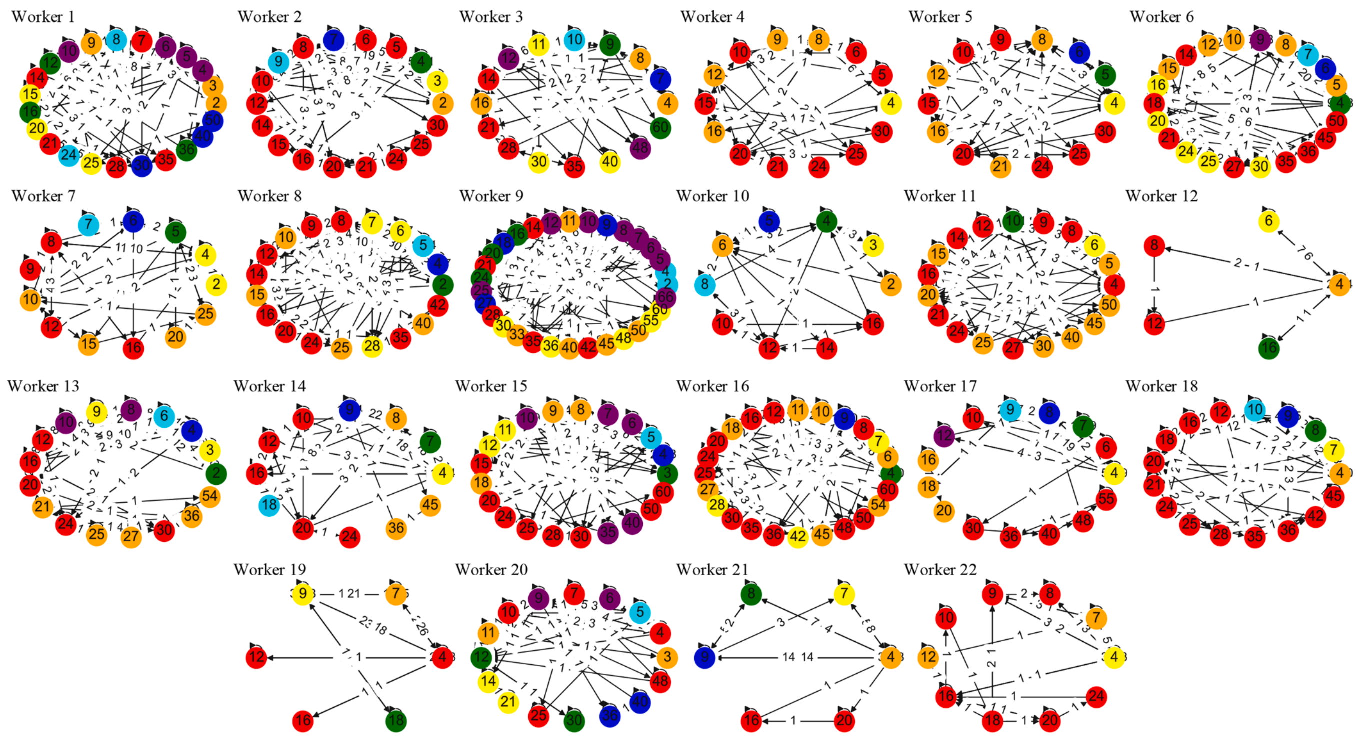


Fig. 12. RTNs for all workers.

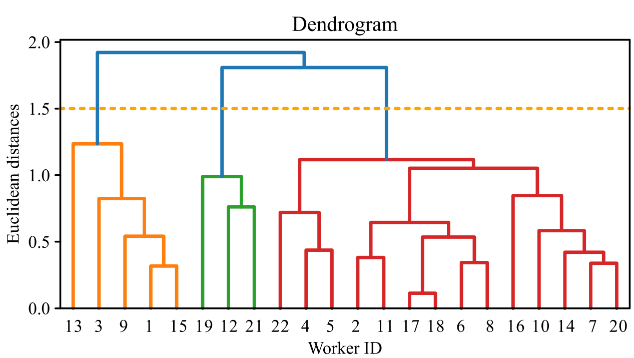


Fig. 13. Hierarchical clustering dendrogram.

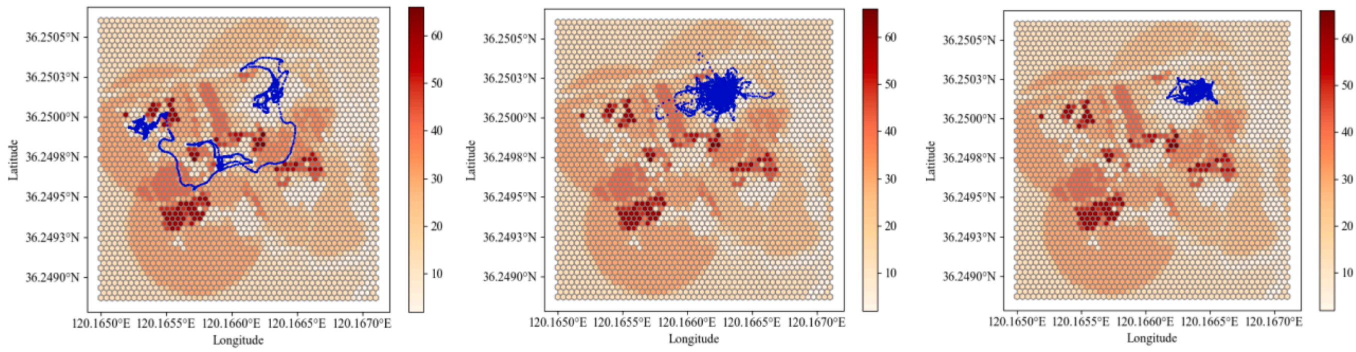
feasibility of the proposed method is verified by the data collected in an actual construction project.

From Fig. 9, it can be seen that the RUTN of workers conforms to the scale-free feature, indicating that most of the risk unit transition is located in some individual areas, that is, there are trajectory staying points. It can also be seen from Fig. 11 and Fig. 14 that the key risk areas for different types of workers are mostly located around the stopping points. The distribution of key risk areas is more concentrated for the same type of work, with differences between different trades. In addition, risk transition patterns of workers are identified. Interestingly, no significant differences were found between trades in the transition patterns. Table 6 uses the one-way analysis of variance (ANOVA) to analyse the differences in the clusters of different types of work. Taking the handyman into account, the ANOVA F-value was 0.7881 and the p-value was 0.5487. Without considering the handyman, the F value of variance analysis was 0.2549, and the p-value was 0.8565. This indicates that the risk transition pattern of different types of workers is not significantly similar. The demographic information of workers in each cluster is analysed. All 22 workers in the sample are male. Cluster 0 has an average age of 40.20 years and consists of 1 carpenter, 1 rebar binder, and 3 handymen. Cluster 1 has an average age of 41.43 years and consists of 3 carpenters, 2 handymen, 2 rebar makers, 3 rebar binders, and all 3 scaffolders in the sample. Cluster 2 has an average age of 36.33 years and consists of 1 rebar maker, 1 rebar binder, and 1 carpenter. Relatively speaking, workers within the same cluster have similar patterns of risk transition, which may be facilitated by factors such as job tasks, work experience, personal habits, and risk perception abilities.

The main contributions of this study are summarized. First, a safety risk assessment method for construction sites that combines the distribution of hazard sources and group trajectories is proposed. This method expands the original method of risk classification through the interaction between workers and risk areas [32,35]. The integration enriches the site safety risk measurement method using historical accident-free areas. The result is represented intuitively in the form of a heatmap. The method systematically considers the exposure and likelihood of safety risks and provides a new perspective for quantitative risk management on construction sites. It can also be extended to a dynamic site risk classification system by monitoring the dynamics of the hazard sources on site. Secondly, based on the site risk heatmap, the complex network theory is used to convert the trajectory into a risk unit transition

Table 5
Network measures in each cluster.

Cluster	Average complexity			Average tightness			Proportion
	Number of nodes	Strength	Entropy	Cluster	Transitivity	Modularity	
0	22.75	154.73	0.98	0.0012	0.34	0.76	18.18%
1	16.00	319.37	0.91	0.0007	0.37	0.48	68.18%
2	5.67	915.11	1.00	0.0008	0.29	0.34	13.64%



a. Worker 15 (cluster 0)　b. Worker 18 (cluster 1)　c. Worker 21 (cluster 2)

Fig. 14. Worker trajectories in different clusters.

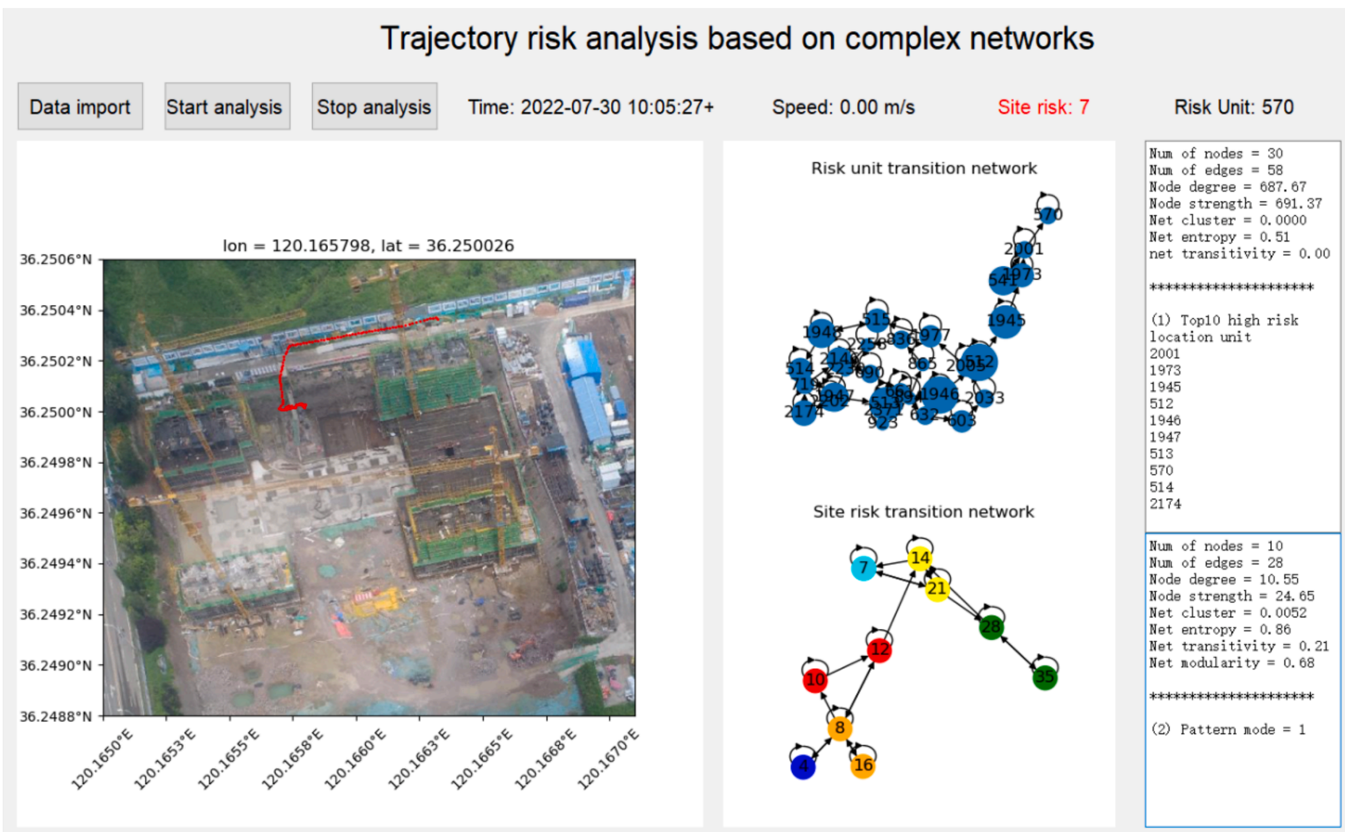


Fig. 15. Trajectory safety analysis program interface.

Table 6
Results of one-way ANOVA.

Situation	Sources	SS	df	MS	F	P-value	F crit
With handyman	Between groups	1.0879	4	0.2720	0.7881	0.5487	2.9647
	Within groups	5.8667	17	0.3451			
Without handyman	Between groups	0.2745	3	0.0915	0.2549	0.8565	3.4105
	Within groups	4.6667	13	0.3590			

and risk transition network, providing a new way to analyse spatial–temporal risk patterns from a system perspective. Previously, trajectory-based safety risk analysis has been studied in the fields of transportation [51], aerospace [61], and construction [2]. This study extends the traditional approach to trajectory safety analysis based on graph theory. It integrates the relationships between workers' spatial–temporal locations and risk information into a complex network, providing a reference for the analysis of risky traffic information on site.

As stated in previous studies [2,44], the risk transition patterns such as clustering of high-risk areas do not mean that workers will have accidents. But it will help to analyse high-risk activities of workers and conduct differentiated safety analysis, which will be of great help in improving the efficiency of safety training for construction workers [13]. For example, workers' health and safety may be compromised if they remain in areas containing dust, smoke, and toxic for longer than the prescribed working hours [28]. Practically, The method helps to address the issue of data recording at the bottom of the Heinrich safety pyramid [18]. Moreover, the smartphone (or other low-cost GPS) as a widely used communication device offers the opportunity for implementation of the method. Additionally, it is possible to use the program we have developed to monitor the location of workers in real-time and analyse their historical key risk areas and patterns of change, which helps to develop personalized behaviour correction strategies.

In practice, the proposed approach can be implemented in conjunction with a real-time location system. Initially, worker's trajectory data can be directly collected using GPS, and then fed into the designed application. The application can automatically generate the corresponding network graphs, calculate network measures, and determine critical risk areas and behavioral clusters at a data collection frequency. To ensure the reliability of the results, project managers can set a fixed time period (e.g., 30 min, 60 min, 180 min) as a monitoring cycle. Targeted interventions can be developed based on changes in risk areas and risk transition features in a worker's trajectory over one or more cycles. In terms of risk areas, project managers can provide individual workers with risk area warnings through personal interviews and other means. If these areas are difficult to bypass in the work task, managers should focus on monitoring these critical risk areas. With regard to risk transition patterns, project managers can periodically organize adaptive safety training for workers with similar risk transition patterns during the previous monitoring cycle to improve training efficiency.

There are some limitations and research directions to be investigated in the future. Firstly, only the exposure duration of workers within different risk units is considered in the generation of the site risk heatmap. The travel speed, altitude, approach distance, and direction to hazard sources also include some additional safety information. That information is expected to be integrated into the method and improve the accuracy of the site risk measurement. Similar characteristics and connections between individual workers in the same cluster is also a topic that deserves further research. In addition, this research involves workers' sensitive movement trajectory information, and the security of those data is very important to protect personal privacy. Therefore, it is necessary to study trajectory data privacy protection methods in practical applications. Finally, as a method that comprehensively reflects macro and micro changes, complex networks have broad application prospects for future research and application of safety management, such as trajectory risk assessment, and anomaly diagnosis.

6. Conclusion

Understanding the spatial–temporal risk patterns of workers at construction sites is important for the behaviour-based safety management. In this study, we propose a spatial–temporal analysis method of safety risks for construction workers based on complex network theory. Using a comprehensive construction site safety risk heatmap, complex networks are constructed to analyse the spatial–temporal patterns in risk location transitions and risk transitions. The feasibility of the proposed method is verified through a case study. The study also found significant differences in the distribution of key risk areas between different work types, while no significant differences were observed in the patterns of risk transition.

Theoretically, this study enriches behaviour-based safety management research with a graph-based approach that integrates workers' spatial–temporal location and risk information. The use of complex networks to extract macro and micro features in trajectories contributes to the development of risk analysis theories and methods. In addition, the method has the potential to improve the quantitative management of near-miss incidents. In practice, it helps to assist companies in developing valuable trajectory-based safety management strategies based on the patterns. Adaptive or personalized behavioural correction measures and actions can be developed to reduce the likelihood of safety accidents. For instance, critical control areas can be identified based on workers' historical trajectories, and management and monitoring in these areas can be strengthened. In addition, stakeholders can customize training materials and organise regular and differentiated safety training for workers in the same clusters.

Declaration of Competing Interest

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

Data availability

The relevant code for the chronnet network generation can be found at https://github.com/PinshengDuan/Chronnets-python.

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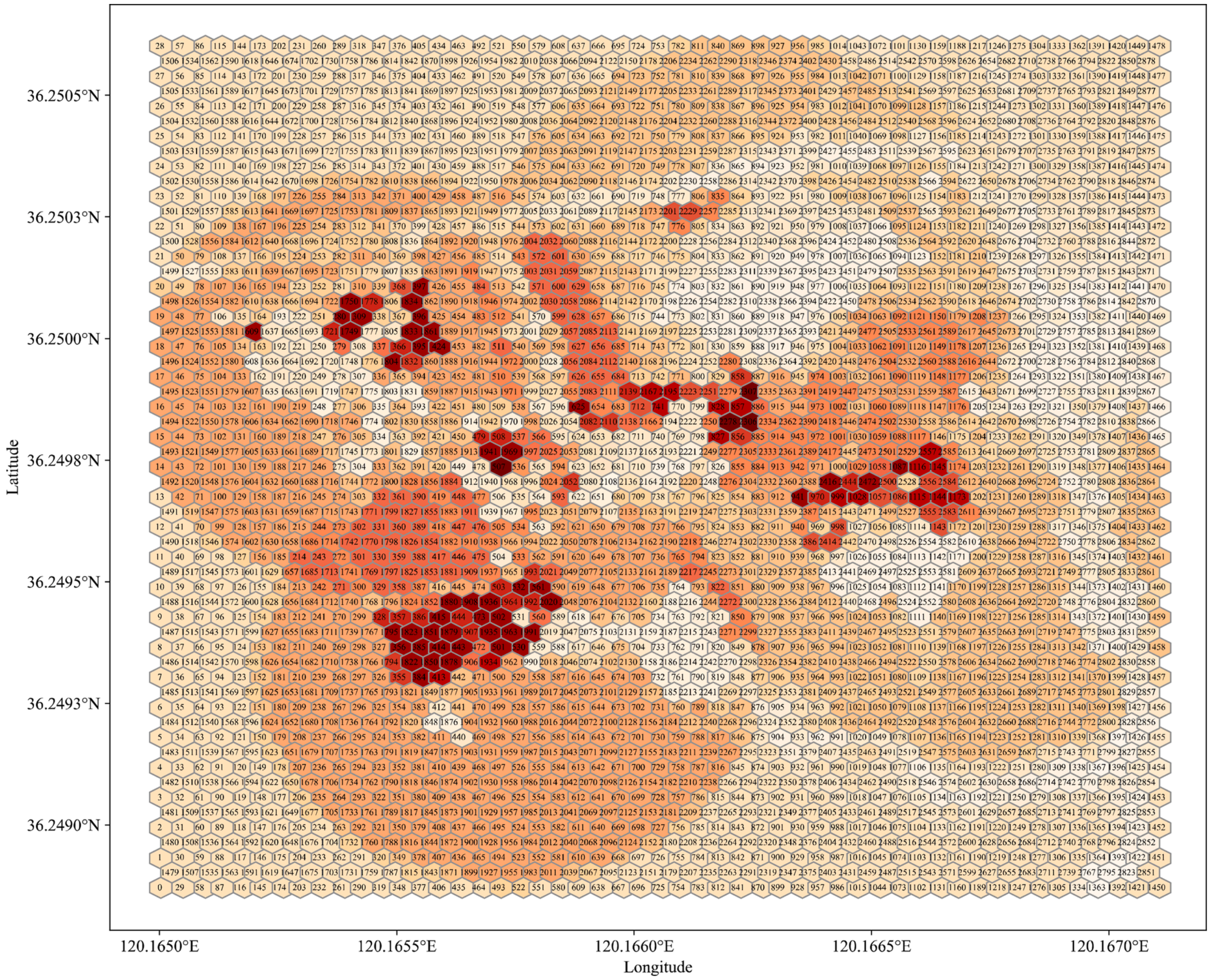
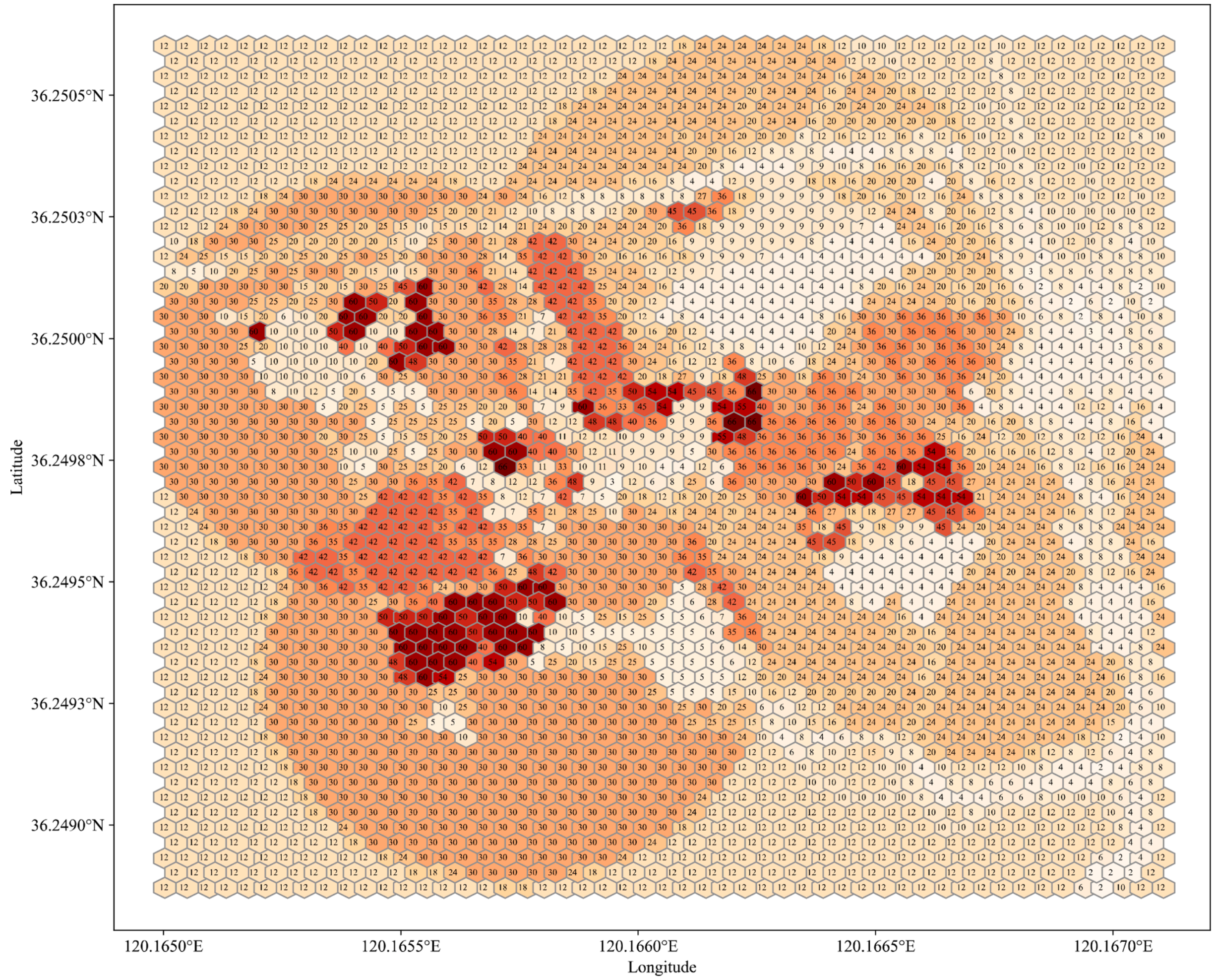
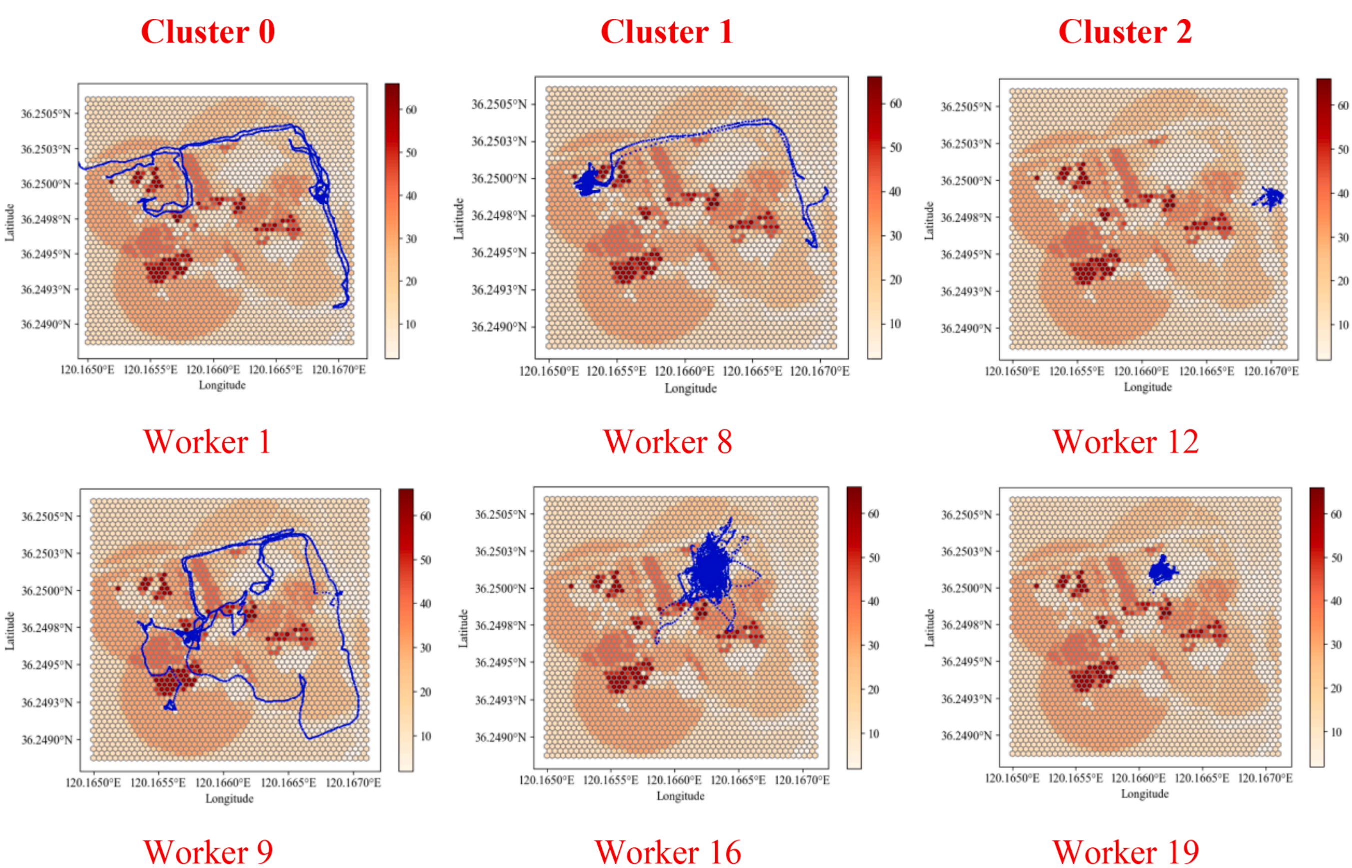
Appendix A. Risk unit number



Appendix B. Risk level of risk units



Appendix C. The trajectories of workers for each cluster



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