



RESEARCH ARTICLE

Dual-network analysis of supply chain structure in civil construction projects in the Southeast region of Vietnam using Social Network Analysis

Tran Phu Loc^{1,*}, Tran Quang Phu¹, Huynh Thi Yen Thao¹

¹ Ho Chi Minh City University of Transport, Vietnam

ARTICLE INFO

Received: 03/05/2026
Revised: 08/07/2026
Accepted: 05/08/2026
Published online: 15/09/2026

KEYWORDS

Construction Supply Chain
Social Network Analysis
Main contractor
Subcontractor
Fragmentation

ABSTRACT

The construction supply chain (CSC) is characterized by complex inter-organizational relationships involving multiple tiers of main contractors (MCs) and subcontractors (SCs). This study analyzes the network structure and connectivity patterns of the construction supply chain using a dual-network approach, examining both the directed MC–SC network and the undirected SC–SC network. The research aims to clarify structural differences between formal and informal network layers and to quantify the level of fragmentation. Social Network Analysis (SNA) is applied to empirical data from 37 civil construction projects in the Southeast region of Vietnam during the period 2018–2025, involving 10 MCs and 1,545 SCs. The directed MC–SC network comprises 1,660 edges representing contractual relationships, while the undirected SC–SC network contains 121,340 edges representing co-participation among subcontractors. The MC–SC network exhibits a strongly concentrated structure (bipartite density 0.107; a clustering coefficient of 0, which is expected for a bipartite network; 8 contractor-centered communities; modularity $Q = 0.625$ on the unweighted network) and extreme fragmentation, with 94.3% of SCs working with only one MC. The SC–SC network is dense by construction (average degree 157.1; average local clustering 0.898), since it is a one-mode projection in which the SCs of each project form a clique; this structure reflects extensive co-participation and potential channels for informal coordination rather than directly observed collaboration. These findings contribute to advancing the theoretical understanding of CSC structure as a basis for seeking solutions to improve CSC effectiveness in increasingly complex project environments.

1. Introduction

The construction industry operates through complex, multi-tiered supply chains involving a wide range of interdependent actors, including MCs, SCs, suppliers and consultants. Unlike manufacturing supply chains, CSCs are inherently project-based, temporary, and highly fragmented, with relationships formed and dissolved around individual projects. Traditional views in CSC management primarily focus on the bilateral relationship directly between MC and SCs, viewing the supply chain as a hierarchical, tree-like structure governed by formal contractual agreements [1], [2]. However, this perspective overlooks the vast informal collaborative networks that form among SCs who frequently work together on multiple projects. These informal networks of colleagues can play a crucial role in knowledge sharing, resource coordination, and collective problem solving, yet they are largely overlooked in conventional supply chain analyses. Recent advances in SNA have provided powerful tools for mapping and analyzing complex inter-organizational relationships within the construction industry. SNA allows researchers to quantify network structure through indicators such as density, clustering coefficients, community structure, identify key actors, and as-

sess network resilience. Several studies have applied SNA to the construction context, examining primary MC–SC networks, procurement networks, and inter-organizational collaboration in international projects. SNA is used to link procurement contractual relationships with group integration in off-site production projects, reporting normalized centrality measures for project actors [3]. SNA was also used in a study of 100 UK cross-laminated timber (CLT) projects, finding a scale-independent collaborative network based on influential centers and noting vulnerability to disruptions [4]. With 251 international construction projects involving 156 Chinese companies, SNA revealed that large enterprises formed dense, large networks, while small and medium-sized enterprises maintained sparse, small networks with varying centralization measures affecting performance differently for each group [5]. The research literature has not systematically compared formal contractual networks between MC and SC with informal collaborative networks among SCs themselves in the same empirical context. This dual network is essential because the supply chain operates simultaneously through both layers, with a formal hierarchy regulating contractual obligations and resource flows, and an informal col-

* Corresponding author: Tran Phu Loc

DOI: <https://doi.org/10.55228/j.uth.150501>

laborative network facilitating knowledge exchange, mutual support, and shared adaptation to project challenges. Understanding the interaction between these two network layers can reveal potential weaknesses, untapped collaboration opportunities, and strategic intervention opportunities to improve supply chain performance.

This study addresses these gaps by conducting a comprehensive dual-network analysis of the CSC in the Southeast region, considering both the directed network between MC–SC and the undirected network between SC–SC drawn from the same set of 37 civil engineering projects. The study utilizes a set of SNA indices, including density, cluster coefficient, hierarchical distribution, measures of centrality, modularity, and community structure, to describe and compare the structure of both networks.

2. Theoretical Background

SNA has become a crucial tool in supply chain management and research in recent years. Unlike traditional analytical methods that focus on individual entities, network analysis allows for the study of relationships and interactions between actors, thereby providing a comprehensive view of the system's structure and dynamics [6]. In the context of supply chains, network analysis offers significant benefits, helping to identify key actors in the supply chain. Through central indicators such as Degree Centrality, it is possible to identify contractors who play the most important role in connecting the network, controlling the flow of information and materials, or who have a significant influence on other actors [7]. Network analysis allows for the assessment of the overall structure of the supply chain through indicators such as Network Density, Clustering Coefficient, and Modularity. These indicators provide information on the degree of connectivity, the formation of collaborative clusters, and the degree of fragmentation of the network [8]. Understanding network structure helps managers make strategic decisions about strengthening linkages, diversifying supply sources, or restructuring the supply chain to improve efficiency and resilience. Network analysis supports understanding collaborative patterns and relationships between actors. By analyzing the weights of edges (number of repeated collaborations), the sustainability of relationships and long-term or short-term collaboration trends can be assessed. This is crucial in building partnership development strategies and managing subcontractors. Numerous studies have shown a link between network characteristics and project outcomes such as quality, schedule, cost, and stakeholder satisfaction; high-density [3], [9] networks with large clustering coefficients are often associated with better coordination and less conflict among parties. Community structure analysis helps understand the degree of fragmentation, the formation of distinct ecosystems, and the extent of resource sharing among main contractors. Based on this, specific and feasible recommendations are made to improve the structure and effectiveness of CSC in the Southeast region.

Nodes: These are the basic elements of a network, representing individuals or groups of entities participating in the social network. On a graph, each node is represented by a vertex.

Edge: This is the connection between two nodes, representing a specific relationship or interaction between the two agents. The link can be directed or undirected. A pair of nodes can have multiple types of links coexisting.

Network: A network is a collection of nodes and the links between them that form an overall structure, which may include a single connecting component or multiple separate groups. The smallest social network is a single network of two nodes with a single link between them, from which triangles and more complex structures can be formed.

Centrality: Indicators used to measure the importance or dominance of a node in a network. Degree centrality counts the number of direct links a node has; betweenness centrality measures the number of shortest paths through the node. Centrality reflects whether a node acts as a hub or bridge in the network; nodes with high centrality can be considered influential or powerful within the network. In-degree and out-degree are defined only for directed networks, whereas degree, degree centrality, and betweenness centrality are defined for undirected networks; when normalized, the latter two are bounded in [0, 1].

Clustering/Community: A subgroup of nodes with a higher density of internal connections to each other compared to the rest of the network. Community detection or clustering methods help identify these group structures. Other metrics, such as the clustering coefficient, which measures the proportion of complete triangles appearing in the network, are also common in network analysis.

Network metrics. A two-mode network and its one-mode projection are structurally different objects, and the same metric name can denote different quantities in each.

A one-mode network derived from two-mode data is not observed directly but constructed by projection. Let B denote the subcontractor–project incidence matrix, in which $B_{ip} = 1$ if subcontractor i participates in project p . The one-mode projection onto the subcontractors is defined as [10]:

$$w_{ij} = \sum_p B_{ip} B_{jp}, \quad (i, j) \in E \Leftrightarrow w_{ij} \geq 1, \quad i \neq j \quad (1)$$

where w_{ij} is the number of projects shared by subcontractors i and j . Equation (1) carries a direct structural consequence: all subcontractors of a given project are mutually linked and therefore form a clique, so the edges of the projection are generated by this rule rather than observed. For the same reason the edge weight, and not the mere presence of an edge, is the informative signal. Equation (1) applies to two-mode (bipartite) data only, and its output is by construction an undirected weighted one-mode network, since $w_{ij} = w_{ji}$. The weight is bounded by the number of projects P , so that $w_{ij} \in \{0, 1, \dots, P\}$.

Density is the ratio of realized to possible edges, but the set of possible edges depends on the class of network. In a two-mode network, edges can only run between the two node sets; in a one-mode network, any pair of nodes may be linked [10]:

$$d_{\text{bip}} = \frac{E}{n_{\text{MC}} n_{\text{SC}}}, \quad d_{\text{dir}} = \frac{E}{n(n-1)},$$

$$d_{\text{und}} = \frac{2E}{n(n-1)} \quad (2)$$

where E is the number of edges, n_{MC} and n_{SC} are the numbers of nodes in each of the two modes, and n is the number of nodes of a one-mode network. The three expressions are not interchangeable: d_{bip} applies only to two-mode networks, d_{dir} only to directed one-mode networks, and d_{und} only to undirected one-mode networks. All three are bounded in $[0, 1]$. The two-mode and undirected one-mode expressions are those of the two-mode framework of Latapy et al.; the directed expression is the standard definition for a directed graph. Applying a one-mode expression to two-mode data counts within-mode pairs that cannot exist by construction, so it systematically understates connectivity; the resulting value is an artefact of the formula rather than a property of the data.

The clustering coefficient quantifies the extent to which triangles are closed [10]:

$$C_i = \frac{2e_i}{k_i(k_i-1)}, \quad \bar{C} = \frac{1}{n} \sum_i C_i, \quad T = \frac{3\Delta}{\tau} \quad (3)$$

where e_i is the number of edges among the k_i neighbors of node i , Δ is the number of triangles, and τ is the number of connected triples. A two-mode network contains no triangles, so its average clustering is 0 identically. In a one-mode projection, the reverse holds: by equation (1), the neighborhood of any subcontractor that participates in exactly one project is a complete clique, which forces $C_i = 1$ for that node. Average local clustering and transitivity are therefore reported separately, since they weight nodes and triangles differently. Equation (3) applies to undirected networks and requires $k_i \geq 2$; nodes of degree 0 or 1 are conventionally assigned $C_i = 0$. All three quantities are bounded in $[0, 1]$. For a directed two-mode network, they are computed on its undirected version, and because a bipartite graph contains no cycles of odd length, it has no triangles, so $C_i = 0$ for every node and $T = 0$. These are structural values, not empirical findings. Directed generalizations of the clustering coefficient exist but are not used here [11].

$$C_D(i) = \frac{k_i}{n-1}, \quad C_B(i) = \frac{2}{(n-1)(n-2)} \sum_{s < t} \frac{\sigma_{st}(i)}{\sigma_{st}} \quad (4)$$

where σ_{st} is the number of shortest paths between nodes s and t , and $\sigma_{st}(i)$ the number of those paths that pass through node i . The summation runs over unordered pairs $s < t$ with $s, t \neq i$. The normalization of degree centrality is by the $n-1$ nodes to which a node could be adjacent; the betweenness definition and the factor $2/((n-1)(n-2))$ are those of Freeman and apply to undirected networks. After normalization, both measures are bounded in $[0, 1]$. Degree centrality identifies nodes with many ties, whereas betweenness identifies nodes that bridge otherwise weakly connected groups. Both are defined for undirected networks.

Permutation Test Modularity: To assess the statistical significance of the observed community structure in the

network, this study applies a permutation test based on degree-preserving randomization. This approach allows testing whether the observed modularity value differs significantly from expectations from a random network with the same degree sequence, thereby providing evidence for the existence of a true community structure in the network.

First, the network's community structure is determined by the Louvain algorithm, an effective and widely used modularity-optimization method for large-network analysis [12]. The modularity value Q is calculated using the standard modularity formula proposed by Mark Newman [13].

$$Q = \frac{1}{2m} \sum_{ij} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta(c_i, c_j) \quad (5)$$

In this case A_{ij} is the element of the adjacency matrix, k_i and k_j is the degree of the nodes i, j , and m is the total number of edges in the network, and $\delta(c_i, c_j)$ is the Kronecker function which takes the value 1 if two nodes belong to the same community and 0 otherwise. The modularity index reflects the extent to which the density of internal community linkages exceeds expectations in a stochastic network with the same degree distribution [13]. Equation (5) is bounded in $[-1/2, 1]$; by convention, $Q > 0.3$ indicates a meaningful community structure and $Q > 0.5$ a strong one. It uses the one-mode null model $k_i k_j / 2m$, which assigns non-zero expected weight to within-mode pairs that cannot occur in a two-mode network. Replacing that term with the directed null model, in which the expected weight of an edge from i to j is the out-degree of i multiplied by the in-degree of j and divided by m , removes the defect: when all edges run from one mode to the other, nodes of the receiving mode have zero out-degree and nodes of the sending mode zero in-degree, so the expectation is non-zero only on the between-mode pairs that can actually occur. For a two-mode network of this kind, the directed modularity coincides exactly with the bipartite modularity [14]. This method is particularly suitable in network analysis because it maintains the basic structural constraints, avoiding biased comparisons with simpler stochastic models. For a two-mode network, the swaps must additionally preserve the bipartite structure: only the assignments of nodes in one mode to nodes in the other are traded, so that the degree of every node in both modes remains unchanged. Unrestricted edge swapping would create within-mode edges that cannot exist, yielding a null model that is not comparable with the observed network. For each stochastic network, the community structure is determined by the Louvain algorithm and the corresponding modularity value. The distribution of random modularity values Q_{random} is used to estimate the p -value using the Monte Carlo test [15]:

$$p = \frac{1 + \#(Q_{\text{random}} \geq Q_{\text{observed}})}{N + 1} \quad (6)$$

where N is the number of random networks generated. Adding 1 to both the numerator and denominator follows the standard correction for Monte-Carlo p -values, which prevents an empirical value of exactly zero; the smallest attainable p -value is therefore $1/(N + 1)$. Equation (6) is a test procedure rather than a network metric: it applies to a

statistic computed on either a directed or an undirected network, provided the randomization preserves the structural constraints relevant to that statistic. Its value is bounded in $[1/(N + 1), 1]$.

3. Research Design

This study aims to measure the fragmentation and connectivity of civil CSC in the Southeast region of Vietnam through SNA. The research steps are shown in Figure 1. The implementation sequence includes:

Step 1: Data Collection

The research sample was selected based on the criteria of being major contractors in the civil construction sector in the Southeast region of Vietnam, with large revenue, high reputation, and participation in many important projects.

Data was collected from 37 civil construction projects, including apartments, hotels, offices, training centers, schools, etc., carried out by the MC in the period 2018–2025.

Step 2: Data Normalization

Contractor Name Standardization: Because the same contractor may appear under different names in documents (full name, abbreviation, old/new name), standardization is necessary to ensure each contractor is represented by only one node in the network. This process uses a combination of tax code lookup, string comparison, and manual verification. SCs are categorized by specialization based on company name, job description in the contract, and business registration information lookup. Key areas include: concrete, steel, HVAC, elevators, inspection, finishing materials, glass doors, paint, waterproofing, etc. Businesses with transaction data but not belonging to the CSC are excluded. Duplicate contractor information is removed.

From the initial 2,502 cooperative transaction records, the data were normalized by excluding non-CSC entities and merging recurring relationships between the same pair of contractors, yielding 2,412 valid collaborations. Collapsing repeated ties between the same MC–SC pair produces the final MC–SC network of 1,660 unique edges, whose weights record the number of shared projects (mean $2,412/1,660 \approx 1.45$).

Step 3: Build the network database.

The directed MC–SC network has 1,555 nodes and 1,660 edges, where 10 nodes are main contractors (out-going edges only) and 1,545 nodes are SCs (incoming edges only). The undirected SC–SC network consists of 1,545 subcontractor nodes and 121,340 edges. The SC–SC network is not observed directly but obtained as a one-mode projection of the subcontractor–project bipartite structure: two subcontractors are linked whenever they participate in at least one common project. A structural consequence is that the subcontractors of each project form a complete clique; accordingly, the high clustering, density, and community structure of the SC–SC network are, in large part, mechanical properties of this projection rather than direct evidence of dyadic collaboration. SC–SC edges are therefore interpreted as indicators of co-participation and opportunity for interaction, with edge weight (the number of shared projects) as the more informative signal of repeated, and hence plausibly preferential, col-

laboration. All network metrics were computed in Python using the NetworkX and igraph libraries, community detection used the Louvain method, and the network layouts were produced in Gephi. In-degree and out-degree are obtained from the directed MC–SC network, while modularity and the clustering coefficient are computed on its undirected version. Degree, degree centrality, betweenness centrality and clustering are computed on the undirected SC–SC projection, and betweenness is computed exactly rather than from a sampled approximation. The statistical charts were generated in Python using matplotlib and seaborn. To test whether the high clustering of the SC–SC network is a mechanical consequence of equation (1), the subcontractor–project incidence matrix was randomized while preserving both the number of projects per subcontractor and the number of subcontractors per project, and the randomized matrix was re-projected; five independent randomizations were generated. The permutation test reported in Section 4.2 applies the same principle to the main-contractor–subcontractor incidence matrix, so that every randomized network remains bipartite and preserves both degree sequences.

4. Results and Discussion

In this ForceAtlas2 layout, node color marks the community detected by the Louvain method (with eight communities); larger nodes have a higher degree; each edge is an MC–SC contractual tie. The network resolves into ten hub-and-spoke stars. The dominant central star is MC2, which alone links 903 subcontractors, while the sparse links between star centers correspond to the 5.7% of subcontractors that work with more than one main contractor.

Table 1. Information table of all nodes in the network

Node_ID	Label	Type
96950580	SAIGON CONSTRUCTION INSPECTION JOINT STOCK COMPANY	SC
76973049	THU DUC CENTRIFUGAL CONCRETE JOINT STOCK COMPANY	SC
MC1	BCONS CONSTRUCTION INVESTMENT JOINT STOCK COMPANY	MC
MC2	COTECCONS CONSTRUCTION JOINT STOCK COMPANY	MC
MC5	PHUOC THANH CONSTRUCTION JOINT STOCK COMPANY	MC
.....		

Table 2. Side table containing information about MC–SC partnerships

Source	Target	Type	Weight
MC2	15094027	directed	1
MC2	21502213	directed	3
MC2	10261525	directed	2
MC2	59887748	directed	1
MC6	97315131	directed	1
.....			

Table 3. Side table containing information about SC–SC partnerships

Source	Target	Type	Weight
2611937	98910279	undirected	2
3421419	98910279	undirected	1
3529703	98910279	undirected	4
42710651	74176255	undirected	2
26824174	59465636	undirected	2
.....			

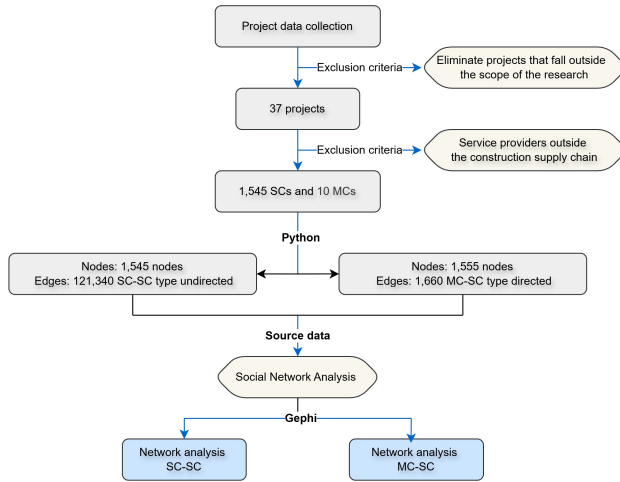


Figure 1. Research diagram

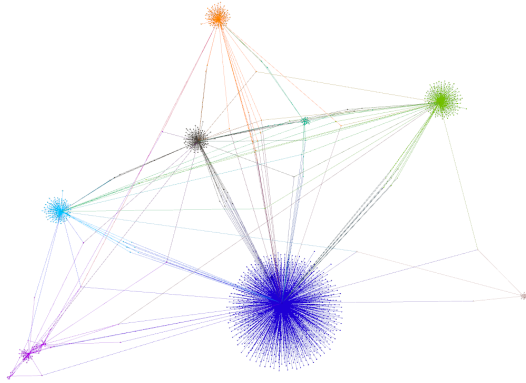


Figure 2. MC–SC linkage model from Gephi

4.1. Overall scale and characteristics of the MC–SC directed network

The MC–SC network connection model is shown in Figure 2 using Gephi software. The results of the SNA of the directed MC–SC network reveal a complex system with a large scale and a unique structure.

The large-scale supply chain network, with 1,555 nodes, reflects the complexity and diversity of the construction supply system in the Southeast region. The ratio of MCs to SCs is 1:154.5. On average, each main contractor contracts 166 distinct subcontractors (1,660 ties across 10 MCs); this mean is heavily skewed by MC2 (903 subcontractors), so most main

contractors work with far fewer. The total number of edges (1,660) exceeds the number of unique SCs (1,545) by 115 ties, which indicates that some SCs work with more than one main contractor. This surplus is produced by 88 subcontractors (5.7%) that hold contracts with two or more main contractors, 68 with two, 14 with three, 5 with four, and 1 with five, while the remaining 1,457 subcontractors (94.3%) work with only a single main contractor.

The total number of collaborations (2,412) is greater than the total number of edges (1,660) by a ratio of 1.45, indicating that each relationship is repeated approximately 1.45 times on average. This reflects a relatively low level of repeated collaboration, with many relationships occurring only once. The strongest repeated relationship has weight 11 (MC2 – SC 16117121); the two parties appear together in 11 projects, the clearest case of a sustained, recurring MC–SC relationship in the sample.

4.2. Permutation test results – modularity of the MC–SC directed network

The modularity of the experimental network in Figure 3 shows that $Q = 0.625$ is always higher than that of random networks (mean value $Q \approx 0.619$, maximum value $Q \approx 0.622$). Across 1,000 randomizations that preserve the bipartite structure together with the degree sequence of every main contractor and every subcontractor, no random network reached the observed value, giving an empirical p -value of $1/1,001 \approx 0.001$ the smallest value attainable at $N = 1,000$. Because no random network reached the observed value, this figure is an upper bound ($p \leq 0.001$) rather than a point estimate, and the true p -value may be considerably smaller. The difference is statistically unambiguous but substantively small: random bipartite networks with the same degree sequences already attain $Q \approx 0.619$, so almost all of the observed modularity is imposed by the degree sequence, and in particular by the fact that 94.3% of subcontractors have degree 1, rather than by any distinctive contracting pattern. The permutation test therefore confirms that the partition is not a random artifact, while the size of the effect confirms that it is largely a structural consequence of the contracting pattern.

4.3. Degree centrality of the MC–SC directed network

In directed networks, degree is divided into in-degree and out-degree to reflect the two dimensions of cooperative relationships. As shown in Figure 4, the in-degree distribution in the upper left corner is strongly concentrated at value 1, with an overwhelming frequency compared to the other values. This indicates that the majority of SCs cooperate with only a single main contractor. Only a very small number of SCs have in-degrees of 2 or higher, reflecting a limited role in connecting communities.

Regarding out-degree, the distribution shows a very pronounced right-skew, with the majority of nodes having values of 0 or very low, while only a few nodes have very high out-degree. In particular, the appearance of an extremely large value (approximately 900) reflects the existence of a central MC2 node, which has a significantly larger number of cooperating SCs than the rest.

Nodes: 1555
Edges: 1660
Randomizations (N): 1000
Observed modularity: 0.6252
Mean random Q: 0.6188
Max random Q: 0.6218
p-value = $(r+1)/(N+1) = 0.0010$

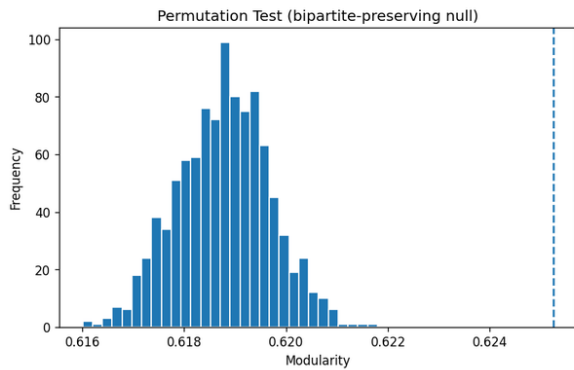


Figure 3. Modularity permutation test (matplotlib)

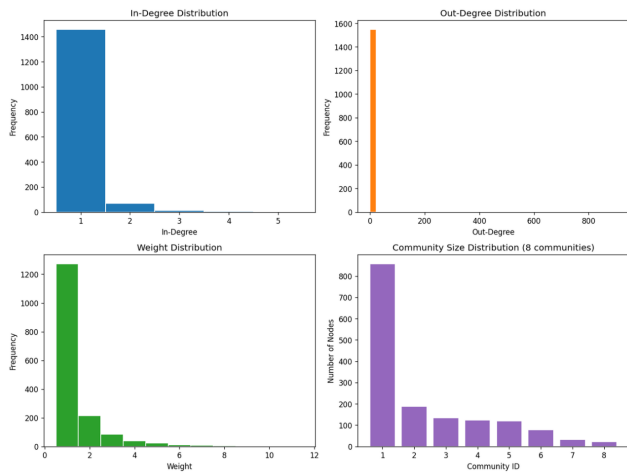


Figure 4. Distribution of structural features of the MC-SC network (matplotlib)

Table 4. Community Analysis Table

No.	MCs	Number of SCs	Number of edges	Per (%)
1	MC2	856	856	55.4%
2	MC6	187	187	12.1%
3	MC1	132	132	8.5%
4	MC5	123	123	8.0%
5	MC3	118	118	7.6%
6	MC7, MC8, MC9	76	101	4.9%
7	MC4	31	31	2.0%
8	MC10	22	22	1.4%

The stark difference between these two distributions confirms a fragmented network structure, where MCs act as central connectors, SCs are largely peripheral and dependent on one or very few relationships. Simultaneously, the uneven hierarchical distribution also indicates a high degree of stratification within the collaborative network.

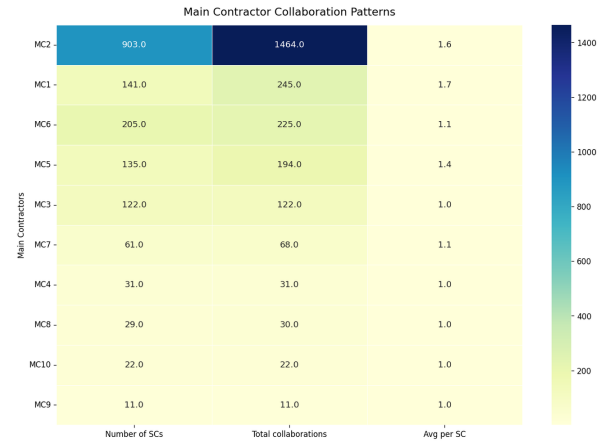


Figure 5. Heat-map of main-contractor collaboration patterns (matplotlib)

4.4. Network density of the MC-SC directed network

This is one of the most important indicators for evaluating the overall connectivity of a network. Gephi reports a graph density of 0.000687 for the directed MC-SC network, which corresponds to d_{dir} in equation (2). This one-mode metric is, however, not appropriate for a two-mode (bipartite) network: computed correctly as $E/(n_{MC} \times n_{SC}) = 1,660/(10 \times 1,545)$, the bipartite density is 0.107. The MC-SC network is therefore characterized not by low density but by extreme concentration. This low density reflects that each main contractor only works with a small set of SCs that match the specific needs of the project and their supply strategy. There is no tendency to work with all the SCs available on the market. The subcontractor market is highly fragmented with many small, specialized businesses. Each main contractor tends to build its own network rather than sharing a common group of subcontractors. Densities reported in other CSC studies are not directly comparable because density depends strongly on network size and the way the network is constructed. Studies of project-level interorganizational collaboration networks report a density of 0.027 [16].

Clustering Coefficient: measures the degree of tightly knit cluster formation within the network, specifically the appearance of triangles. The average clustering coefficient, computed on the undirected version of the network, is 0.000 (equation 3). Because the MC-SC network is bipartite (edges run only from MCs to SCs), it contains no triangles by construction, so the clustering coefficient is 0 by definition (equation 3); this reflects the network's structure and is not, in itself, evidence of fragmentation. The valid evidence of fragmentation is the subcontractor attachment distribution: 88 subcontractors are linked to more than one main contractor (in-degree ≥ 2) — 68 to two, 14 to three, 5 to four, and 1 to five — while 1,457 (94.3%) are linked to a single main contractor. A Clustering Coefficient of 0 also reflects the star structure of the network, where each MC is the center of a star with SCs as surrounding points. This structure is characterized by a central main contractor controlling all connections with subcontractors; SCs have no direct connections with each other and depend on the main contractor for project access. Compared to other studies, a clustering coefficient of 0 is char-

acteristic of a two-mode network, unlike many other studies on supply chain networks, such as social network analyses of information sharing in prefabricated construction supply chains [17] and of collaborative networks in cross-laminated timber construction [4]. This difference stems from the fact that the aforementioned studies analyzed one-mode networks where all nodes are of the same type, while this study analyzed a two-mode network with two distinct types of nodes.

4.5. Modularity and community structure of the MC–SC directed network

Modularity is an index that measures the degree to which the network is divided into distinct communities. By standard, modularity > 0.3 is considered to have a significant community structure, and modularity > 0.5 is considered very high [8], [18]. The analysis shows a modularity of $Q = 0.625$ (equation 5, computed on the undirected, unweighted version of the network; the corresponding weighted value is 0.561) with 8 communities. Evaluating the same partition with the directed null model, which for this two-mode network coincides exactly with Barber's bipartite modularity [14], gives $Q = 0.626$; the reported value is therefore not an artifact of treating the network as undirected. Because 94.3% of subcontractors attach to a single main contractor, the network approximates a disjoint union of stars, and the recovered partition coincides almost exactly with individual main contractors (Table 4). The permutation test confirms that this partition is not a random artifact, but the partition itself is largely a structural consequence of the contracting pattern rather than an emergent, non-obvious community structure. The value of 0.625 is higher than the modularity of 0.342 reported for a project-level interorganizational collaboration network in construction, though such cross-study comparisons are limited because modularity depends on network size and construction [16]; comparison is further limited when social network analysis is applied to risk propagation structures rather than to contractual networks, as in studies of schedule risk in prefabricated building projects [19]. This difference also reflects the product specificity of the supply chain between residential and prefabricated construction projects. High fragmentation also indicates a lack of collaboration among primary contractors, with a tendency to build private networks rather than sharing subcontractors.

Each MC forms separate communities; in most cases, each main contractor and their network of SCs forms a distinct community. This reflects the high fragmentation of the supply chain, with each main contractor building its own ecosystem. Communities vary greatly in size, from 22 subcontractors (MC10) to 856 subcontractors (MC2), reflecting the clear stratification in the construction market with large and small contractors. The three smallest contractors, MC7, MC8, and MC9, are grouped into a community, indicating they share some SCs and have relatively close networks. A key analysis assessing the level of subcontractor sharing across communities shows that only 5.7% of subcontractors work with more than one main contractor, while 94.3% work with only a single main contractor. This is a very low sharing rate, reflecting high fragmentation and a lack of horizontal integration in the

supply chain.

The results of the heat-map visualization in Figure 5 show that the collaborative structure among the MC in the construction network is unevenly distributed. MC2 stands out as a central node with 903 collaborating SCs and a total of 1,464 collaborations, significantly surpassing the other contractors. The average number of collaborations per partner is 1.6, indicating a relatively high level of relationship repetition, reflecting MC2's important coordinating and connecting role in the network. Conversely, most other contractors such as MC4, MC8, MC9, and MC10 have a low number of partners and low collaboration frequency, with an average value of approximately 1.0. This suggests that collaborative relationships are primarily short-term, project-by-project, lacking long-term repetition and engagement. The group of intermediate contractors, such as MC1, MC5, and MC6, has a higher level of connectivity but is still far behind MC2, indicating a clearly hierarchical network structure. The results show that the CSC is fragmented, temporary, and heavily dependent on a few central actors, thus highlighting the need for enhanced long-term cooperation to improve the efficiency and resilience of the system.

In this ForceAtlas2 layout, node color marks the Louvain community; larger nodes have a higher degree; an edge links two subcontractors that share at least one project. The dense core is formed by subcontractors active in several projects, whereas the radial arms are project-specific cliques of subcontractors that appear in a single project (1,129 nodes, 73.1%).

4.6. Overall scale and characteristics of the SC–SC co-participation network (undirected)

The SC–SC network connection model is illustrated using Gephi software as shown in Figure 6. The density of the SC–SC network is 0.102. Edge weights range from one to nine shared projects. Density is not directly comparable between the two networks, however, because they are structurally different objects: the MC–SC network is two-mode (bipartite) while the SC–SC network is its one-mode projection. Computed consistently, the bipartite density of the MC–SC network (0.107) is essentially equal to the SC–SC density, so the contrast between the two layers is not one of density. The SC–SC network is dense largely by construction, since the co-members of each project form a clique; most SCs are therefore structurally connected to many others, which may facilitate the sharing of information, experience, and mutual support; information, innovation, or even risk can spread rapidly within the network. Dense networks generally have higher sustainability because there are many alternative paths when some nodes or edges are disrupted. The average degree reaches 157.1 connections per node. This value is high, but it measures co-participation rather than realized collaboration: on average, each subcontractor has shared at least one project with about 157 others. This contrasts with the MC–SC network, where each subcontractor typically contracts with only a single main contractor.

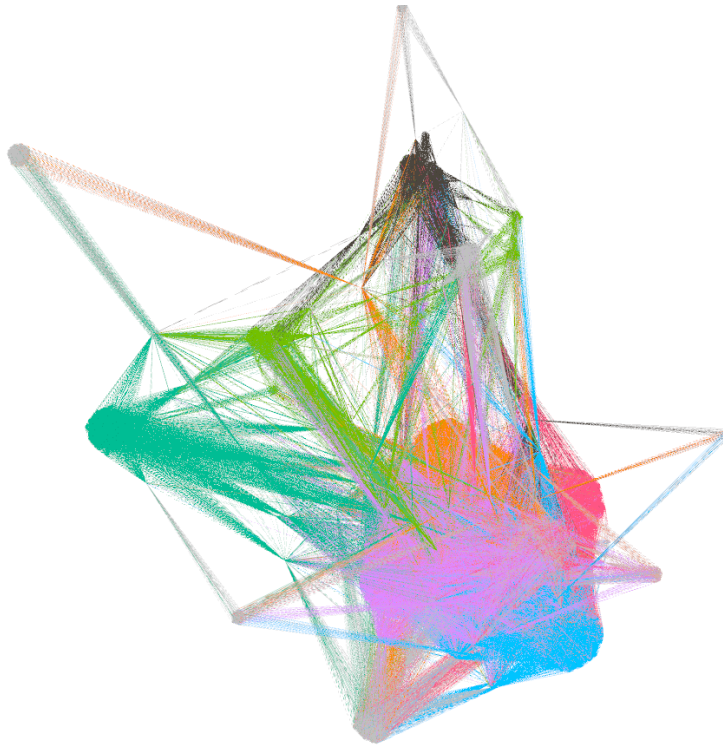


Figure 6. SC-SC linkage model from Gephi

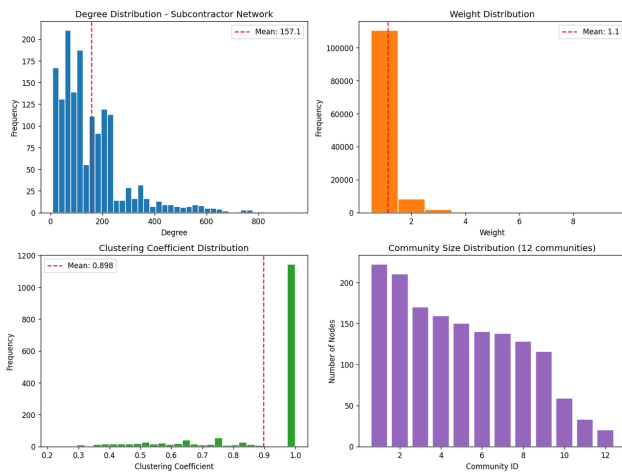


Figure 7. The distribution of structural features of the SC collaborative network (matplotlib)

Data analysis shows that in the SC-SC network, some SCs have very high degrees (941 connections), while others have lower degrees. Figure 7 summarises these distributions; most subcontractors fall below the mean of 157.1, edge weights are almost entirely 1, confirming that most co-participation ties stem from a single shared project.

4.7. Clustering coefficient of the SC-SC network (undirected)

The average local clustering coefficient of the SC-SC network is 0.898 (this is Gephi's "Average Clustering Coefficient"; the global clustering, or transitivity, is 0.63). A high value is expected here, rather than surprising, because the network is a projection in which each project forms a clique, 73.1% of subcontractor nodes have a local clustering coef-

ficient of exactly 1, their entire neighborhood is a complete clique. This share is not incidental: 1,129 of the 1,545 subcontractors (73.1%) participate in exactly one project, and for such a node the whole neighborhood is the clique of that single project, so a local clustering coefficient of 1 is forced by equation (1). A degree-preserving randomization of the incidence matrix confirms the point directly: re-projected random networks yield an average local clustering of 0.879 (SD 0.0004), only 0.019 below the observed 0.898. Virtually all of the clustering in the SC-SC network is therefore attributable to the projection itself rather than to preferential collaboration among subcontractors. These values therefore describe the topology induced by shared project membership and should not be read as a direct measure of collaborative intensity or trust. They do indicate that many SCs repeatedly share the same project environments, which creates opportunities, not evidence for building working relationships; the number of shared projects (edge weight) is a more informative signal of sustained collaboration.

4.8. Community structure of the SC-SC network (undirected)

The SC-SC network is partitioned into 12 communities. Because the network is a projection of project co-participation, these communities largely reflect groups of projects (and the main contractors behind them) rather than organically emergent collaborative groups: two SCs fall in the same community mainly when they share projects, directly or transitively. Some SCs act as bridges between communities, appearing across several project groups. Figure 8 makes this explicit. Betweenness centrality is exactly zero for 1,131 subcontractors and strictly positive for the remaining 414. The 1,131 comprise the 1,129 subcontractors that appear in a single project

— a node whose entire neighborhood is one clique cannot lie on a shortest path between two other nodes — together with two firms that appear in more than one project but lie on no shortest path between groups. In this projection, betweenness is therefore a close but not exact indicator of multi-project participation, and the two groups separate cleanly in Figure 8.

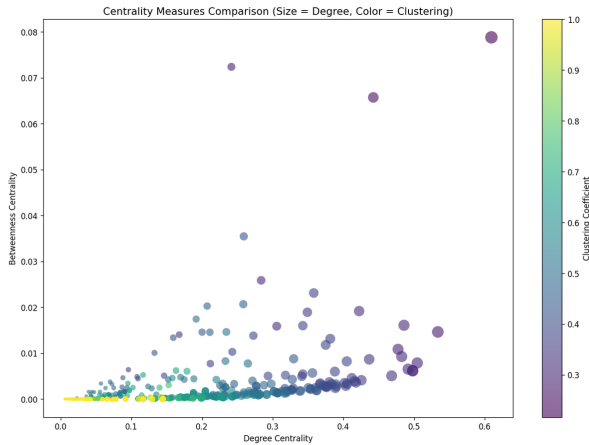


Figure 8. Relationship between Degree Centrality, Betweenness Centrality, and Clustering Coefficient (matplotlib)

5. Conclusion

The SNA provided a structural characterization of the civil CSC in the Southeast region, revealing that the supply chain is characterized by high fragmentation, a predominance of short-term relationships, and the dominance of a few large main contractors. Despite strengths such as large scale, diversity, and the presence of high-quality MC and subcontractors, the supply chain still faces numerous challenges regarding sustainability, efficiency, and resilience to risks. Recommendations focus on enhancing subcontractor sharing, building long-term relationships, developing key subcontractors, increasing horizontal linkages between communities, and diversifying the network for smaller contractors.

However, MC–SC network analysis only reflects one aspect of CSC: the contractual, hierarchical, and one-way relationship from the main contractor to the subcontractors. In reality, SCs not only interact with the main contractor but also have opportunities to meet, work together, and form collaborative relationships when participating in a project. These relationships, although not explicitly stated in the formal contract, can play a crucial role in sharing information, experience, resources, and mutual support. These relationships are not recorded in the formal contract, yet they define the environments in which subcontractors repeatedly encounter one another, and they therefore fall outside the scope of an analysis restricted to the contractual layer. The research analyzed the interconnected network between SC–SC, an undirected network in which nodes represent subcontractors, and two nodes are connected by an edge if the two SCs have participated in at least one construction project together. Unlike MC–SC networks, which represent contractual relationships from the main contractor to subcontractors, SC–SC networks are undirected networks that represent potential collaboration

and interaction among subcontractors. Much of the research on CSCs focuses on hierarchical relationships between tiers. SC–SC network analysis adds a perspective on horizontal relationships between actors at the same tier. Social network theory suggests that actors within the same system tend to form informal relationships based on proximity, frequent interaction, and shared interests. SC–SC network analysis helps test this hypothesis in the context of CSCs. SC–SC networks can reveal how SCs organize themselves into groups and communities based on expertise, geography, or collaborative experience. The SC–SC network can help MCs and owners identify experienced subcontractor teams that can work together, thereby optimizing subcontractor selection and coordination.

The SC–SC co-participation network is dense and highly clustered (121,340 edges, average degree 157.1, average local clustering 0.898). As a one-mode projection of shared project membership, this structure shows that subcontractors are repeatedly embedded together in the same project environments, rather than being connected only vertically to a main contractor. This co-participation structure opens up many opportunities for SCs to learn from each other's experiences, construction methods, and new technologies. When facing difficulties with resources, equipment, or personnel, SCs can support each other. This cooperation network can be a source of innovation when SCs with diverse expertise combine their knowledge and skills.

They also contribute to network theory by providing empirical evidence of a dual-network structure in a real-world industrial context. From a practical perspective, the results imply that improving supply chain performance requires a shift from purely hierarchical management approaches toward strategies that recognize and leverage informal collaboration networks. Encouraging subcontractor sharing, fostering long-term relationships, and integrating informal networks into formal coordination mechanisms may enhance both efficiency and resilience in construction supply chains.

Overall, the results confirm that a single-layer perspective is insufficient to capture the complexity of CSC structures. Only by integrating both formal and informal dimensions can a comprehensive understanding of supply chain dynamics be achieved, thereby providing a more robust foundation for both theoretical development and managerial decision-making.

Author contributions

Tran Phu Loc: Methodology, Data management, Formal analysis, Investigation, Validation, Visualization, Grant acquisition, Feedback on peer review, Writing – original manuscript. Tran Quang Phu: Methodology, Formal analysis, Validation, Writing – original manuscript. Huynh Thi Yen Thao: Methodology, Formal analysis, Validation, Writing – original manuscript.

Declaration of competing interest

The authors declare the absence of any potential conflicts of interest from this study and affirm that the paper has not been previously published.

Data availability

Data will be provided upon request.

References

- [1] F. S. Almutairi, “The Contractor-Subcontractor Relationship Types in the Construction Industry in Saudi Arabia,” *Open J. Bus. Manag.*, vol. 10, no. 06, pp. 3500–3530, 2022, doi: [10.4236/ojbm.2022.106173](https://doi.org/10.4236/ojbm.2022.106173).
- [2] M. Jagtap and S. Kamble, “Evaluating the modus operandi of construction supply chains using organisation control theory,” *Int. J. Constr. Supply Chain Manag.*, vol. 5, no. 1, pp. 16–33, 2015, doi: [10.14424/ijscsm501015-16-33](https://doi.org/10.14424/ijscsm501015-16-33).
- [3] X. Hu and H. Y. Chong, “Integrated frameworks of construction procurement systems for off-site manufacturing projects: social network analysis,” *Int. J. Constr. Manag.*, vol. 22, no. 11, pp. 2089–2097, 2022, doi: [10.1080/15623599.2020.1766188](https://doi.org/10.1080/15623599.2020.1766188).
- [4] H. Said, A. Rajagopalan, and D. M. Hall, “Longitudinal analysis of interorganizational collaborative networks of cross-laminated timber (CLT) construction,” *Constr. Innov.*, vol. 25, no. 6, pp. 1840–1864, 2024, doi: [10.1108/CI-01-2023-0012](https://doi.org/10.1108/CI-01-2023-0012).
- [5] C. Liu, J. Cao, G. Wu, X. Zhao, and J. Zuo, “Interenterprise Collaboration Network in International Construction Projects: Evidence from Chinese Construction Enterprises,” *J. Manag. Eng.*, vol. 38, no. 2, p. 05021018, Mar. 2022, doi: [10.1061/\(ASCE\)ME.1943-5479.0001006](https://doi.org/10.1061/(ASCE)ME.1943-5479.0001006).
- [6] H. Wang and Z. Zhou, “Identification of Key Risk Nodes and Vulnerability Analysis of Construction Supply Chain Networks,” *Buildings*, vol. 14, no. 7, p. 1997, Jul. 2024, doi: [10.3390/buildings14071997](https://doi.org/10.3390/buildings14071997).
- [7] M. Hadid, M. Gunduz, and Y. H. Kwak, “Assessing Interorganizational Relationships Among Key Supply Chain Partners (KSCPs) in Public Construction Projects,” *IEEE Trans. Eng. Manag.*, vol. 71, pp. 8839–8856, 2024, doi: [10.1109/TEM.2023.3293469](https://doi.org/10.1109/TEM.2023.3293469).
- [8] S. Shabani Ardakani and M. Nik-Bakht, “Social network analysis of project procurement in Iranian construction mega projects,” *Asian J. Civ. Eng.*, vol. 22, no. 5, pp. 809–829, Jul. 2021, doi: [10.1007/s42107-021-00348-1](https://doi.org/10.1007/s42107-021-00348-1).
- [9] H. Wu, Q. K. Qian, A. Straub, and H. Visscher, “Exploring transaction costs in the prefabricated housing supply chain in China,” *J. Clean. Prod.*, vol. 226, pp. 550–563, Jul. 2019, doi: [10.1016/j.jclepro.2019.04.066](https://doi.org/10.1016/j.jclepro.2019.04.066).
- [10] M. Latapy, C. Magnien, and N. Del Vecchio, “Basic notions for the analysis of large two-mode networks,” *Soc. Networks*, vol. 30, no. 1, pp. 31–48, Jan. 2008, doi: [10.1016/j.socnet.2007.04.006](https://doi.org/10.1016/j.socnet.2007.04.006).
- [11] L. C. Freeman, “A Set of Measures of Centrality Based on Betweenness,” *Sociometry*, vol. 40, no. 1, pp. 35–41, Mar. 1977, doi: [10.2307/3033543](https://doi.org/10.2307/3033543).
- [12] V. D. Blondel, J. L. Guillaume, R. Lambiotte, and E. Lefebvre, “Fast unfolding of communities in large networks,” *J. Stat. Mech.: Theory Exp.*, vol. 2008, no. 10, p. P10008, Oct. 2008, doi: [10.1088/1742-5468/2008/10/P10008](https://doi.org/10.1088/1742-5468/2008/10/P10008).
- [13] M. E. J. Newman, “Modularity and community structure in networks,” *Proc. Natl. Acad. Sci.*, vol. 103, no. 23, pp. 8577–8582, Jun. 2006, doi: [10.1073/pnas.0601602103](https://doi.org/10.1073/pnas.0601602103).
- [14] M. J. Barber, “Modularity and community detection in bipartite networks,” *Phys. Rev. E*, vol. 76, no. 6, p. 066102, Dec. 2007, doi: [10.1103/PhysRevE.76.066102](https://doi.org/10.1103/PhysRevE.76.066102).
- [15] B. V. North, D. Curtis, and P. C. Sham, “A Note on the Calculation of Empirical P Values from Monte Carlo Procedures,” *Am. J. Hum. Genet.*, vol. 71, no. 2, pp. 439–441, Aug. 2002, doi: [10.1086/341527](https://doi.org/10.1086/341527).
- [16] D. Zhao, M. Duva, S. Mollaoglu, K. Frank, A. Garcia, and J. Tait, “Integrative Collaboration in Fragmented Project Organizations: Network Perspective,” *J. Constr. Eng. Manag.*, vol. 147, no. 10, p. 04021115, Oct. 2021, doi: [10.1061/\(ASCE\)CO.1943-7862.0002149](https://doi.org/10.1061/(ASCE)CO.1943-7862.0002149).
- [17] R. Zhu and L. Li, “Intelligent construction technology based information sharing network for prefabricated building supply chain: a social network analysis approach,” *Kybernetes*, vol. 54, no. 9, pp. 5158–5180, Apr. 2024, doi: [10.1108/K-01-2024-0128](https://doi.org/10.1108/K-01-2024-0128).
- [18] M. E. J. Newman and M. Girvan, “Finding and evaluating community structure in networks,” *Phys. Rev. E*, vol. 69, no. 2, p. 026113, Feb. 2004, doi: [10.1103/PhysRevE.69.026113](https://doi.org/10.1103/PhysRevE.69.026113).
- [19] Q. Luo, C. Sun, G. Li, Y. Li, J. Xue, and G. Zhang, “Hierarchical schedule risk structures and mitigation strategies in prefabricated building projects: an integrated SNA-ISM approach,” *Eng. Constr. Archit. Manag.*, vol. 33, no. 7, pp. 5737–5759, Jun. 2026, doi: [10.1108/ECAM-12-2024-1746](https://doi.org/10.1108/ECAM-12-2024-1746).