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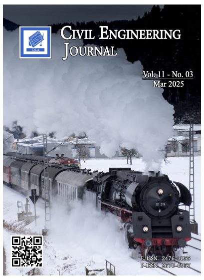

Statistics on Small Networks in Construction Design Offices

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Abstract

This study explores communication structures in construction design offices using social network analysis (SNA) to compare directed and undirected networks. The objective is to understand how these network types influence hierarchy, information flow, and collaboration within small design teams. Data were collected from nine construction design offices, constructing both directed and undirected networks based on survey responses. Various graph theory metrics, including clustering coefficient, network diameter, centrality, and connectivity, were analyzed to assess communication efficiency. The results show that directed networks emphasize hierarchical structures with limited reciprocal exchanges, while undirected networks confirm mutual interactions, fostering collaboration. Despite variations in size, most networks exhibit small-world properties, indicating that key individuals act as bridges, ensuring effective communication. These findings highlight that network structure, rather than size, plays a crucial role in team coordination. This study contributes to Architecture, Engineering, and Construction (AEC) research by providing insights into optimizing team dynamics, balancing hierarchical control with flexible collaboration, and improving project management strategies.

Keywords: SNA; Construction Project; Design Team; Hierarchy; Communication.

1. Introduction

In the construction industry, social network analysis (SNA) has been used to assess design team communication during collaborative work, with the interactions mediated by computer communication technologies [1]. This technique works because the flow of value in design and service tasks is mainly related to the flow of information [2]. It has been established that the informal structures (social networks) formed through project members' communications go beyond the formal structures to make their work more efficient [3]. A social network can be represented as a mathematical graph or network describing a particular set of interrelationships or links between individuals who are the graph's nodes; links (represented as graph or network edges) between individuals help to establish their behavior, conduct, opinions, and position within the real-world social networks [4, 5]. When two nodes share a vertex, they are said to be adjacent [6]. Such information helps project teams to propose efficient and well-founded solutions to the problem of information exchange, taking into account the frequency of formal or informal communication between project participants, the density of networks, and the centrality of actors with building knowledge [7-12], as well as the centrality that actors develop through interaction [13, 14]. SNA produces information useful for good decision-making and knowledge sharing among participants [10, 15, 16].

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SNA is widely used to characterize social network structures and to assess team communication and has been associated with performance metrics such as productivity and team efficiency [13, 17, 18]. There is a considerable corpus on this topic that focuses specifically on construction companies and their projects [11]. While network theory is well-established, small project design teams remain an underexplored area despite their suitability for detailed analysis of communication structures and hierarchy. Rather than constructing new theoretical models, this study applies existing frameworks to examine team coordination and information flow, offering practical insights for improving collaboration within the Architecture, Engineering, and Construction (AEC) industry [19].

Traditional SNA theories and probabilistic models of social networks are relatively ineffectual because they do not sufficiently reflect the reality of interactions adequately. Only a few studies focus on small social work networks with the goal of explaining communication of their members in terms of the non-random links between them and the expected hierarchies within work teams [20]. In addition, small networks tend to quickly saturate potential connections among their members, rendering some metrics applicable to large social networks useless, such as emergent structural changes over time [6]. Consequently, it is necessary to start with identifying the statistical properties of these small social networks so that they can be compared and evaluated for their interactions, hierarchies, and information management, which is an indispensable input during the design process [15]. This research aims to establish the characteristics of the social networks formed in design offices, depending on their work activity, by analyzing the statistics of their communication connections. This information is relevant for design offices to identify hierarchies and recommend improvements in their work teams' communication [7, 21, 22].

This research article investigates communication and hierarchical structures within social networks in construction design offices. First, a comprehensive literature review establishes the theoretical framework and identifies key gaps in the current understanding of small social network dynamics. The data collection section details the procedures employed for participant selection and survey administration. The next section describes the development of both directed and undirected networks, providing the basis for analyzing communication patterns. These networks are analyzed statistically to quantify key metrics related to connectivity, clustering, and hierarchy. These metrics are then analyzed for inferences regarding team interactions and organizational structures. Finally, the discussion and conclusion section synthesizes the key findings, with a particular focus on the observed small-world properties of these networks, and offers practical recommendations for enhancing collaboration and communication within design office settings.

1.1. Literature Review

SNA allows the study of the linkages between individuals and how specific resources are managed within the network/organization [23]. Among these resources, one of the most critical is connectivity, as a necessity for transmitting information among the network's members [4, 14]. Connectivity has been studied in the social context on the assumption that the world is small because, when it comes to linking two people through social networks, only a small number of links suffices, and the intermediaries need not be immediate neighbors [24], a feature that makes it easy to transfer information [25]. Connectivity is a network-wide characteristic determined by its edges and their directionality. Edge direction represents the reciprocity (or non-reciprocity) of a relationship or communication produced by affinity, necessity, or the very structure of the real-world communication required in a specific situation [26]. Not all connections within a social network involve exchange; directed connections from one person to another can be unidirectional and represented by a directed edge. For example, giving an order may not imply a response beyond being obeyed, ignored, or disregarded [27, 28]. On the other hand, nondirected edges reflect reciprocal relationships such as mutual friendship [29] or the mutual monitoring of communications [30].

The strength of the edges depends on the extent of contact with neighbors. Strong edges appear when there are frequent and close contacts between network members. Such edges manifest the reciprocal friendships and closeness among members, revealing groups that share common information and affinities. On the other hand, weak edges, which appear when there is little overlap between the people, indicate bridges between communities by which to communicate new information. Should weak relationships be broken, subgroups can become isolated [31].

The relationships observed between nodes in a network at a given time can be considered as probabilistic outcomes of underlying network processes [32]. When the distribution of vertex properties is described statistically, the principles of central tendency and dispersion apply in the same way as they do to other variables [26].

Network statistics include several standardized metrics for analysis. Among these, the network structural metrics relate to the number of edges within the network, and their distribution reflects patterns of connectivity. These metrics include mean degree, clustering coefficient, density, network diameter, average distance, betweenness, and fragmentation [27, 33]. The route length is the shortest possible route between all nodes in the network measured across their links, and the average distance is the average of the shortest possible route lengths or paths between pairs of nodes in the network [4].

The diameter is the maximum number of vertices needed to traverse the network graph and is associated with the two most distant nodes (which may not be unique). The diameter is usually smaller than the number of nodes. Even the largest real-world social networks are estimated to have diameters of less than 6, which can make the world feel small when it comes to connecting people [34]. There are also relationships to be observed between social network statistics.

For example, when the average distance decreases, it is accompanied by an increase in the clustering coefficient [35], which indicates the fraction of nodes that tend to cluster in triads in the network as a whole. Triads are, as the name suggests, three nodes in which each pair is mutually connected. Triadic clustering can occur in networks with joint small-world and complex characteristics [22, 36].

Under normal conditions, the connection density between team members (and hence the nodes representing them) decreases as the size increases, the average distance between nodes also increases, and the information flow during design tasks is focused on small groups, teams, or workstations defined by the tasks assigned to each individual [12]. Given their size, social networks in design offices should obey small-world rules, but short distances between nodes are atypical due to the non-randomness of connection between members. In a broad sense, the size of the office was positively correlated to the density or agglomeration of nodes [12].

A property based on the number of links a node has with other nodes in the network is the degree, which represents the number of members it communicates with; dividing the total number of edges by the number of nodes gives the average network degree that summarizes the connectivity of the network: a high average degree indicates a network with densely connected nodes [32]. On the other hand, a low average degree indicates limited information propagation due to few opportunities for interaction between nodes. Density is the number of edges in a network compared to the total possible edge number; densities close to 1 indicate ease of information dissemination and propagation, and low densities close to 0 indicate fewer node connections, limiting communication and information flow. In small networks, it is easy to achieve high densities; in this case, the average degree is more straightforward to interpret than the density [6]. The division of the network into subgroups is measured by the network fragmentation; high fragmentation values in a network indicate many isolated subgroups or communities, which can mean the presence of different areas of interest or like-minded groups. However, greater modularity entails less interconnection; a more cohesive network with more interconnection between nodes has low fragmentation [37].

Social networks have two types of properties. Static properties describe structures represented by a graph (or network) at a given time, whereas dynamic properties describe the evolution of those structures under the social network's environmental conditions [29, 38]. A temporal graph of social relations represents a social network. At the local level, the social influence of a node is related to the number of links connecting it to other nodes. At the global level, the most influential factor is how the nodes are associated rather than merely the number of links [29].

Graphs represent connectivity between nodes; the edges help us to understand individuals' social behavior [39]. Graphs can be constructed using relationships, such as formal roles or communications between individuals, to expose hierarchical structures and information flows within organizations [5, 40]. Graphs are mathematical objects; some are complex, so it is better to interpret them statistically [4, 7], as effective communication on social networking sites is associated with better project performance [13]. Directed graph edges can represent asymmetrical relationships in which the direction is crucial [4], whereas undirected edges represent reciprocal or mutually confirmed connections.

Edges are often undirected because, during data collection, members of the network forget to mention the people with whom they are in communication; just the fact that one member claims communication with another member is understood to indicate a mutual link, so a new and symmetric adjacency is created. This rule is known as the "OR" or "join" rule. Alternatively, a stricter rule can be adopted if there is reason to suspect that a name has been mentioned only casually: only if both people mention each other is the relationship considered confirmed. This is called the "AND" or "intersection" rule. The join rule creates denser networks, while the intersection rule makes them more dispersed [6].

Edge directionality distinguishes social networks in which the nodes have confirmed interactions from information networks in which the nodes are sources of information and the connection events correspond to actions such as searching for references [31]. The latter are assimilated into the working interactions of consultants in a design office [20].

SNA also facilitates understanding of the social network's structure and the interactions between the individuals in it, providing insights for improving organizational structure and the flow of information and ideas [41, 42]. It is assumed that the importance of each link is proportional to the corresponding individual's role in the organization and the information they can bring to the organization [43]. Relationships between roles are explored to improve work teams' performance [12, 44].

Knowing which actors exert the most influence within networks helps managers to improve organizational performance and meet objectives. Influence indicators can be measured by survey and are aimed at understanding the interrelationship between individuals within the organization [40]. The analysis can identify weak inter-departmental connectivity that results in scarce communication or dynamics in which most workers depend on communication with a single employee who controls the processes. If this individual is absent, connections collapse due to isolation between groups; managers must think about internal communication strategies so that organizational objectives are still achieved [41].

Communication in design offices, however, often does not follow a formal organizational structure. However, as in other industries, social networks form through work tasks [21]. For example, the distributions of social network links in architectural design offices have been found to associate with hierarchical and functional organizational structures, which demonstrates the feasibility of using SNA to identify hierarchies through the analysis of communication patterns [12].

2. Material and Methods

The research process is illustrated in Figure 1; the methodology begins with a literature review to establish a theoretical foundation, followed by data collection from design offices that agreed to participate in the study. Social network analysis (SNA) is then applied to examine communication and hierarchical structures within these offices. Finally, the data is analyzed using established metrics to provide meaningful insights into the dynamics of professional interactions in design environments.

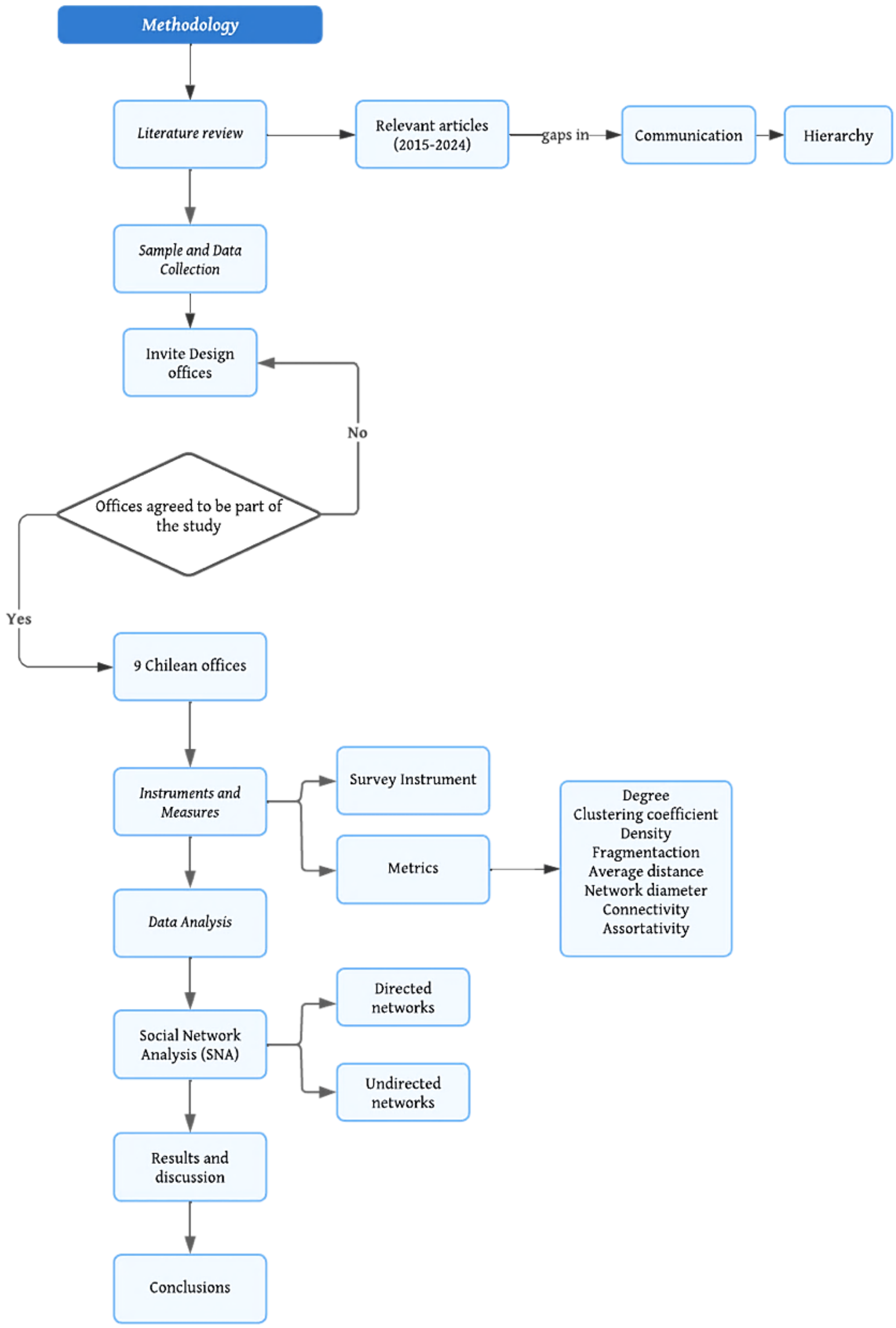

Figure 1. Methodology diagram

In order to establish the state of the art in research on communication and the hierarchical structure of social networks in construction, papers published from 2015 to 2024 were searched using the words "social network", "analysis", "communication", and "construction projects" in the Scopus search engine. The search was limited to articles concerning construction projects. Relevant articles were identified by their content about stakeholder communication and organizational structure in social networks. In addition, the most cited books on social network analysis were consulted to establish the theoretical basis of the research using Google Books.

Eleven Chilean companies dedicated to construction project design were invited to participate. Nine agreed to provide information on the number of members that make up the design work teams and the identification of their positions. Since each office classifies its staff in different positions, the research team grouped the common positions according to their activities, as shown in Table 1. Notably, no digital communication methods, such as email or other electronic means, were used; all information was collected exclusively through direct, in-person interactions.

Table 1. Design team staff

	Companies								
Job description	**E1**	**E2**	**E3**	**E4**	**E5**	**E6**	**E7**	**E8**	**E9**
Architect partner - owner	4	2	0	2	0	5	3	4	1
Office Manager - Architect	0	0	2	7	1	6	0	7	1
Project Manager - Architect	0	5	8	8	3	1	3	4	3
Architect-designer	21	17	0	18	2	10	9	22	8
Design specialist	0	0	7	0	4	10	0	3	0
Assistant Technician	0	2	1	0	0	0	0	2	0
Administrative staff	3	4	2	5	1	5	1	7	3
Total, network members	**28**	**30**	**20**	**40**	**11**	**37**	**16**	**49**	**16**

Participants voluntarily answered questions about whom they contacted to provide information relevant to their work in the last six months, where "relevant information" is understood to mean that the information is necessary, provides added value, and is not openly available [6]. Therefore, static information on the network structure was obtained, and no link weights were considered [29].

This research uses Social Network Analysis (SNA) to examine communication structures in construction design offices, comparing directed and undirected networks. Edge directionality is often assigned to reflect hierarchical, top-down communication, while undirected networks speak to reciprocal interactions and collaboration. Rooted in structuralist network theory and small-world network theory, this study highlights how key individuals facilitate information flow, ensuring efficiency despite hierarchical constraints. Statistical graph metrics such as clustering coefficients and centrality reveal that team size is less important than the structure of communication itself. These findings provide insights into optimizing collaboration by balancing hierarchy with flexible, knowledge-driven networks, offering a foundation for future research on evolving communication patterns in design teams.

For the conformation of the undirected networks, the intersection rule was chosen to obtain symmetrically confirmed networks. Statistics were applied to the groups studied based on the limited information from a sample of their joint activity time during relevant communications. The directed network was analyzed for information hierarchies within the social work networks [28], comprising the relationships by which some members are "followers" of others who constitute sources of information or dispositions. On the other hand, non-directed network representations were analyzed to double-check members' answers and to confirm the connection between the network members [40] in search of hierarchies of affinity and trust within structures of co-communication or mutual relationships— these are characteristics of work interaction in which shared information is confirmed or discussed [30].

Undirected networks are assumed to be a partial representation of social networks that are, in reality, directed, implying that a large part of the communication occurs between nodes due to a requirement beyond formal organizational arrangements [40].

Both directed and undirected networks were analyzed using the Ucinet 6 v.6.629 software, which provides several tools and techniques to obtain the metrics that define networks [45]. For the statistical analysis of the metrics, we use RStudio version 4.2.2, which has libraries and tools to create, manipulate, analyze, and estimate statistical models of the networks [46]. The metrics analyzed are the same for both network types; this dual analysis is done in consideration that undirected networks are related to the flow of information needed to perform the work, while directed networks are more related to the hierarchical structure of the organizations [28]. These are essential aspects to consider in the context of small networks [31].

In order to conduct a hierarchy analysis of the directed networks, the degree of each node was calculated to classify them into four groups according to quartile; nodes of degree above the third quartile are considered to exert significant influence in the network and are classified into group G1. Nodes of degree between the third quartile and the median are classified into group G2, corresponding to members with above-average but not exceptional influence. Nodes of degree from the median to the first quartile are classified into group G3, for members of below-median but not exceptional influence. The lowest quartile is assigned to group G4; these correspond to members with the lowest degree of influence. The metrics reported below were obtained using Gephi 0.10.1 and contrasted by implementing an algorithm in R version 4.2.2.

3. Results

The literature search uncovered 13 papers, of which five focus on the interpretation of statistics and communication of social networks with current knowledge on the subject. Also, seven books were reported as the most cited books on the topic of social networks and statistics so far in the 21st century [5, 6, 26, 27, 31, 32 ,47], although the latter is from the 20th century, it is a crucial reference text in social network analysis, frequently cited for its comprehensive coverage of both theory and statistical methods. Table 2 shows the metrics analyzed in this study and their interpretation concerning communication and hierarchies within social networks.

Table 2. Summary of metrics and their interpretation according to the literature

Source	Metrics	Interpretation
Hanneman & Riddle (2005) [26] and Cherven (2015) [4]	Degree and medium degree	A high-degree actor, having many links, has access to more resources of the network as a whole. They are often third parties and negotiators in exchanges with others and can benefit from this intermediation. In directed networks, if an actor receives many links, it is said to be prominent. The average degree reports the typical number of contacts per node.
Wasserman & Faust (1994) [5]	Clustering coefficient	It is the fraction of a node's pairs of friends that are connected to each other. High clustering coefficient scores reflect a network where this is more likely. High scores are found in smaller, more cohesive groups, while dispersed networks might be expected to produce lower scores.
Śladowski et al. (2019) [21]	Density	A high value is interpreted as increased communication effectiveness within the organization.
Pappi & Scott (1993) [27]	Fragmentation	In a fragmented network, it is more difficult for information or resources to flow to people, and they may become more dependent on their immediate local situation.
Cherven (2015) [4]	Average distance	It measures the efficiency of communication in the network. It is the average of the shortest possible paths between all nodes in the network. Low values indicate that the network is more efficient in handling the flow of information.
Wasserman & Faust (1994) [5]	Network diameter	Considering communication in a network, where information is transmitted between nodes, a small diameter should ensure that information travels quickly between actors further apart in the network.
Hanneman & Riddle (2011) [48]	Connectivity	If there are many different paths connecting two actors, they have high connectivity because there are multiple ways for a signal to get from one to the other.
Cherven (2015) [4] and Newman (2002) [49]	Assortativity	Networks with high levels of homophily based on one or more attributes (e.g., employment status) are selective in those elements. Network nodes with many connections tend to be connected to others with many connections. Assortative networks are more resistant to removing their higher-degree vertices, while disassortative networks are more vulnerable.

3.1. Directed Networks

The following analysis considers the group or network statistics to understand the direction and flow of information to reveal communication patterns between network members and to understand information propagation. Table 3 shows the clustering coefficients for nine directed networks (E1–E9), providing a measure of local interconnectedness within each network. The table lists the number of nodes (members) in each network alongside their corresponding clustering coefficient. Networks E7 and E9 exhibit the highest clustering coefficients, 0.6862 and 0.7553 respectively, indicating strong local clustering and a high degree of interconnectedness within their constituent subgroups. Conversely, network E8 demonstrates the lowest clustering coefficient at 0.4296, suggesting weaker local clustering and more dispersed connections among its members. The remaining networks (E1–E6) fall within a moderate range of clustering coefficients, implying a degree of local interconnectedness somewhere between the extremes. These variations in clustering coefficients across the networks suggest potentially different communication patterns and group dynamics, highlighting the importance of considering this metric alongside other factors for a more comprehensive understanding of network structure.

Table 3. Clustering in Directed Networks

Network	Number of nodes	Clustering coefficient
E1	28	0.5146
E2	30	0.4872
E3	20	0.4326
E4	40	0.4598
E5	11	0.5543
E6	37	0.4857
E7	16	0.6862
E8	49	0.4296
E9	16	0.7553

Table 4 presents cohesion measures for the networks participating in this study, including the output and input centralities. These measures give us information about the strength and quality of relationships within the network.

Table 4. Cohesion in directed networks

Network	Number of nodes	Density	Average distance	Network diameter	Output centrality	Input centrality	General connectivity
E1	28	0.2421	2.0356	4	0.7476	0.2099	0.9286
E2	30	0.2069	2.3325	6	0.8205	0.1784	0.9333
E3	20	0.1921	2.0438	4	0.4626	0.3518	0.7211
E4	40	0.1667	2.2866	5	0.4339	0.3287	0.9506
E5	11	0.2727	1.6250	3	0.4700	0.3600	0.5818
E6	37	0.1344	2.0600	4	0.4329	0.2901	0.5128
E7	16	0.5042	1.4800	3	0.3867	0.3867	0.9375
E8	49	0.0727	2.7628	7	0.2760	0.1427	0.8980
E9	16	0.6208	1.3792	2	0.4044	0.4044	1.0000

Analyzing multiple measures of cohesion together provides a complete picture. Specifically, Table 4 provides insights into communication efficiency and influence. Density, representing the proportion of potential connections present, ranges from 0.0727 in E8 to 0.6208 in E9, indicating substantial variation in network interconnectedness. Average distance, reflecting the average path length between node pairs, ranges from 1.3792 in E9 to 2.7628 in E8, suggesting differences in information flow efficiency. Network diameter, the longest shortest path over all node pairs, ranges from 2 in E9 to 7 in E8. Centrality measures, including output (influence exerted) and input (influence received) centralities, reveal variations in individual node importance within the networks. Finally, general connectivity provides an overall measure of network reachability.

Moreover, when a horizontal organization is suggested, meaning that the outgoing and incoming centrality are equal, the relationships are less hierarchical and more collaborative, with more feedback of information, as shown in Figure 2. This figure illustrates the output degree centrality distributions within two directed networks, E1 and E9. The nodes in this figure are drawn proportional to output degree to highlight the relative influence of individual actors within each network. The structure of Network E1 is less centralized, with a relatively even distribution of output degree across its nodes. While some variation in node size is apparent, suggesting differing levels of influence, no single dominant actor emerges. In contrast, network E9 displays a highly centralized structure, characterized by a single, significantly larger node. This node's prominence indicates a substantially higher output degree compared to the remaining nodes, suggesting a central authority exerting considerable influence within the network. The visual distinction between these two networks underscores the impact of network topology on the distribution of influence, with E1 representing a more equal structure and E9 demonstrating a clear hierarchical organization.

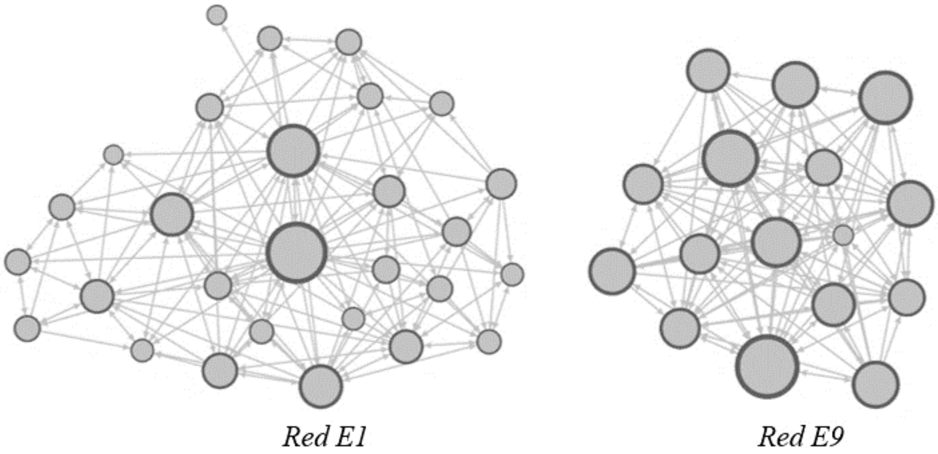

Figure 2. Output degree of directed networks E1 and E9

3.2. Undirected Networks

The undirected networks exhibit a symmetry resulting from cross-checking communication between pairs of nodes [40]. Table 5 shows the values obtained for centrality measures; Table 6 the cohesion measures of the undirected networks.

Table 5. Clustering in undirected networks

Network	Number of nodes	Clustering coefficient
E1	28	0.4009
E2	30	0.3568
E3	20	0.3871
E4	40	0.4093
E5	11	0.4091
E6	37	0.3820
E7	16	0.4615
E8	49	0.3770
E9	16	0.4853

Table 6. Cohesion in undirected networks

Network	Number of nodes	Density	Average distance	Network diameter	Average degree	General connectivity	Fragmentation	Assortativity
E1	28	0.1376	2.5723	5	3.7143	0.8598	0.1402	0.1321
E2	30	0.1195	2.7077	6	3.4667	0.7471	0.2529	0.0532
E3	20	0.1316	2.0549	4	2.5000	0.4789	0.5211	-0.2433
E4	40	0.1192	2.5804	5	4.6500	0.9013	0.0987	-0.2148
E5	11	0.1636	1.5714	2	1.6364	0.3818	0.6182	-0.6014
E6	37	0.0721	2.6014	6	2.5946	0.4144	0.5856	-0.2307
E7	16	0.3417	1.6476	3	5.1250	0.8750	0.1250	-0.2513
E8	49	0.0449	3.3045	7	2.7419	0.7679	0.2321	-0.0627
E9	16	0.4000	1.6000	2	6.0000	1.0000	0.0000	-0.4953

Table 5 details the clustering coefficient for each network, a metric reflecting the degree to which nodes tend to form interconnected subgroups. E9 exhibits the highest clustering coefficient (0.4853), indicating a greater prevalence of tightly-knit triads within its structure. Conversely, E2 demonstrates the lowest clustering coefficient (0.3568), suggesting a less pronounced tendency towards local clustering.

Table 6 expands the analysis to encompass measures of overall network cohesion. This table includes the number of nodes, density, average distance, network diameter, average degree, general connectivity, fragmentation, and assortativity. Density ranges from 0.0449 in E8 to 0.4000 in E9, highlighting substantial variation in network interconnectedness. Average distance ranges from 1.5714 in E5 to 3.3045 in E8, indicating differences in communication efficiency. Network diameter varies from 2 in E5 and E9 to 7 in E8. Average degree ranges from 1.6364 in E5 to 6.000 in E9. General connectivity provides a global measure of node reachability across its network. Fragmentation, which assesses the network's susceptibility to partitioning into disconnected subnetworks, and assortativity, which measures the tendency of nodes to connect with similar others, offer further insights into network structure.

These metrics provide a comprehensive characterization of the structural properties of these nine undirected networks, enabling a deeper understanding of their potential for information diffusion and collaboration. Furthermore, Figure 3 illustrates the network diameter for Office E8. This diagram aids in understanding the potential reach and efficiency of communication pathways within this office.

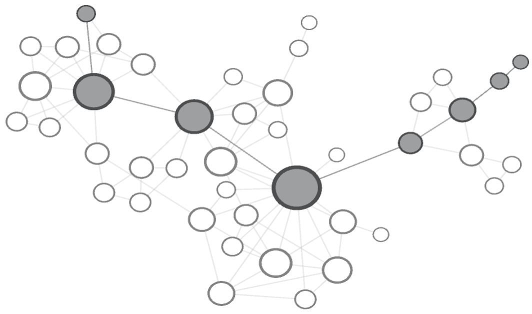

Figure 3. Network Diameter - Office E8

Figure 4 compares the general connectivity of three contrasting networks: E1, E5, and E9. E1 appears relatively dispersed, while E9 appears more centralized. E5 exhibits a highly centralized, star-like topology, with one dominant node connected to all others, indicating a potential single point of influence or vulnerability. These visualizations underscore the variation in network characteristics across different organizational units and provide a qualitative basis for further investigation into the relationship between network structure and organizational function.

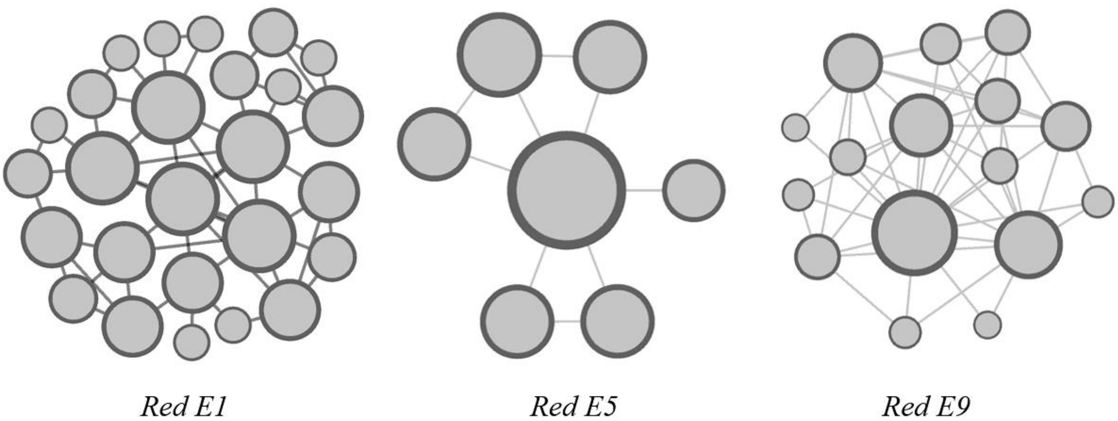

Figure 4. General connectivity – Networks E1, E5 y E9

3.3. Hierarchies

Using the hierarchy analysis established by the degree of the nodes, the team members were classified by quartile. Hierarchical degrees can be observed within each network; the results are shown in Table 7.

Table 7. Hierarchical groups of undirected networks

Network	Quartile Q1	Quartile Q2	Quartile Q3
E1	4.00	6.00	10.00
E2	4.00	6.00	12.00
E3	4.00	6.00	9.00
E4	4.00	8.00	12.50
E5	4.00	4.00	6.00
E6	4.00	6.00	9.50
E7	6.00	10.00	14.00
E8	4.00	6.00	10.00
E9	6.00	11.00	17.00

Figure 5 shows diagrams for networks E1, E5, and E9 elaborated using the Network Splitter 3D algorithm to separate the nodes by the quartile thresholds in Table 7. The networks are stratified into levels (G1–G4), illustrating a hierarchy from more influential or well-connected nodes in G1 to peripheral participants in G4. The sizes and blackness likely indicate centrality or importance within the network, with darker and larger nodes representing key connectors or influencers.

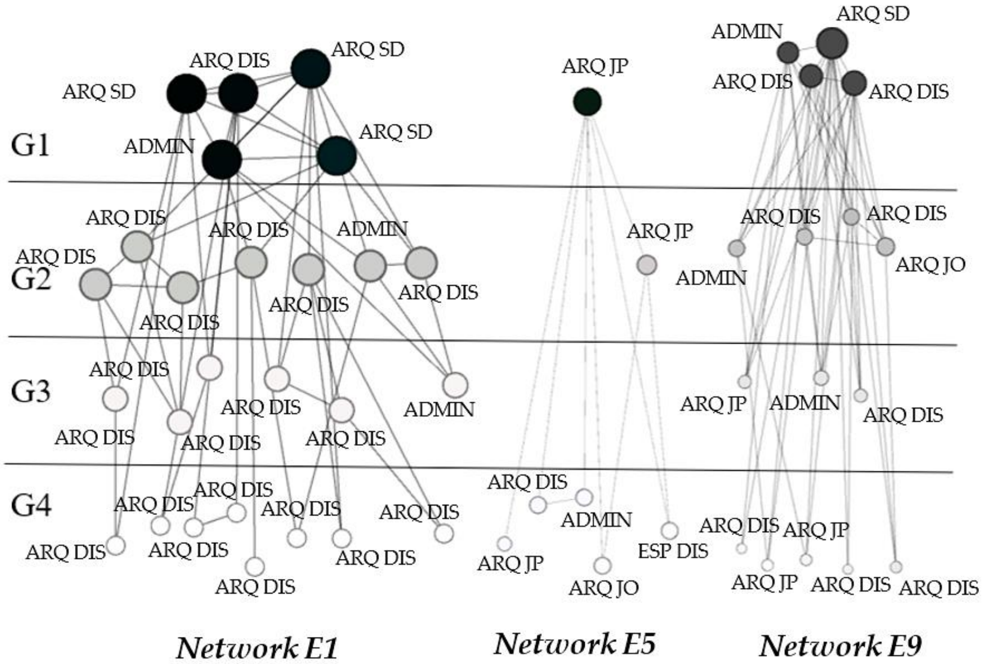

Figure 5. Hierarchical structure – Networks E1, E5 and E9

4. Discussion

The analysis has revealed key differences between hierarchical and other organizational settings. Hierarchical and scale-free networks, like social or biological systems, tend to have a large number of nodes but low density, maintaining connectivity through a few highly connected hubs. They exhibit small-world properties, with short average distances and small diameters, ensuring efficient communication. While hierarchical networks typically have a broad degree distribution with hubs sustaining global connectivity, infrastructure networks maintain a more uniform degree to ensure stability. Fragmentation is low in hierarchical settings but can be higher in highly modular yet weakly connected systems. Assortativity further distinguishes network types, with social networks favoring high-degree nodes linking to each other, while technological and biological networks exhibit disassortative mixing, where hubs primarily connect to low-degree nodes. These structural variations highlight how different networks balance connectivity, modularity, and efficiency depending on their organizational needs [50].

The organization of positions in Table 1 within design offices is repetitive and relatively simple. The project manager and/or the architect-partner or owner assign tasks and responsibilities to the team members, assuming a managerial role. The office manager prospects for and attracts clients, selects and recruits teams, and is responsible for operations. In small design offices, some of these functions overlap as the architect-partners or owners sometimes recruit clients, recruit staff, and assign tasks. The other positions carry out the design work supported by the administrative staff.

The differences between directed and undirected networks in construction design offices emphasize how communication patterns, hierarchy, and efficiency shape team dynamics. In directed networks, it is assumed that communication has occurred, highlighting the influence of hierarchical structures in which project managers and senior architects function as central nodes with high output centrality but lower input centrality, limiting reciprocal exchanges [5]. In contrast, undirected networks confirm communication between nodes, leading to stronger reciprocal relationships and collaboration. Statistical analysis shows that directed networks have lower density, emphasizing top-down decision-making, while undirected networks exhibit higher clustering coefficients, indicating trust-based and cooperative interactions [40]. The study also confirms that larger offices, such as E8 with 49 members, tend to have higher network diameters (up to seven steps), leading to longer communication paths, while smaller offices, such as E9 with 16 members, maintain tightly connected structures, reflecting small-world characteristics allowing for more frequent and direct exchanges [31]. Additionally, directed networks provide a structured communication flow, whereas undirected networks, by cross-verifying links, highlight natural hierarchies based on affinity and trust rather than solely on formal roles.

The study's findings have implications for project efficiency in design teams. The methodology assumes that directed networks inherently contain communication, while undirected networks only include confirmed interactions, leading to different statistical interpretations. Directed networks effectively establish hierarchies necessary for structured workflows but may hinder adaptability and information feedback. In contrast, undirected networks encourage knowledge-sharing and dynamic collaboration, though they require coordination mechanisms to maintain efficiency [31]. The observed small-world properties indicate that, despite hierarchical structures, information can still flow efficiently when key connectors facilitate cross-team communication. The results highlight the need to consider both network types when analyzing organizational structures, as each presents distinct advantages and limitations. Given that the fragmentation of networks is not necessarily determined by size but by work methodology, as evidenced in the variation among firms, these findings can guide improvements in communication strategies in construction design offices. Future research should explore the long-term effects of these network structures on project outcomes and investigate strategies for integrating hierarchical and collaborative communication models in small and large design teams.

4.1. Directed Networks

It is observed in Table 3 that the networks studied present clustering coefficients above 40%, which implies that there are separate groups that provide the opportunity for the emergence of weak links conducive to disseminating new ideas within the networks. An exception to this is network E9, which has the highest clustering coefficient, implying the presence of a close-knit group, a characteristic it shares with two other small networks in the study group (E5 and E7). A correlation analysis was conducted between the studied metrics and the number of nodes in the networks. There is no statistically significant correlation between the number of managers and the clustering coefficient ($r(9) = -0.5863$, $p = 0.09703$), H_0: $\rho = 0$, which means that the workgroups within the team are not necessarily led by some of these positions, due to the complexity of the tasks, project type or simply because of the way they are organized in each of the offices. On the other hand, it was established that there is a moderate inverse, non-significant correlation between the clustering coefficient and the number of nodes ($r(9) = -0.653$, $p = 0.056$). Here is a tendency within small groups to form a more significant number of closed triads [51], such a condition should facilitate the flow of information within the design office or could be an effect of teams sharing resources in their tasks, which is common in small offices, in line with what is expressed by Wasserman and Faust [5].

Regarding cohesion, Table 4 shows a strong and statistically significant direct correlation between the average distance and the number of nodes (r (9) = 0.889, $p = 0.001352$), H_a: $\rho \neq 0$. As the number of nodes increases, the average distance between nodes increases; however, the distances remain below 3. Diameter similarly exhibits a substantial direct correlation with network size (r (9) = 0.832, $p = 0.001352$), ranging from 2 for a 16-node network to 7 for a 49-node network. Small networks have short communication paths even when divided into task groups. When it comes to diameter, there is no significant difference compared to large and randomly connected networks with a limiting distance of 6 [31]; the presence of many task groups may result in more than 6 degrees of separation between their members.

Generally, high connectivity between nodes is observed, indicating that information does reach network members [26]. The overall connectivity in seven of the nine companies is high, with values above 0.70. Despite this, there is no correlation between connectivity and the network size ($r(9) = 0.109$, $p = 0.7805$), H_0: $\rho = 0$. Connectivity reflects a high communication intensity due to the work that these organizations are developing, which could be due to factors such as how they work and the complexity of the projects they develop.

In the networks studied, input centrality is lower than output centrality, implying that little communication is reciprocal between work team members. This metric does not reach 0.50 despite output centralities reaching 0.8205. For example, in company E2, the confirmed information is only 18%; such asymmetry is characteristic in groups where much information is pushed from the team leaders or mentors, configuring a hierarchical structure noticed by Tatti [28]. Only in networks E7 and E9 are the outgoing and incoming centrality equal, suggesting a horizontal organization with a less hierarchical working relationship structure, more collaboration, and more feedback of information, as shown in Figure 2. In contrast, network E1, with an outgoing centrality of 0.7476, has few nodes that concentrate communication. The size of the nodes represents the number of outgoing links.

The small density values, averaging 0.2681, indicate that these are economical networks in which links and contacts are selective, typical of in-training or work networks, with slight communication effectiveness within the network [21]. Again, the exception is networks E7 and E9, with size 16 and densities of 0.5042 and 0.6208, respectively; they exhibit characteristics more associated with a social network with back-and-forth communication monitoring, than a typical workplace network. On the other hand, if these were random networks, they should have higher densities still, highlighting the influence of division into task teams.

4.2. Undirected Networks

The clustering coefficient differs from those shown in Table 3 as it includes only the nodes with interconnection confirmed by the two members; consequently, several isolated nodes also appear. No correlation was detected between the clustering coefficient and the number of nodes ($r(9) = -0.568$, $p = 0.1106$), H_0: $\rho = 0$. High values would be expected for smaller networks since this coefficient is related to the connection probability. This is the percentage of grouping by communication of information at work that implies the actors' dialogue beyond considering only superiors' orders or assignments. According to Krackhardt & Hanson [40], this network of relationships gets the job done. It can be assumed that work communication generates an average clustering of 40% in design offices and Zhang et al. [52] mentions that links between nodes within the same cluster tend to be more prevalent.

High diameters are observed in networks with a more significant number of participants, which is due to the distribution of several projects in an equal number of work teams that are connected by a single person or coordinator, resulting in a diameter greater than 6 in office E8 (Figure 3), as noted above. High network diameter values do not guarantee fast information between the most distant team members, resulting in loss of information [5]. As it is a non-random working network, the trend of a maximum of 6 steps between its members is not observed [31]; the work practice in that office involves a line of communication between group leaders, which is a typical structure of design offices.

There is a correlation between log (n), where n is the number of nodes, with the network diameter (r (9) = 0.940, p = 0.0001638, H_0: $\rho = 0$), the studied networks evidence a small-world property [36]. A correlation was found between the number of nodes with the average distance ($r(9) = 0.914$, $p = 0.0005719$, H_0: $\rho = 0$). No correlation was found between the number of nodes and the average degree of the network ($r(9) = 0.136$, $p = 0.728$, H_0: $\rho = 0$). According to the theory for random networks, small sizes imply high average degrees as they tend to saturate quickly, which does not occur with these networks because communication is conditioned by the formation of the work teams.

No correlation was found between overall connectivity and network size (r (9) = 0.1238, $p = 0.751$, H_0: $\rho = 0$). In small network sizes, overall connectivity is expected to be high if communication were random [8], as seems to be the case in networks E1 and E4. In most cases, the non-random connection is observed in these networks, which shows marked differences between network E9 with 16 members and an overall connectivity of 100% to another small network, such as E5 with a connectivity of only 38.18% (Figure 4). This is attributed to the formation of working subgroups or isolated components as is typical of design office work practice. The metric to understand this phenomenon within a social network is fragmentation; a high fragmentation indicates that the network is divided into multiple subgroups (that may be understood as having similar interests), but with less interconnection between them; a value close to zero indicates greater cohesion of the network. Information in fragmented networks does not flow freely [27].

The offices range widely in their social network structures, ranging from highly fragmented networks caused by the formation of teams that divide design tasks to networks with a very flat hierarchical structure. Negative assortativity indicates that high- degree members are communicating with low-degree subordinates. The exception is office E9, which is a single, non-fragmented group; the assortativity here shows that there is a hierarchical group with high connectivity working with subordinates with lower connectivity but who are nevertheless interrelated with the whole group, which favors an efficient use of the staff's capacities.

4.3. Hierarchies

High-degree nodes in level G1 are observed in Table 7; these represent people who manage information resources and are prominent work team members [4, 26]. In network E1, the communication of its members circulates through all four levels; the most influential members redistribute the communication among the members of groups G2 to G4, creating a typical organizational structure in which work instructions pass through all levels. In the case of network E5, there only three levels are occupied, and there is a marked hierarchy comprising one person above his subordinates, marking a direct communication between the head of the group and all its members; the absence of the G3 group is noticeable, which could be due to the size of the network.

The E9 network presents four groups; it is interesting to note that, in G1, one member coordinates the work communications very closely with the other three members of this group. Communication is from group G1 to all of G2, G3, and G4, but there is no effective communication between groups G3 and G4. It is noticeable that the groups are very close but that the communication is not necessarily between them, respecting the hierarchical levels. The members of G1 pass information on to all other groups. This structure is comparable to hierarchies in healthcare teams, where senior physicians hold central positions in communication networks, while nurses and technicians have lower-degree roles [53].

These hierarchies emerge naturally from network analysis rather than being predefined by formal organizational roles. Gilbert et al. [54] discovered that such emergent hierarchies often do not align with official organizational roles, as real influence and communication patterns depend on actual interactions rather than formal job titles. Their work highlights that while organizations may have explicit reporting structures, the true flow of information and decision-making often follows an informal, network-driven hierarchy.

Additionally, Figure 5, which visualizes the hierarchical structure of networks E1, E5, and E9, highlights how hierarchies naturally emerge from network interactions rather than strictly following formal organizational charts. This finding supports [2] research, which showed that informal communication networks often override formal hierarchies in professional settings. In contrast, studies on software development teams suggest that network-driven hierarchies emerge based on expertise rather than assigned roles [55]. These differences highlight how construction design offices maintain more rigid, role-based authority structures, whereas software teams rely on a more flexible, modular hierarchy facilitated by digital collaboration tools.

5. Conclusion

The statistics of working connections in the design offices studied show differences between directed and undirected networks. In all the cases analyzed, it is evident that these links are not a random product but rather the result of the conformation of the task teams assigned to the development of the design projects. Despite this non-randomness, the networks each behave like a small world, with short communication paths, although the diameters can be more than 6 edges apart.

In the social work networks formed in design offices, the size or number of members is not a determining factor for the formation of work subgroups or fragmentation of the networks; it is generally believed that a small network should be compact or that a large network should be more fragmented. The way of working determines the statistics of the networks, which is why small networks with fragmentation values of zero and large networks with small fragmentations were found. Furthermore, most networks feature communication between high-degree nodes that communicate with low-degree nodes. There is no evidence of preferences involving connections or communication between nodes with similar characteristics.

The study of undirected networks revealed very well-defined hierarchical structures generated by the flow of information necessary for the work, both in small and large networks; however, the network size is not a predetermining factor in this aspect. It is usual for offices to manage information at three or four hierarchical levels, with the presence of members who centralize information and collect and distribute it to the group.

One limitation of this study is that it refers to the participating group of design offices, so its conclusions need to be more generalizable. However, given that design offices' working methods follow a standard process, there are expected to be no significant differences in the cases of other countries.

The information presented could encourage frequent communication within the design team, improving metrics such as density and average degree and reducing the occurrence of clusters. Facilitating a safe and inclusive environment that encourages participation and a willingness to share ideas and ask questions should also be a priority, as good communication has been linked to the development of successful projects.

6. Declarations

6.1. Author Contributions

Conceptualization, R.H.; methodology, K.J.; software, K.J.; validation, T.C.; formal analysis, K.J. and T.C.; investigation, A.A.; resources, R.H.; data curation, R.H. and K.J.; writing—original draft preparation, K.J., T.C., A.Z., A.A., and R.H.; writing—review and editing, A.Z.; visualization, K.J. and A.Z.; supervision, T.C.; project administration, T.C. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author..

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6.4. Conflicts of Interest

The authors declare no conflict of interest.

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