Journal of Computing Theories and Applications ISSN:3024-9104

Research Article

A Composite Centrality Framework for Evacuation Planning in Meso-Scale Spatial Networks with Semi-Structured Connectivity

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Abstract: Evacuation planning in spatial networks requires the identification of critical nodes that maintain connectivity, accessibility, and flow distribution during emergency situations. Existing approaches often rely on individual centrality measures, which capture only a single structural dimension of node importance and may therefore produce incomplete or biased prioritization. To address this limitation, this study proposes a Composite Centrality Framework for identifying critical nodes in meso-scale spatial networks with semi-structured connectivity. The network is modeled as a weighted undirected graph, and Degree, Betweenness, and Closeness Centrality are integrated into a unified composite index to capture complementary structural roles. The framework is implemented in MATLAB and evaluated using a real-world campus spatial network consisting of 30 nodes and a synthetic network comprising 16 nodes with comparable structural characteristics. The results reveal a highly uneven distribution of node importance, with a small set of structurally dominant nodes consistently identified across both networks. In the campus network, node P1 achieves the highest composite centrality score (0.2195) and ranks first across the individual centrality measures, indicating its dominant role in maintaining network connectivity, accessibility, and flow distribution. Quantitative evaluation demonstrates strong agreement between the composite ranking and the individual measures, with Spearman rank correlation coefficients of 0.94, 0.89, and 0.91 for Degree, Betweenness, and Closeness Centrality, respectively. However, only one node (P1) appears simultaneously in the top five of all rankings, highlighting the complementary nature of the individual centrality measures and supporting the need for multi-criteria integration. Sensitivity analysis across three weighting scenarios yields rank correlations exceeding 0.97, confirming ranking stability and methodological robustness. Overall, the proposed framework provides a balanced and reliable approach for identifying critical nodes and demonstrates potential applicability to evacuation planning and spatial network analysis in semi-structured environments.

Keywords: Composite centrality; Disaster risk reduction; Evacuation planning; Graph centrality analysis; Meso-scale spatial networks; Resilient infrastructure; Spatial connectivity; Weighted graph.

Received: March, 27th 2026
Revised: June, 5th 2026
Accepted: June, 6th 2026
Published: June, 23rd 2026

1. Introduction

Spatial networks provide an effective representation of complex systems composed of interconnected entities and pathways, where nodes and edges capture the structural and functional relationships within a given environment. Among these systems, meso-scale spatial networks with semi-structured connectivity are frequently encountered in institutional com-

DOI : 10.62411/jcta.15916

plexes, industrial facilities, transportation hubs, and public infrastructures. Such networks exhibit structured yet non-uniform connectivity patterns that often create localized bottlenecks, uneven accessibility, and congestion under high-demand conditions. These characteristics become particularly critical during emergency situations, where efficient evacuation depends not only on route availability but also on the structural role of individual nodes within the network.

Evacuation planning in spatial networks remains a challenging problem due to the need to maintain accessibility, minimize congestion, and support efficient movement under constrained conditions. Conventional evacuation approaches predominantly rely on shortest-path algorithms, optimization techniques, or heuristic routing methods that focus on identifying efficient paths between origin and destination locations [1], [2]. Although these approaches provide useful operational solutions, they often overlook the underlying structural characteristics of the network, particularly the varying importance of nodes in facilitating, controlling, or constraining flow. As a result, evacuation strategies based solely on route optimization may fail to identify critical nodes whose disruption could significantly affect overall network performance.

To overcome these limitations, recent studies have increasingly adopted graph-based representations of spatial environments, enabling the analysis of connectivity, accessibility, and structural dependencies through network-theoretic approaches [3]. Within this context, centrality analysis has emerged as one of the most widely used techniques for evaluating node importance in transportation systems, urban infrastructures, and evacuation-related applications [4], [5]. Degree Centrality quantifies local connectivity, Betweenness Centrality identifies nodes that control shortest-path flows, and Closeness Centrality measures global accessibility across the network. In parallel, other graph-theoretic approaches, including metric dimension and partition dimension, have been investigated to characterize node distinguishability and structural uniqueness within graph topologies [6], [7]. Collectively, these studies demonstrate the growing importance of network analysis for understanding the structural behavior of complex spatial systems.

Despite their widespread adoption, individual centrality measures capture only a single aspect of node importance and may therefore produce incomplete or biased interpretations. Nodes with high degree centrality may exhibit strong local connectivity while contributing little to global network control. Conversely, nodes with high betweenness centrality may function as critical transit points but provide limited accessibility, whereas nodes with high closeness centrality are globally accessible without necessarily controlling network flow. Consequently, reliance on a single centrality metric may lead to inconsistent prioritization of critical nodes, particularly in evacuation scenarios where connectivity, accessibility, and transit control must be considered simultaneously [8].

Several studies have attempted to combine multiple centrality measures to provide a more comprehensive assessment of node importance. However, existing composite centrality approaches are primarily developed and validated on large-scale, abstract, or highly connected networks, with limited evaluation in meso-scale spatial environments [9], [10]. Furthermore, studies applying centrality analysis to evacuation problems commonly focus on a single metric, most frequently betweenness centrality, without systematically investigating how different centrality perspectives influence node prioritization or how integrated measures compare against individual metrics [11], [12]. This limitation is particularly relevant in semi-structured spatial networks, where the interaction between local connectivity, transit control, and global accessibility is often non-trivial and cannot be adequately represented by a single structural indicator.

Accordingly, a significant research gap remains in the development of a systematic framework capable of integrating multiple centrality perspectives for evacuation planning in meso-scale spatial networks with semi-structured connectivity. Existing studies provide limited evidence regarding the robustness, consistency, and practical interpretability of composite centrality approaches in real-world spatial environments. Moreover, comparative analyses between individual and composite centrality measures remain scarce, making it difficult to assess whether integrated approaches provide meaningful advantages over conventional single-metric evaluations.

To address these challenges, this study proposes a Composite Centrality Framework for identifying critical nodes in evacuation planning scenarios. The proposed framework models the spatial environment as a weighted undirected graph and integrates Degree Centrality, Betweenness Centrality, and Closeness Centrality into a unified composite index. By simultaneously considering local connectivity, transit significance, and global accessibility, the framework aims to provide a more balanced and structurally representative assessment of node criticality than any individual centrality measure.

To the best of our knowledge, this study represents one of the first systematic investigations of composite centrality analysis for evacuation planning in meso-scale spatial networks with semi-structured connectivity, supported by both real-world and synthetic network validation. The main contributions of this study are fourfold: (1) the development of a graph-based framework for identifying critical nodes in evacuation-oriented spatial networks; (2) the integration of multiple centrality measures into a unified Composite Centrality Index; (3) a quantitative comparison between individual and composite centrality measures using ranking comparison, Spearman rank correlation, and top-k overlap analysis; and (4) validation of the proposed framework using both a real-world campus network and a synthetic network with comparable structural characteristics to evaluate robustness and potential generalizability.

Although a campus environment serves as the primary case study, the proposed framework is intended as a general analytical approach for semi-structured spatial networks rather than a campus-specific solution. Therefore, the findings may provide insights for a broader range of applications, including institutional facilities, public infrastructures, and other environments where network structure influences accessibility, movement efficiency, and evacuation performance, subject to further domain-specific validation. The remainder of this paper is organized as follows. Section 2 reviews the related literature and theoretical background. Section 3 presents the proposed methodology and composite centrality framework. Section 4 discusses the experimental results and network analysis. Section 5 compares the proposed approach with existing methods. Finally, Section 6 concludes the paper and outlines directions for future research.

2. Literature Review

This section reviews existing studies on evacuation modeling and network-based analysis, with particular emphasis on graph-based spatial representations and centrality analysis. The strengths and limitations of prior approaches are discussed to establish the motivation for the proposed Composite Centrality Framework and to identify the research gaps addressed in this study.

2.1 Graph-Based Spatial Network Modeling

Evacuation planning in complex environments has increasingly been investigated using computational and network-based approaches. Traditional evacuation methods commonly rely on shortest-path algorithms, optimization techniques, and heuristic routing strategies to identify efficient evacuation routes. While these approaches provide practical solutions for route selection, they primarily focus on path optimization and often overlook the structural characteristics of the underlying spatial network. Consequently, they may fail to identify critical nodes whose disruption could significantly affect accessibility, connectivity, and evacuation efficiency [1], [2].

To address these limitations, recent studies have adopted graph-based representations of spatial environments, where physical locations are modeled as nodes and accessible routes are represented as weighted edges. This modeling paradigm enables the systematic analysis of spatial structure, connectivity patterns, and movement constraints within complex environments [1]–[3]. By incorporating distance and connectivity information into a unified framework, graph-based models provide a more realistic representation of evacuation scenarios and support data-driven decision-making.

An important advantage of graph-based spatial modeling is its ability to reveal structural properties that are not directly observable through conventional route-planning approaches. Previous studies have shown that network topology strongly influences accessibility, congestion formation, bottleneck emergence, and overall evacuation performance [8]. As a result, graph-based analysis has become an increasingly valuable tool for understanding movement dynamics in environments characterized by complex and semi-structured connectivity, including campuses, public facilities, and institutional infrastructures.

2.2 Centrality Measures in Network Analysis

Centrality analysis is one of the most widely used approaches for evaluating node importance in graph theory and network science. Different centrality measures capture distinct structural roles within a network and provide complementary perspectives on node significance. Degree Centrality measures the number of direct connections associated with a node, reflecting its local connectivity and accessibility [4], [5], [10]. Betweenness Centrality quantifies the extent to which a node lies on shortest paths between other nodes, thereby identifying critical transit points and potential bottlenecks that influence network flow [9], [10]. Closeness Centrality evaluates how efficiently a node can reach all other nodes in the network, representing global accessibility and communication efficiency [13]–[15].

These measures have been successfully applied across a wide range of domains, including transportation systems, urban planning, biological networks, and infrastructure analysis [4], [10], [16], [17]. In evacuation-related applications, centrality measures provide valuable insights into the structural roles of nodes and their potential impact on movement efficiency. For example, nodes with high Betweenness Centrality often play a dominant role in directing evacuation flow but may also become congestion hotspots under high demand. Conversely, nodes with high Closeness Centrality tend to be more suitable as coordination points or evacuation destinations due to their superior accessibility [11], [12], [18].

Despite their usefulness, individual centrality measures provide only a partial representation of node importance. Each metric emphasizes a specific structural characteristic while neglecting others. Consequently, relying on a single centrality measure may produce inconsistent rankings and potentially biased interpretations of critical nodes, particularly in evacuation scenarios where local connectivity, transit control, and global accessibility must be considered simultaneously.

2.3 Composite and Multi-Criteria Centrality Approaches

To overcome the limitations of single-metric evaluation, several studies have explored the integration of multiple centrality measures into composite or multi-criteria assessment frameworks. The underlying rationale is that node importance is inherently multi-dimensional and cannot be fully represented by any individual centrality metric. By combining multiple structural perspectives, composite approaches aim to provide a more balanced, robust, and interpretable evaluation of network importance.

Joseph and Chen [19] introduced the concept of Composite Centrality as a normalized and scalable framework for evaluating node importance in complex evolving networks. Similarly, Liu et al. proposed approaches for quantifying node importance through the integration of multiple structural indicators, demonstrating that composite measures can improve the representation of node significance in multidimensional network settings [20], [21]. Collectively, these studies suggest that integrating complementary centrality measures can reduce the limitations associated with individual metrics and provide a more comprehensive assessment of network structure.

However, most existing composite centrality studies have been developed and validated using large-scale, abstract, or highly connected networks. Relatively little attention has been given to meso-scale spatial networks characterized by semi-structured connectivity patterns, where network topology, accessibility constraints, and flow dynamics differ substantially from those of large theoretical networks. Furthermore, limited evidence is available regarding the effectiveness of composite centrality approaches in practical evacuation planning scenarios, particularly when compared systematically against individual centrality measures.

2.4 Research Gap

Based on the literature reviewed above, several important research gaps can be identified. First, conventional evacuation planning approaches primarily emphasize route optimization and do not explicitly evaluate the structural importance of nodes within spatial networks. Second, although centrality analysis provides valuable structural insights, individual centrality measures capture only a single dimension of node importance and therefore cannot fully represent the complex interplay between local connectivity, transit control, and global accessibility. Third, while composite centrality approaches have been proposed in the broader network science literature, their application to meso-scale spatial networks with semi-structured connectivity remains limited.

More importantly, existing studies rarely provide systematic quantitative comparisons between individual and composite centrality measures, making it difficult to assess the practical advantages of integrated approaches. In addition, cross-network validation using both real-world and synthetic spatial networks of comparable scale remains largely unexplored. These limitations motivate the development of the proposed Composite Centrality Framework, which integrates multiple centrality perspectives and evaluates their effectiveness through quantitative comparison and validation across different network instances.

3. Proposed Method

This section presents the proposed Composite Centrality Framework for identifying critical nodes for evacuation planning in meso-scale spatial networks with semi-structured connectivity. The framework consists of four sequential stages: (1) spatial network construction and preprocessing, (2) computation of individual centrality measures, (3) integration of normalized centrality scores into a Composite Centrality Index, and (4) ranking and validation of critical nodes. The overall workflow is designed to provide a balanced assessment of node importance by simultaneously considering local connectivity, transit significance, and global accessibility.

3.1 Spatial Network Modeling, Data Acquisition, and Preprocessing

The spatial environment is represented as a weighted graph $G = (V, E)$, where V denotes the set of nodes and E represents the set of edges connecting them. Each node corresponds to a functional location within the spatial system, such as a building or facility, while each edge represents an accessible route between locations [2], [3]. Each node corresponds to a functional location within the study area, such as a building, facility, or service point, while each edge represents a pedestrian-accessible route between two locations [2], [3]. Throughout this study, the term critical nodes for evacuation planning refers to nodes identified by the proposed Composite Centrality Framework as structurally important for maintaining connectivity, accessibility, and flow distribution during evacuation scenarios. The term node importance is used only when referring to the structural significance indicated by individual centrality measures. Edge weights are assigned based on the physical distance between connected locations, allowing the graph to capture the spatial characteristics of the environment. This representation enables the analysis of connectivity patterns, accessibility relationships, and structural dependencies within the network [4], [10].

The spatial dataset was constructed from campus layout maps and validated through direct field observation. Buildings and key facilities were modeled as nodes, while pedestrian-accessible pathways connecting these locations were modeled as edges. Distances between connected nodes were estimated from the campus map and subsequently verified through on-site observation. All distances are expressed in meters and used as edge weights in the weighted graph model. The network was constructed under several simplifying assumptions:

- The network is considered static, with no temporal variation in movement patterns.
- All routes are assumed to be bidirectional.
- Edge weights represent physical travel distances only.
- Behavioral factors, congestion effects, and crowd dynamics are not explicitly modeled.

Based on these assumptions, the adjacency matrix was created in Microsoft Excel and subsequently imported into MATLAB for further analysis.

3.2. Centrality Measures

To identify critical nodes for evacuation planning, three complementary centrality measures are computed for each node in the weighted spatial network. Degree Centrality captures local connectivity, Betweenness Centrality represents transit significance, and Closeness Centrality reflects global accessibility. Together, these measures provide complementary perspectives on node importance and serve as the inputs for the proposed Composite Centrality Framework.

3.2.1. Degree Centrality

Degree Centrality is computed to quantify the local connectivity of each node within the spatial network. Nodes with higher degree values have more direct connections to neighboring locations and therefore provide greater flexibility for movement and access during evacuation. [22], [23]. The normalized Degree Centrality is defined as:

$$C_D(v) = \frac{\deg(v)}{N-1} \tag{1}$$

where $\deg(v)$ denotes the degree of node v, and N is the total number of nodes in the network. In this study, raw degree values are normalized by $(N-1)$, ensuring that all scores lie within the interval $[0,1]$ and are directly comparable with other centrality measures. Nodes with higher Degree Centrality are expected to provide greater local accessibility and multiple evacuation route options [12].

3.2.2. Betweenness Centrality

Betweenness Centrality is computed to identify nodes that play an intermediary role in movement across the network. In evacuation scenarios, these nodes often facilitate flow distribution between different parts of the network but may also become potential bottlenecks under high-demand conditions [9], [20]. The metric is calculated as:

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{2}$$

where σ_{st} is the total number of shortest paths between nodes s and t, and $\sigma_{st}(v)$ denotes the number of those paths that pass through node v. Betweenness values are normalized using the factor $(N-1)(N-2)/2$, following the standard formulation. Weighted shortest paths are computed using Dijkstra's algorithm based on distance-weighted edges. Nodes with high Betweenness Centrality play an important role in maintaining network connectivity but may also become congestion points during emergency situations [11], [24].

3.2.3. Closeness Centrality

Closeness Centrality is used to evaluate the accessibility of each node relative to all other locations in the network. Nodes with higher closeness values can be reached more efficiently and are therefore considered favorable candidates for evacuation coordination or gathering points[22], [23]. The metric is calculated as:

$$C_C(v) = \frac{1}{\sum_{u \neq v} d(v,u)} \tag{3}$$

where $d(v,u)$ denotes the weighted shortest-path distance between nodes v and u, computed using Dijkstra's algorithm. Higher Closeness Centrality values indicate superior accessibility and shorter average travel distances to other locations, making such nodes attractive candidates for coordination and evacuation functions [25].

3.2.4. Composite Centrality Model

The three centrality measures capture different structural characteristics and frequently produce different node rankings. Degree Centrality emphasizes local connectivity, Betweenness Centrality highlights transit significance, and Closeness Centrality reflects global accessibility. To obtain a more balanced assessment of critical nodes for evacuation planning, the normalized centrality values are integrated into a Composite Centrality Index.

Prior to aggregation, all centrality values are normalized to the range [0,1] using min-max scaling to ensure comparability across metrics. The Composite Centrality Index for each node is then calculated as:

$$C_{comp}(v) = \alpha C_D(v) + \beta C_B(v) + \gamma C_C(v) \tag{4}$$

where α, β, and γ are weighting coefficients satisfying $\alpha + \beta + \gamma = 1$. In this study, equal weighting is adopted, with $\alpha = 0.33$, $\beta = 0.33$, and $\gamma = 0.34$. This weighting scheme serves as a neutral baseline by assigning equal importance to local connectivity, transit significance, and global accessibility [6], [26].

The suitability of the equal-weighting assumption is subsequently evaluated through sensitivity analysis. Rather than assuming that a particular weighting configuration is optimal, the analysis examines whether the ranking of critical nodes remains stable under alternative weighting scenarios. This procedure ensures that the resulting rankings are driven primarily by the network structure rather than by a specific parameter selection.

To evaluate robustness, three weighting scenarios are considered: (1) equal weighting ($\alpha = 0.33$, $\beta = 0.33$, $\gamma = 0.34$); (2) betweenness-priority weighting ($\alpha = 0.20$, $\beta = 0.50$, $\gamma = 0.30$); and (3) closeness-priority weighting ($\alpha = 0.20$, $\beta = 0.30$, $\gamma = 0.50$). The resulting node rankings are compared using Spearman rank correlation. Across all scenarios, the correlation exceeds 0.97, indicating that the Composite Centrality Framework produces highly stable rankings despite moderate variations in weighting parameters. This result suggests that the proposed framework provides a robust and reliable assessment of critical nodes for evacuation planning [19], [20].

3.3. Computational Implementation

The proposed Composite Centrality Framework was implemented in MATLAB R2023b. The spatial network was represented as a weighted undirected graph using the adjacency matrix and distance-weight matrix derived from the preprocessing stage. The adjacency matrix was imported from Microsoft Excel using the readtable function, and the graph structure was constructed using MATLAB's graph() function. Edge weights correspond to physical distances between connected nodes and are incorporated into all shortest-path computations.

For each node, Degree Centrality, Betweenness Centrality, and Closeness Centrality were computed using MATLAB's built-in graph analysis functions. Degree Centrality was normalized by $(N-1)$, while Betweenness Centrality was normalized using the factor $(N-1)(N-2)/2$. Closeness Centrality was calculated using weighted shortest paths derived from Dijkstra's algorithm. To ensure comparability across metrics, all centrality values were subsequently normalized to the interval $[0,1]$ using min-max scaling before aggregation into the Composite Centrality Index. The resulting normalized centrality values were combined according to Equation (4), producing a composite score for each node. Nodes were then ranked in descending order based on their composite scores to identify critical nodes for evacuation planning. The complete computational procedure is summarized in Algorithm 1.

Algorithm 1. Computational procedure of the proposed Composite Centrality Framework

```
INPUT: Adjacency matrix $A\ (n \times n)$; Weight matrix $W\ (n \times n)$; Weighting coefficients $\alpha, \beta, \gamma$ where $\alpha + \beta + \gamma = 1$
OUTPUT: Composite centrality vector $C_{comp}$; Ranked list of critical nodes $R$.
Construct weighted undirected graph $G = (V, E, W)$ from $A$ and $W$
FOR each node $v$ in $V$:
    Compute raw degree: $\deg(v) = |\{u: (v,u) \in E\}|$
    Normalize: $C_D(v) = \deg(v)/(n-1)$
    Apply Dijkstra's algorithm to compute all-pairs shortest path $D(u,v)$
FOR each node $v$ in $V$:
    Compute Betweenness : $C_B raw(v) = \sum[\sigma_{st}(v)/\sigma_{st}]$
    Normalize : $C_B(v) = C_B raw(v)/[(n-1)(n-2)/2]$
    Compute Closeness: $C_C(v) = 1/\sum d(v,u)\ \forall u \neq v$
Normalize all centrality vectors to $[0,1]$ using min-max scaling
Compute Composite: $C_{comp}(v) = \alpha \cdot C_D(v) + \beta \cdot C_B(v) + \gamma \cdot C_C(v)$
Rank all nodes by $C_{comp}$ in descending order $\rightarrow R$
Return $C_{comp}, R$
```

3.4. Methodological Workflow

The proposed Composite Centrality Framework integrates multiple stages of spatial network analysis to identify critical nodes for evacuation planning. Rather than relying on a single structural indicator, the framework combines complementary perspectives of node importance, including local connectivity, transit significance, and global accessibility, into a unified evaluation process. The workflow begins with data acquisition and preprocessing, where spatial information is collected from campus maps and field observations. Functional locations are represented as nodes, pedestrian-accessible routes are represented as edges, and physical distances are assigned as edge weights. These data are then transformed into a weighted graph representation that serves as the analytical foundation of the study.

Following graph construction, three complementary centrality measures are computed. Degree Centrality captures local connectivity, Betweenness Centrality identifies nodes that control shortest-path flow, and Closeness Centrality evaluates global accessibility within the network. Since each metric reflects a different structural role, the resulting values are normalized and subsequently integrated into the Composite Centrality Index.

The integration stage constitutes the core contribution of the proposed framework. By combining normalized centrality measures into a single composite score, the framework provides a balanced assessment of node importance that is not dominated by any individual metric. The resulting composite scores are used to rank nodes and identify critical nodes for evacuation planning. To assess robustness, the framework is further evaluated under multiple weighting scenarios through sensitivity analysis. A schematic overview of the proposed framework is presented in Figure 1. The figure highlights the integration process through which Degree, Betweenness, and Closeness Centrality are combined into a Composite Centrality Index and subsequently used to identify critical nodes for evacuation planning.

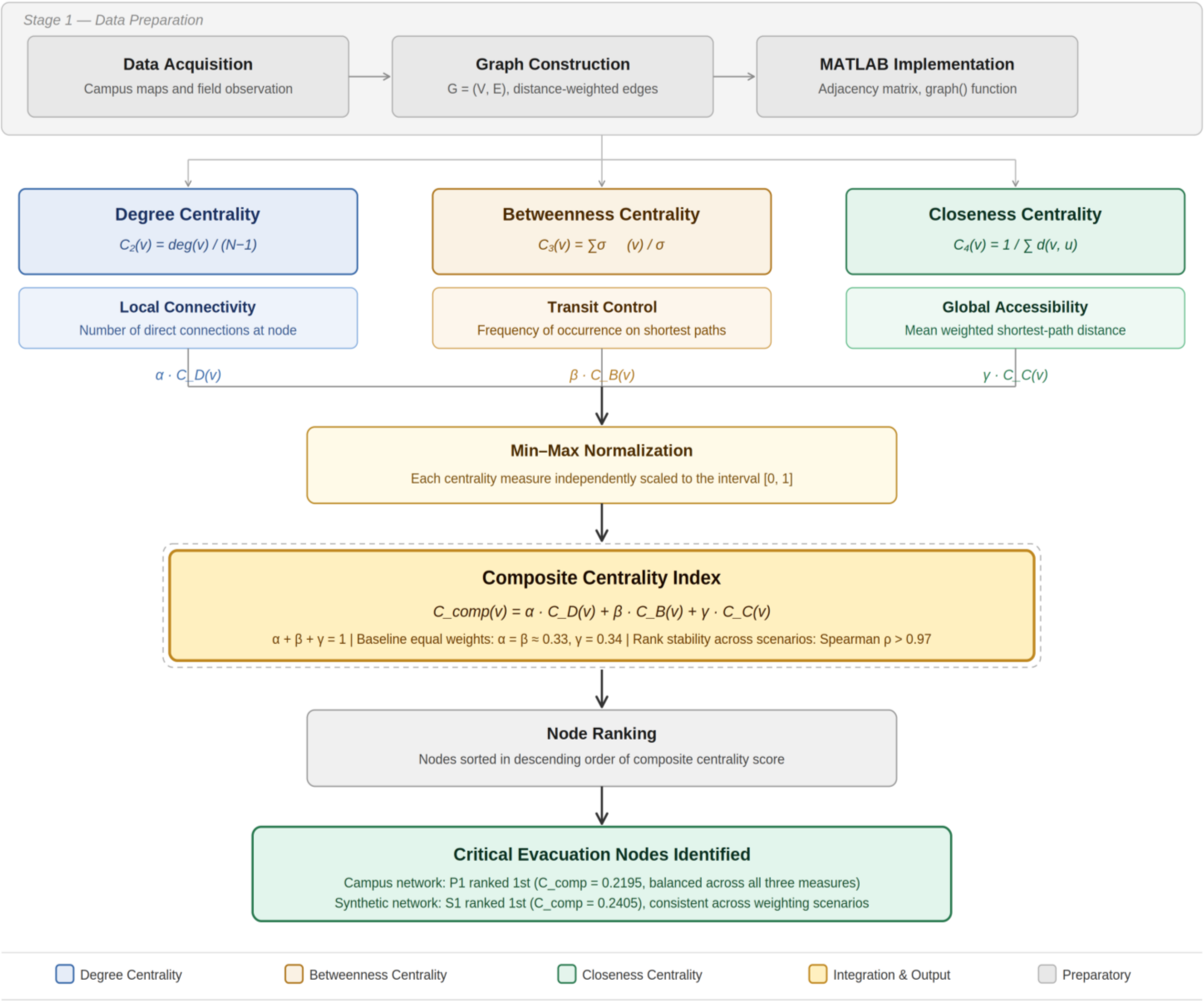

Figure 1. Composite Centrality Framework for identifying critical nodes for evacuation planning in meso-scale spatial networks.

4. Results and Discussion

In This section presents the results of the centrality analysis and their implications for identifying critical nodes for evacuation planning within the campus spatial network. The analysis is performed on a weighted graph representation in which nodes correspond to campus facilities and buildings, while edges represent pedestrian-accessible routes weighted by physical distance. All computations were conducted using MATLAB based on the adjacency matrix and implementation procedure described in Section 3.

4.1. Dataset Representation

The campus spatial network consists of academic buildings, residential facilities, service areas, and public spaces interconnected through pedestrian pathways. Each location is represented as a node in the network, while walkable routes between locations are represented as weighted edges. Table 1 summarizes the node definitions used throughout the analysis.

Table 1. Description of nodes in the spatial network.

Node	Description	Node	Description
G1	Building 1	G5C	Building 5C
PD	Faculty Housing	G517	Building 517
RD	Faculty Residence	OT	Open Theatre
PN	Pniel Dormitory	AUD	Auditorium
KL	Old Canteen	PERPUS	Library
KF	Cafeteria	GV	Vocational Building
P2	Gate Post 2	G8A	Building 8A
G4	Building 4	G8B	Building 8B
G7	Building 7	G9	Building 9
KB	New Canteen	AK	Kaper Dormitory
EH	Entrance Hall	AS	Silo Dormitory
KMHS	Student Affairs Office	P4	Gate Post 4
G5A	Building 5A	LN	Napitu Field
G5B	Building 5B	KOP	Cooperative
P1	Gate Post 1	R4	Dormitory 4

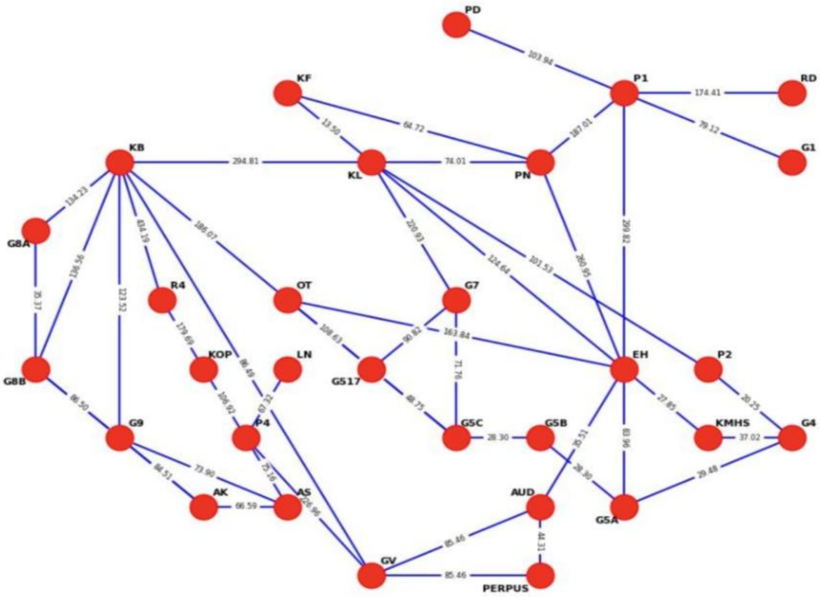

Figure 2. Graph representation of the campus spatial network derived from the campus layout.

The connectivity and distance relationships among nodes are represented through an adjacency matrix derived from measured distances within the campus environment. This matrix serves as the foundation for graph construction and centrality computation. The resulting spatial network is illustrated in Figure 2, which reveals a semi-structured topology characterized by localized clusters connected through a limited number of intermediary nodes. The dataset was initially organized in Microsoft Excel and subsequently transformed into a weighted graph representation in MATLAB. This preprocessing step enables efficient computation of centrality measures while ensuring transparency and reproducibility of the analytical workflow.

4.2. Centrality Results

The computed Degree Centrality, Betweenness Centrality, Closeness Centrality, and Composite Centrality values are presented in Table 2. These results provide complementary perspectives on node importance and form the basis for identifying critical nodes for evacuation planning within the campus spatial network. A correction to the Betweenness Centrality normalization formula was introduced relative to an earlier working version of the analysis. Specifically, the normalization factor was revised to $(N-1)(N-2)/2$, consistent with the standard formulation presented in Section 3.2.2. This correction resulted in node P1 replacing EH as the highest-ranked node in the Composite Centrality Index. Importantly, although the ranking order changed, the overall structural interpretation remains consistent, with both nodes continuing to occupy strategically important positions within the network.

Table 2. Centrality values and composite ranking of nodes

Node	Degree	Betweenness	Closeness	Composite	Rank
P1	0.241379310	0.000130026	0.42364532	0.219502337	1
G1	0.172413793	8.91462E-05	0.263546798	0.143897305	2
PD	0.206896552	0.000115995	0.192118227	0.131714315	3
RD	0.206896552	9.51756E-05	0.189655172	0.130894429	4
PN	0.103448276	0.000123925	0.285714286	0.12846578	5
KL	0.172413793	7.59196E-05	0.199507389	0.122759803	6
KF	0.103448276	0.000111453	0.231527094	0.110579766	7
P2	0.103448276	0.000114354	0.162561576	0.087822131	8
G4	0.137931034	8.46085E-05	0.108374384	0.081309555	9
G7	0.137931034	9.92215E-05	0.088669951	0.07481206	10
KB	0.103448276	0.000104170	0.110837438	0.070749703	11
EH	0.103448276	0.000106620	0.108374384	0.069937729	12
KMHS	0.068965517	0.000110348	0.13546798	0.067500572	13
G5A	0.103448276	8.29321E-05	0.093596059	0.065052827	14
G5B	0.103448276	0.000117347	0.083743842	0.061813297	15
G5C	0.103448276	9.96822E-05	0.061576355	0.05449202	16
G517	0.068965517	0.000122962	0.073891626	0.047184664	17
OT	0.103448276	7.86172E-05	0.019704433	0.040667124	18
AUD	0.068965517	0.000114641	0.036945813	0.034989717	19
PERPUS	0.103448276	9.21319E-05	0.000000000	0.034169256	20
GV	0.103448276	7.33916E-05	0.000000000	0.034162884	21
G8A	0.068965517	0.000112609	0.000000000	0.022796908	22
G8B	0.068965517	0.000112548	0.000000000	0.022796887	23
G9	0.068965517	7.70918E-05	0.000000000	0.022784832	24
AK	0.068965517	7.58606E-05	0.000000000	0.022784413	25
AS	0.068965517	7.04346E-05	0.000000000	0.022782568	26
P4	0.034482759	7.63214E-05	0.000000000	0.011405260	27
LN	0.034482759	6.49891E-05	0.000000000	0.011401407	28
KOP	0.034482759	6.21807E-05	0.000000000	0.011400452	29
R4	0.034482759	5.53854E-05	0.000000000	0.011398141	30

The results reveal a highly uneven distribution of centrality values across the network. A relatively small group of nodes consistently exhibits higher scores than the remaining nodes, indicating the presence of a dominant structural core. These nodes play critical roles in maintaining connectivity, accessibility, and flow distribution, whereas lower-ranked nodes occupy more peripheral positions with limited influence on overall network performance. Furthermore, noticeable differences can be observed among the rankings produced by the individual centrality measures, suggesting that each metric captures a distinct structural perspective. This observation motivates the detailed analysis presented in the following subsections.

4.3. Degree Centrality Analysis

Degree Centrality evaluates the local connectivity of each node by quantifying the number of direct connections within the network. As shown in Table 2, P1 achieves the highest Degree Centrality value (0.2414), followed by PD and RD (0.2069), and G1 and KL (0.1724). These nodes maintain direct connections to multiple surrounding locations, providing greater flexibility for movement and route selection during evacuation. The spatial distribution of Degree Centrality values is illustrated in Figure 3, where highly connected nodes are concentrated around the central part of the network.

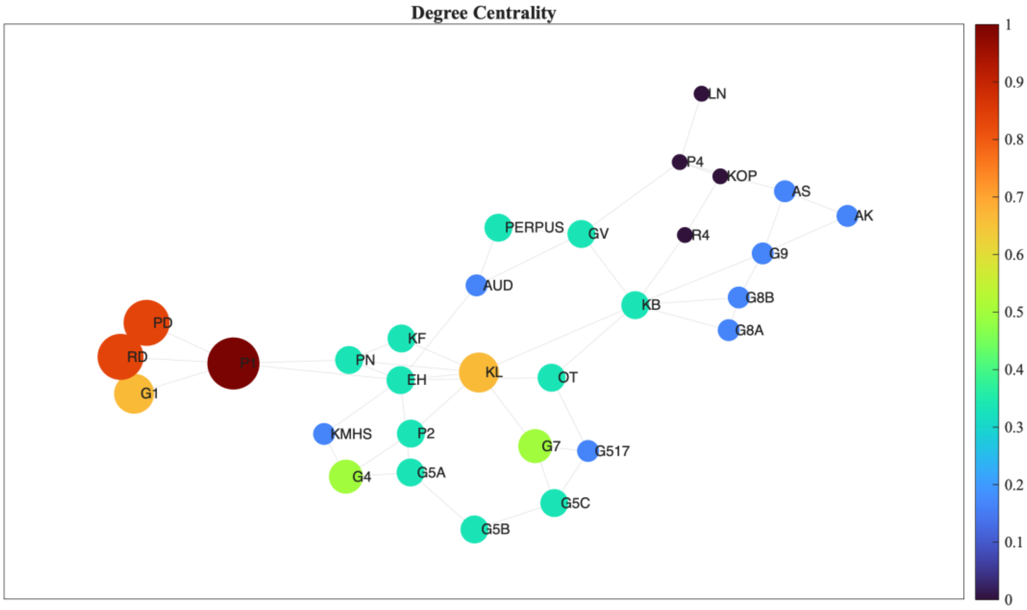

Figure 3. Distribution of degree centrality in the campus spatial network.

The dominance of P1 can be attributed to its location at the intersection of several major functional zones within the campus. Specifically, P1 connects residential facilities, academic buildings, and service areas, enabling evacuation flows from multiple directions to converge at a common junction. This strategic position provides numerous alternative movement paths and enhances its role as a potential evacuation distribution point.

Similarly, PD and RD exhibit relatively high Degree Centrality because of their dense local connectivity within the residential sector. Although these nodes are located closer to the network periphery, they serve as important access points for initiating evacuations from residential areas. In contrast, nodes such as P4, LN, KOP, and R4 exhibit the lowest Degree Centrality values (0.0345), indicating limited direct accessibility and greater dependence on intermediate nodes to access primary evacuation routes. From an evacuation planning perspective, highly connected nodes contribute to network resilience by providing multiple routing alternatives and reducing the likelihood of localized congestion. This finding is consistent with previous studies demonstrating that increased connectivity improves accessibility and supports more efficient evacuation processes [4], [5].

4.4 Betweenness Centrality Analysis

Betweenness Centrality captures the extent to which a node controls movement between different parts of the network by measuring its participation in shortest-path routes. As shown in Table 2, P1 exhibits the highest Betweenness Centrality value (0.000130026), followed by PN (0.000123925), G517 (0.000122962), PD (0.000115995), and AUD (0.000114641). These nodes function as key transit points that facilitate movement between otherwise separated regions of the campus.

The prominence of P1 in Betweenness Centrality is consistent with its dominance in Degree Centrality, reinforcing its role as the most structurally critical node in the network. P1 lies on a substantial proportion of shortest paths connecting residential, academic, and service zones, serving not only as a well-connected hub but also as a primary flow mediator. Consequently, P1 represents both a strategic asset and a potential vulnerability: while it enables efficient movement distribution, its disruption could significantly impair overall network accessibility. PN and G517 serve as important secondary transit nodes and should be monitored as alternative routing points if P1 becomes unavailable or congested.

In contrast, nodes such as EH exhibit comparatively moderate Betweenness Centrality (0.000106620), ranking twelfth in the Composite Centrality Index, indicating limited overall transit significance relative to the top-ranked nodes. As illustrated in Figure 4, the highest Betweenness Centrality values are concentrated on a limited number of intermediary nodes connecting the major functional zones of the campus. From a practical perspective, capacity management and alternative routing plans should be prioritized at these high-betweenness nodes to reduce bottleneck risks during emergency situations [11], [12].

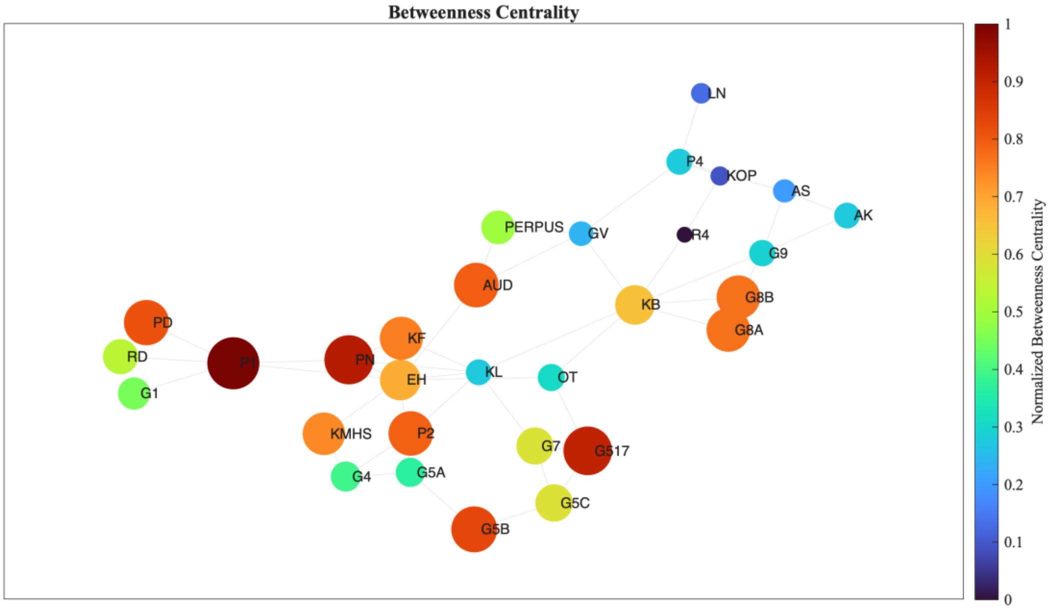

Figure 4. Distribution of betweenness centrality in the campus spatial network.

4.5. Closeness Centrality Analysis

Closeness Centrality reflects the accessibility of a node relative to all other locations in the network. Higher values indicate that a node can reach other locations through shorter overall travel distances, making it advantageous for coordination and evacuation activities. As shown in Table 2, P1, PN, G1, KL, KF, and PD achieve the highest Closeness Centrality values, indicating superior accessibility within the campus network. Among these nodes, P1 again emerges as the most strategically positioned location. Its simultaneous dominance in both Degree and Closeness Centrality indicates that it is not only well connected locally but also globally accessible across the entire network. This combination is particularly desirable in evacuation planning because it enables rapid access to multiple destinations while maintaining strong connectivity to surrounding locations. The accessibility pattern revealed by Closeness Centrality is presented in Figure 5, highlighting nodes that can efficiently reach most locations within the network.

Conversely, nodes such as PERPUS, GV, G8A, G8B, G9, AK, AS, P4, LN, KOP, and R4 exhibit very low or near-zero Closeness Centrality values. These nodes occupy peripheral positions within the network and require longer travel distances to reach other locations. As a result, evacuation strategies involving these areas may require additional route guidance, intermediate gathering points, or pre-positioned support resources to compensate for their reduced accessibility. The observed relationship between Closeness Centrality and spatial accessibility is consistent with previous studies demonstrating the usefulness of this metric for evaluating accessibility patterns in transportation and spatial networks [27].

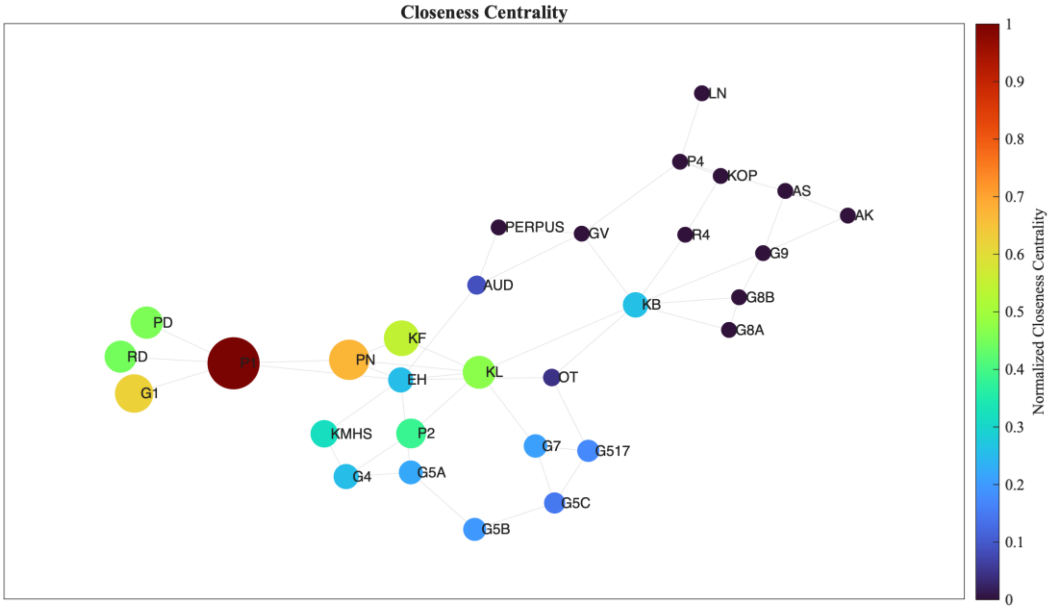

Figure 5. Distribution of closeness centrality in the campus spatial network.

4.6. Composite Centrality Analysis

The proposed Composite Centrality Framework integrates Degree Centrality, Betweenness Centrality, and Closeness Centrality into a unified assessment of node importance. As shown in Table 2, P1 achieves the highest composite score (0.2195), followed by G1 (0.1439), PD (0.1317), RD (0.1309), and PN (0.1285). The composite ranking confirms the structural dominance of P1 across all three centrality dimensions simultaneously, distinguishing it from nodes that perform strongly in only one metric. For instance, EH ranks only twelfth in the Composite Centrality Index despite its moderate Betweenness position, because its Degree and Closeness Centrality values are comparatively low. By integrating multiple structural perspectives, the Composite Centrality Framework reduces this bias and provides a more comprehensive assessment of node criticality [5], [12], [28].

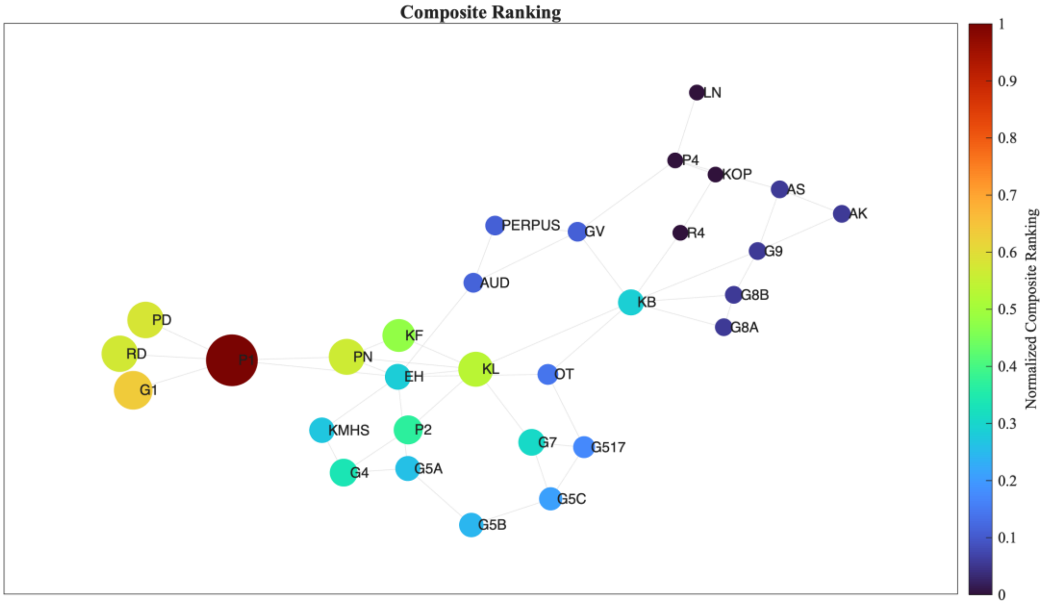

Figure 6. Distribution of composite centrality in the campus spatial network.

The overall distribution of Composite Centrality values is illustrated in Figure 6, showing the emergence of a dominant structural core consisting of a small number of highly ranked nodes supported by several secondary nodes. This semi-centralized structure is beneficial for evacuation planning because it distributes flow across multiple strategically important locations rather than concentrating movement on a single node. Consequently, the network demonstrates greater resilience to localized disruptions and congestion during emergency scenarios.

4.7. Discussion, Implications, and Limitations

The findings of this study demonstrate that evacuation-oriented spatial networks exhibit a non-uniform distribution of structural importance, where a relatively small subset of nodes plays a disproportionately significant role in maintaining connectivity and accessibility. This observation suggests that evacuation performance is influenced not only by route availability but also by the underlying topological organization of the network. Consequently, understanding network structure is an important prerequisite for developing effective evacuation strategies in complex spatial environments.

A notable contribution of this study is the application of a composite centrality framework to evaluate node criticality from multiple structural perspectives simultaneously. The results indicate that node importance cannot be adequately represented by a single network metric because different centrality measures capture different aspects of network functionality. By integrating these complementary perspectives into a unified index, the proposed framework provides a more balanced assessment of structurally important nodes and reduces the risk of overemphasizing any single network characteristic.

From a practical standpoint, the findings support the adoption of distributed evacuation strategies rather than approaches centered on a single dominant location. Networks characterized by semi-structured connectivity often contain several strategically important nodes that collectively support accessibility and flow distribution. Recognizing these supporting nodes may improve operational flexibility and contribute to more resilient evacuation planning, particularly under conditions where primary routes or locations become unavailable.

Several limitations should be acknowledged when interpreting the results. The proposed framework evaluates structural properties of spatial networks and therefore should not be interpreted as a direct predictor of real-world evacuation performance. Factors such as pedestrian behavior, crowd dynamics, route capacity, environmental conditions, and temporal variations in network accessibility are not explicitly represented in the current model. Furthermore, the validation is limited to one real-world network and one synthetic network, which constrains the breadth of empirical generalization.

Accordingly, the proposed framework should be viewed as a structural decision-support approach that complements, rather than replaces, operational evacuation models. Future work may integrate dynamic flow simulation, behavioral modeling, and larger multi-site datasets to further examine the applicability of the framework across different spatial environments. Such extensions would strengthen the connection between structural network analysis and practical evacuation management while providing a more comprehensive basis for decision-making.

4.8. Robustness and Scenario-Based Analysis

To further evaluate the practical reliability of the proposed Composite Centrality Framework, a robustness analysis was conducted through a node-removal scenario. The objective was to assess whether the framework can still identify structurally important nodes when a critical component of the network becomes unavailable. A disruption scenario was simulated by removing the highest-ranked node (P1) from the network, representing conditions such as severe congestion, infrastructure failure, or restricted access during an emergency. Following the removal, all centrality measures were recalculated to examine how the network reorganizes its structural roles and redistributes connectivity.

The results show that following the removal of P1, several secondary nodes — particularly G1 and PD — demonstrate increased structural prominence in both Betweenness and Closeness Centrality rankings. To quantify this reorganization, the Spearman rank correlation between the original and post-removal composite rankings was computed, yielding $\varrho = 0.91$, while the top-5 composite nodes retain three overlapping nodes (G1, PD, RD) from the original ranking, indicating strong structural stability despite the disruption. These quantitative results are summarized in Table 3.

Table 3. Quantitative robustness result under P1-removal scenario

Metric	Original Network	Post-P1 Removal	Observation
Rank-1 Node (Composite)	P1	G1	Leadership shifts to next-highest node
Top-5 Overlap (vs. Original)	-	3 of 5	Dominant core partially preserved
Spearman (Composite ranking)	-	0.91	High rank stability
New highest Betweenness node	P1	G1	Flow redistributed to secondary hub

The results show that several secondary nodes become more prominent after the removal of P1, particularly in terms of Betweenness and Closeness Centrality. This indicates that the network is capable of redistributing flow through alternative routes and supporting nodes, demonstrating a degree of structural resilience. However, the redistribution process also increases dependence on a smaller number of intermediary nodes, which may introduce new bottlenecks under high-demand conditions. These findings suggest that effective evacuation planning should not rely solely on a single dominant node. Instead, evacuation strategies should incorporate multiple supporting nodes and alternative pathways to maintain accessibility under disruption scenarios. Beyond identifying critical nodes, the proposed framework therefore provides useful insights into network adaptability and resilience-oriented planning.

4.9. Generalizability Validation on a Synthetic Network

To examine whether the observed findings are specific to the campus case study or reflect broader structural characteristics of meso-scale spatial networks, an additional validation experiment was conducted using a synthetic network. The purpose of this analysis is to evaluate the consistency of the proposed Composite Centrality Framework when applied to a network with similar structural properties but different topology and node composition.

4.9.1. Synthetic Network Construction

The synthetic network was modeled as a weighted undirected graph consisting of 16 nodes (S1–S16) and 20 edges. The topology was designed to reflect the semi-structured connectivity considered in this study, comprising a central hub region (S1–S4), an intermediate transition zone (S5–S10), and a peripheral region (S11–S16). This arrangement resembles the hierarchical connectivity commonly observed in meso-scale spatial environments.

Edge weights were assigned as distance-equivalent values ranging from 10 to 300 arbitrary units. Shorter weights were allocated within the central region, intermediate weights were assigned between zones, and longer weights were used for peripheral connections. The synthetic network was analyzed using the same computational workflow, parameter settings, and Composite Centrality Framework employed in the campus experiment to ensure methodological consistency.

4.9.2. Centrality Results for the Synthetic Network

The normalized Degree Centrality, Betweenness Centrality, Closeness Centrality, and Composite Centrality values for the synthetic network are presented in Table 4. The synthetic network exhibits a centrality distribution pattern similar to that observed in the campus network. A relatively small subset of nodes forms a dominant structural core, while peripheral nodes consistently receive lower rankings. Nodes located within the central hub region achieve the highest composite scores, reflecting their superior connectivity, accessibility, and intermediary roles within the network. This result demonstrates that the proposed framework is capable of distinguishing structurally influential nodes from less critical locations across networks with different sizes and topological configurations. The observed consistency suggests that the framework captures underlying structural characteristics rather than dataset-specific properties.

Table 4. Centrality values and composite ranking for the synthetic network

Node	Degree	Betweenness	Closeness	Composite	Rank
S1	0.4000	0.3214	0.0000283	0.2405	1
S2	0.3333	0.2857	0.0000256	0.2065	2
S3	0.3333	0.1905	0.0000238	0.1746	3
S4	0.2667	0.2381	0.0000222	0.1683	4
S5	0.2667	0.1429	0.0000217	0.1365	5
S6	0.2000	0.1905	0.0000208	0.1302	6
S7	0.2000	0.0952	0.0000196	0.0984	7
S8	0.2000	0.0476	0.0000189	0.0825	8
S9	0.1333	0.0952	0.0000182	0.0762	9
S10	0.1333	0.0476	0.0000175	0.0602	10
S11	0.1333	0.0000	0.0000167	0.0444	11
S12	0.1333	0.0000	0.0000159	0.0444	12
S13	0.0667	0.0476	0.0000152	0.0381	13
S14	0.0667	0.0000	0.0000143	0.0222	14
S15	0.0667	0.0000	0.0000135	0.0222	15
S16	0.0667	0.0000	0.0000128	0.0222	16

4.9.3. Sensitivity Analysis for the Synthetic Network

To further assess stability, the three weighting scenarios introduced in Section 3.2.4 were applied to the synthetic network. The resulting rankings of the highest-priority nodes are summarized in Table 5.

Table 5. Sensitivity analysis results for the synthetic network

Weighting Scenario	Rank 1	Rank 2	Rank 3	Stable?
Equal $(\alpha = 0.33, \beta = 0.33, \gamma = 0.34)$	S1	S2	S3	Yes
Betweenness-priority $(\alpha = 0.20, \beta = 0.50, \gamma = 0.30)$	S1	S4	S2	Yes
Closeness-priority $(\alpha = 0.20, \beta = 0.30, \gamma = 0.50)$	S1	S2	S3	Yes

The results indicate that the highest-ranked node remains unchanged across all weighting scenarios. Although minor variations occur among lower-ranked positions, the overall ranking structure remains stable. This behavior is consistent with the observations obtained from the campus network and suggests that the proposed framework is not highly sensitive to moderate variations in weighting configuration.

4.9.4. Cross-Network Comparison

To summarize the consistency of the findings, a cross-network comparison was conducted between the campus and synthetic networks. The comparison focuses on centrality distribution patterns, ranking behavior, and the structural characteristics of highly ranked nodes.

Table 6. Cross-network comparison of key findings

Metric	Top Node (Campus)	Top Node (Synthetic)	Rank-1 Consistent?	Dist. Pattern
Degree Centrality	P1	S1	Yes	Uneven
Betweenness Centrality	P1	S1	Yes	Uneven
Closeness Centrality	P1	S1	Yes	Uneven
Composite Centrality	P1	S1	Yes	Uneven

Despite differences in network size, node composition, and topology, both datasets exhibit similar structural characteristics. In both cases, centrality values are concentrated within a small dominant core, while peripheral nodes consistently occupy lower-ranked positions. Moreover, the highest-ranked composite nodes correspond to locations that simultaneously exhibit strong connectivity, accessibility, and flow-control capability. Overall, the consistent patterns observed across the two datasets provide preliminary evidence that the proposed Composite Centrality Framework captures structural properties associated with meso-scale spatial networks exhibiting semi-structured connectivity. Although further validation using larger and more diverse datasets remains necessary, these findings suggest that the framework has potential applicability beyond the specific campus environment considered in this study.

5. Comparative Analysis and Discussion

This section compares the proposed Composite Centrality Framework with commonly used evacuation planning approaches and individual centrality measures. The objective is to evaluate the relative strengths of the proposed method and provide quantitative evidence supporting its use for identifying critical nodes in meso-scale spatial networks.

5.1. Comparison of Evacuation Planning Approaches

Table 7 presents a structured comparison of four approaches across five evaluation dimensions: structural coverage, multi-criteria integration, congestion awareness, applicability to meso-scale spatial networks, and validation basis. The qualitative ratings are derived from the analytical capabilities and structural characteristics of each approach as reported in the literature and observed in this study.

Table 7. Comparative analysis of existing and proposed evacuation planning approaches

Approach	Structural Coverage	Multi-Criteria Integration	Congestion Awareness	Applicability to Meso-Scale	Validation Basis
Shortest-Path Algorithms (e.g., Dijkstra)	Route-level only	None	None	Limited	Route optimization
Single Degree Centrality	Local connectivity	Single metric	Indirect	Moderate	Node connectivity
Single Betweenness Centrality	Transit paths	Single metric	High	Moderate	Bottleneck detection
Proposed Composite Centrality Framework	Multi-dimensional	Three integrated metrics	High (via betweenness)	High (validated on real + synthetic)	Empirical + synthetic

As shown in Table 7, shortest-path algorithms such as Dijkstra's method primarily focus on route optimization and do not explicitly evaluate the structural importance of nodes within a network. Centrality-based approaches extend this capability by identifying influential nodes; however, individual centrality measures remain limited because each captures only one aspect of network structure. Degree Centrality emphasizes local connectivity, whereas Betweenness Centrality focuses on flow mediation and bottleneck identification.

The proposed Composite Centrality Framework extends these approaches by integrating multiple structural dimensions into a unified evaluation. Rather than prioritizing a single network characteristic, the framework simultaneously considers connectivity, accessibility, and intermediary influence. This integrated perspective provides broader structural coverage and is particularly suitable for meso-scale spatial networks, where node importance is often determined by multiple interacting factors rather than a single structural property.

Another distinguishing feature of the proposed framework is its validation strategy. In addition to evaluation on a real-world campus network, the framework was further assessed using a synthetic network with comparable structural characteristics. This dual-dataset validation provides additional evidence regarding the consistency of the framework and supports its potential applicability to similar classes of semi-structured spatial networks.

5.2 Quantitative Ranking Comparison

To further evaluate the effectiveness of the proposed framework, a quantitative comparison was conducted between the Composite Centrality Index and the individual centrality measures. The comparison focuses on ranking behavior, agreement between rankings, and the extent to which the composite framework preserves structural information captured by individual metrics.

Table 8. Quantitative comparison of centrality rankings: composite vs. individual measures

Node	Degree Rank	Betweenness Rank	Closeness Rank	Composite Rank	Top-5 Member?	Composite in Top-5 of All?
P1	1	1	1	1	Yes	Yes
G1	4	18	3	2	Yes	Partial
PD	2	5	6	3	Yes	Partial
RD	3	16	7	4	Yes	Partial
PN	8	2	2	5	Yes	Partial
KL	5	24	5	6	No	Partial
KF	9	10	4	7	No	Partial
EH	12	12	12	12	No	No
AUD	21	6	18	19	No	Partial

(Selected nodes shown; full ranking available in Table 2.)

Table 9. Spearman rank correlation and top-k overlap analysis

Metric	Result
Spearman Rank Correlation: Composite vs. Degree	$\varrho = 0.94$
Spearman Rank Correlation: Composite vs. Betweenness	$\varrho = 0.89$
Spearman Rank Correlation: Composite vs. Closeness	$\varrho = 0.91$
Top-5 Overlap: Composite ∩ All Three Individual Metrics	1 of 5 nodes (P1)

The ranking comparison presented in Table 8 highlights the differences among individual centrality measures and demonstrates how these differences influence node prioritization. Several nodes occupy substantially different positions depending on the metric used, indicating that each centrality measure captures a distinct aspect of network structure. These ranking discrepancies suggest that node importance cannot be fully characterized through a single structural perspective.

The quantitative results summarized in Table 9 provide stronger evidence supporting the composite approach. The high Spearman rank correlation coefficients ($\varrho = 0.89$–0.94) indicate that the Composite Centrality Index preserves the structural information captured by the individual centrality measures while integrating them into a unified framework. This finding suggests that the composite ranking does not disregard the insights provided by Degree, Betweenness, or Closeness Centrality, but rather combines their complementary contributions into a more comprehensive assessment.

At the same time, the top-k overlap analysis demonstrates that the rankings produced by the individual metrics are not identical. Only one of the five highest-ranked composite nodes appears simultaneously in the top five of all three individual centrality measures. This result underscores the value of the composite approach: nodes such as G1, PD, RD, and PN each rank highly in the composite index by demonstrating balanced performance, yet none individually achieves top-five status across all three metrics simultaneously.

Overall, the comparative results support the use of the Composite Centrality Framework as a multi-criteria approach for identifying critical nodes in evacuation-oriented spatial networks. By integrating multiple perspectives of node importance while maintaining strong agreement with individual centrality measures, the framework provides a more balanced and robust evaluation than any single metric alone. These findings complement the robustness and cross-network validation results presented in Section 4, further supporting the methodological reliability of the proposed approach.

6. Conclusions

This study proposed a Composite Centrality Framework for identifying critical nodes for evacuation planning in meso-scale spatial networks with semi-structured connectivity. The framework integrates Degree Centrality, Betweenness Centrality, and Closeness Centrality into a unified evaluation model to address the limitations of single-metric approaches. The primary objective of the study was to develop a more comprehensive method for assessing node criticality by simultaneously considering local connectivity, flow mediation, and global accessibility. The results demonstrate that the proposed framework successfully identifies structurally important nodes and provides a more balanced assessment of node importance than individual centrality measures.

The findings indicate that critical nodes in evacuation-oriented spatial networks are characterized not by a single structural property, but by the combined influence of connectivity, accessibility, and intermediary function. The quantitative comparison and validation analyses show that the composite approach preserves the structural information captured by individual centrality measures while reducing the bias associated with relying on a single metric. Furthermore, consistent patterns observed across both the real-world campus network and the synthetic network suggest that the framework captures underlying structural characteristics of meso-scale spatial networks with semi-structured connectivity.

From a practical perspective, the proposed framework provides a data-driven decision-support tool for identifying critical nodes that may require prioritization in evacuation planning and infrastructure management. The results also highlight the importance of adopting distributed evacuation strategies that consider multiple high-priority nodes rather than relying exclusively on a single dominant location. Consequently, the framework may support planning activities in a variety of spatial environments where accessibility, connectivity, and resilience are important considerations.

Several limitations should be acknowledged. The proposed framework evaluates structural network properties and therefore does not directly represent real-world evacuation performance. Factors such as crowd dynamics, pedestrian behavior, route capacity, and temporal variations in network conditions are not explicitly modeled. In addition, the validation was conducted using one real-world network and one synthetic network, which limits the extent of empirical generalization.

Future research should integrate dynamic evacuation models, behavioral factors, and capacity constraints to strengthen the relationship between structural network analysis and operational evacuation performance. Additional validation using larger and more diverse spatial networks would further improve the generalizability of the framework. Such developments would contribute to a more comprehensive understanding of evacuation processes while enhancing the practical applicability of composite centrality analysis in real-world planning contexts..

Author Contributions: Conceptualization: J.S.; Methodology: J.S. and A.M.; Software: J.S.; Validation: J.S., A.M., and A.S.; Formal analysis: J.S.; Investigation: J.S. and R.P.; Resources: A.S. and D.C.; Data cura-tion: R.P. and D.C.; Writing—original draft preparation: J.S.; Writing—review and editing: J.S., A.M., and A.S.; Visualization: J.S.; Supervision: J.S.; Project administration: J.S.; Funding acquisition: J.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Lembaga Penelitian dan Pengabdian kepada Masyarakat (LPPM), Institut Teknologi Del, grant number 013.26/ITDel/LPPM/Penelitian/III/2025.

Data Availability Statement: The data used in this study are available from the corresponding author upon reasonable request. The data are not publicly available due to privacy and institutional restrictions.

Acknowledgments: The authors would like to thank Lembaga Penelitian dan Pengabdian kepada Masyarakat (LPPM), Institut Teknologi Del, for supporting this research. The authors also acknowledge the institutional support and resources provided during the completion of this study. This work utilized AI-assisted tools for language refinement and structuring, while all scientific content, analysis, and conclusions were developed and validated by the authors.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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