Emergence and Evolution of Network Structures in Complex Interorganizational Project Teams

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Abstract: Networks in complex interorganizational engineering project teams are shaped by individuals' actions to perform specific project functions. These networks are dynamic; they change based on project needs, and each network structure influences the next. Particularly, this study examines how temporary knowledge-transfer networks in architectural, engineering, and construction (AEC) project teams emerge and evolve during project delivery, adopting different structures that are interdependent. We longitudinally analyzed the knowledge-transfer networks of an AEC project team with 79 to 102 members via statistical and qualitative analyses. Results showed that a core-periphery structure originally emerged in the project team network to support team coordination. Later, triangles among core and peripheral members emerged without disassembling the core-periphery structure and generating cohesive subgroups for deep knowledge transfers among team members. The findings shed light on the dynamic nature of knowledge-transfer networks in complex interorganizational project teams. Via informed network interventions, project managers can support knowledge-transfer structures that help improve team and project performance.
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Introduction

Architectural, engineering, and construction (AEC) project teams are interorganizational and interdisciplinary with members gathering temporarily to devise a unique built environment product. Starting from early stages of planning and design, team members with different expertise areas and work procedures develop knowledge-transfer networks to collaborate. The structures of such knowledge-transfer networks can determine the capabilities and eventually performance of project team members (Reagans and McEvily 2003). For example, project network structures can determine individuals' roles, responsibilities, and power in decision making (Davison et al. 2012), their opportunities to access required knowledge for their tasks (Chinowsky et al. 2011), the degree of match between their cognitive capacities and received knowledge (Tortoriello 2015), and levels of trust or opportunistic behavior in knowledge-transfer interactions with others (Coleman 1988).

The structure of knowledge-transfer networks emerges from individual action (Foss et al. 2010). As such, network characteristics at the node, dyadic, and network configuration levels can shape network structures (Broekel and Hartog 2013). For example, at the node level, individuals' might rather interact with those with higher capacity to understand knowledge (Szulanski 1996; Garcia and Mollaoglu 2020); at the dyadic level, pairs of individuals might interact based on their level of trust, or shared values and goals (Chinowsky et al. 2008; Javernick-Will 2012); and at the network configuration level, individuals might preferably develop ties that close network triads (Broekel and Hartog 2013). The combination of these characteristics can contribute to generate dynamic networks in complex systems such as interorganizational AEC project teams. Dynamic networks evolve displaying different structures that are connected to each other with some degree of continuity. That is, a given network structure depends on the network's state at the previous time point and influences the network's state at the following time point (Abotaleb and El-Adaway 2018; Lee et al. 2018).

Therefore, in dynamic networks of AEC project teams, a given structure can partially cause and help predict subsequent structures. Because these structures convey critical knowledge and facilitate coordination, knowledge of them can help managers enhance the performance of such project teams (Abotaleb and El-Adaway 2018). The dynamic nature of networks in the AEC industry has been mostly studied in long-term networks across multiple projects and built upon interactions among organizations (e.g., Tang et al. 2018; Qiang et al. 2021) or interdependencies among project items (e.g., Liu et al. 2019; Eisenberg et al. 2020). Thus, there is a research gap regarding the emergence and evolution of AEC project team networks where a group of individuals from different organizations and disciplines gather

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temporarily for a single project and generate a short-term network to collaborate. Addressing such research gap can help us understand how knowledge-transfer networks dynamically evolve adapting to changing project needs to accomplish project goals. To address this gap, this study examined what are the knowledge-transfer network structures that emerge in AEC project teams, why, and how do they evolve interdependently.

Thus, we first reviewed the literature to identify the network structures for knowledge transfers that are likely to emerge in AEC project teams. In the light of this literature, we tested the presence and interdependence of the identified network structures using longitudinal data from a real-world AEC project. This project team's composition fluctuated between 79 and 102 members from multiple disciplines and organizations during the period the study focused on (i.e., early design phases). We analyzed the knowledge-transfer networks mainly via statistical exponential random graph models (Butts et al. 2014) during different intervals of the project.

Results suggest that the project team initially generated a knowledge-transfer network with a core-periphery structure. By the end of the schematic design phase, multiple cohesive subgroups emerged via triangular patterns around the members in the core subnetwork. The development of network triangles did not dissolve the core-periphery structure. Core-periphery networks enabled team coordination, whereas cohesive subgroups emphasized deep knowledge transfers. The study findings help explain the dynamic nature of knowledge-transfer networks and their evolution in complex AEC project teams including various disciplines and organizations.

Literature Review

AEC Project Team Networks and Functions

As individuals draw on networks to coordinate action and exchange knowledge, performance of project teams is influenced by structure of network relationships among their members (Cohen and Levinthal 1990; Reagans and McEvily 2003). The network structures that individuals unfold through their interactions are meant for specific functions (Lee et al. 2018). For example: in AEC project teams, small-world network structures can facilitate team formation processes, and changing scale-free structures can impulse collaboration across organizational and disciplinary boundaries (Kereri and Harper 2019); structures containing subgroups coordinated with appointed or spontaneous network bridges can enhance conflict resolution (Di Marco et al. 2010; Iorio et al. 2012); and hierarchical network structures can speed up knowledge flows from owner and contractor project managers to field personnel (Lin 2015). In addition, network structures possess global (e.g., density, centrality, and clustering coefficients) and local network parameters (e.g., between centrality, and eigenvector centrality) that can help assess overall team collaboration and individuals' roles and leadership, respectively (e.g., Chinowsky et al. 2008; Wang et al. 2018).

In AEC project teams, the network structures for knowledge transfer should be flexible to adapt to project demands over time (Zhang et al. 2013). Therefore, although network structures' characteristics can be planned beforehand (e.g., Chinowsky et al. 2011; Wang et al. 2018), project networks can help optimize team performance when individuals can develop additional informal and unanticipated network connections to access the knowledge that they deem necessary (Senaratne et al. 2017; Verschoore and Adami 2020). Because members of AEC project teams belong to widely diverse disciplines and organizations, they frequently fail to transfer necessary knowledge to others in a timely fashion and collaborate efficiently (Franz et al. 2016). Thus, AEC project teams' main challenge is to coordinate a diverse group of team members while they engage in many activities involving deep knowledge transfers across organizational and disciplinary boundaries. Therefore, we focus herein on examining dynamic network structures that can help team members coordinate and transfer deep knowledge.

Core-Periphery Networks for Team Coordination

Highly dense and homogeneous networks at initial stages of AEC project delivery might be counterproductive for generating project goals and coordinating team members at the earliest stages of project delivery. Members from different disciplines and organizations might hold dissimilar or even opposing perceptions about project goals (Firth et al. 2015). In addition, too many network links for knowledge transfer might blur team members' understanding of their roles, responsibilities, or hierarchical positions in decision-making processes (Davison et al. 2012; Frank et al. 2015). Instead, knowledge-transfer networks might optimally feature a starlike shape with low clustering coefficients and high centrality at the beginning of project delivery (Parraguez et al. 2015). This structure resembles a core-periphery network composed of a highly dense core subnetwork surrounded by a low-density peripheral subnetwork.

With such network configuration, members in the core subnetwork possess high control over the knowledge flowing through the whole network (Csermely et al. 2013). They can become the only source from which project goals emanate, avoiding network polarization due to the emergence of conflicting goals from separate network areas (Frank et al. 2015, 2018). Therefore, the core members can set and diffuse project goals ensuring that all team members' tasks are aligned with the same goals. Peripheral members can engage in the creation of project goals by providing the necessary resources to the core. Ideally, all members in the core interact with each other to coordinate, whereas peripheral members do not interact much with each other but with some members in the core subnetwork (Borgatti and Everett 2000). Core members primarily work with each other with strong ties while scanning key pieces of knowledge from peripheral members with weaker ties (Capaldo 2007). Hence, this study poses the following research question:

> RQ1: Do core-periphery structures emerge in knowledge-transfer networks in AEC project teams at the early stages of project delivery? If so, why, and how do they evolve?

Cohesive Subgroups and Network Triangles for Deep Knowledge Transfer

After the earliest stages of AEC project delivery, the core-periphery networks discussed previously might not be effective for transferring complex knowledge in detailed design activities (Parraguez et al. 2015). Peripheral members are embedded in sparse network areas; however, deep knowledge transfers might require increased cohesion among team members. In highly cohesive networks, ties are denser and individuals can easily access each other's knowledge with fewer intermediaries that could attenuate or distort it (Hansen 1999, 2002). When team members can interact directly and frequently, they can improve their joint capacity to detect and solve project issues (Dossick et al. 2014). Thus, higher network cohesion can generate deep knowledge transfers, that is, reinforcing and recurrent interactions that improve understanding of the transferred knowledge, especially among members from distinct organizations and disciplines (Tortoriello et al. 2012). In addition, network cohesion helps promote common collaborative norms because shared partners can attribute status to those who transfer knowledge (Blau 1964; Coleman 1988; Frank et al. 2020).

Networks where the density of ties is unevenly distributed might develop cohesive subgroups. The subgroups are highly cohesive network areas with interactions concentrated within subgroups boundaries and sparse between the boundaries (Frank 1995, 1996; Holland and Leinhardt 1978). These structures allow increasing cohesion only in local network areas where selected individuals need to collaborate tightly, thus mitigating the need to increase the global network cohesion via unnecessary ties that could overwhelm team members (Zhang et al. 2020). Lastly, in AEC project teams, subgroups can expand the scope of individuals' ties beyond their own organizations to acquire new knowledge and improve their capacity to innovate (Xu et al. 2019). As opposed to core-periphery structures, cohesive subgroups decentralize power in decision making (Csermely et al. 2013). Individuals in a subgroup can focus on deeply discussing every matter and, thus, make the most important decisions about it.

AEC project team networks typically develop cohesive subgroups with a dynamic composition and size, incorporating or dropping members based on project needs (Zhang et al. 2013; Poleacovschi and Javernick-Will 2016; Laurent and Leicht 2019). The challenge is to coordinate action between subgroups through boundary spanning or bridging ties (Di Marco et al. 2010; Iorio et al. 2012; Comu et al. 2013) and avoid team fragmentation (Franz et al. 2016). Individuals can transition from core-periphery structures to cohesive subgroups by forming triangular patterns for knowledge transfers. Triangles increase cohesion within local network areas; thus, they can accumulate as seeds around which cohesive subgroups emerge. The emergence of subgroups does not necessarily entail the dissolution of a prior core-periphery structure. Subgroups typically involve members from the core subnetwork but might also involve some from the periphery (Rombach et al. 2017). Thus, we pose the following research question:

> RQ2: Do triangles and cohesive subgroups emerge in knowledge-transfer networks in AEC project teams after the earlier stages of project delivery? If so, why, and how do they evolve?

Summarizing, AEC project teams face two challenges during project delivery. First, they must coordinate all team members to create and disseminate project goals. The literature suggests core-periphery structures as the most suitable ones for team coordination. However, AEC project teams must also engage in deep knowledge-transfer activities that, based on the literature, are better performed within networks via cohesive subgroups that can be formed through network triangles. Fig. 1 visualizes the three knowledge-transfer structures that can emerge in complex interorganizational AEC project teams during project delivery.

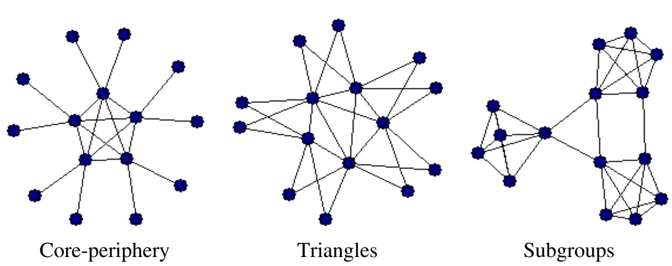

Fig. 1. Network structures in complex interorganizational AEC project teams.

Methodology

Data Collection and Coding

To respond to the research questions, we collected data from an AEC project team that designed and built an institutional renovation and addition project [3,252 m^2 (35,000 sq ft)] located in a Midwest state in the US. The project duration was 2 years, with 7 months in the design phase and 17 months in the construction phase. The project started with a $20 million budget and was delivered via Construction Management at Risk. The study followed mixed methods to data collection (i.e., archival documents, surveys, observations, and email exchange data) and analysis (i.e., statistical and qualitative analyses). The scope of this paper is limited to the emergence and early stages of network structures' evolution during project delivery that took place during schematic design.

Project Meetings, Documents, and Observations

One of the authors and an additional coder attended the project team's weekly meetings, collected meeting minutes and other project documents (i.e., archival data), and coded observations of the meetings to gain additional insights about team member participation in meetings, project status, activities, and goals. Coders identified participants' contributions in project team meetings in one of the three categories: (1) providing input (e.g., "We will add a wall to separate these two areas"); (2) asking a question (e.g., "Are there any power boxes on the floor?"); and (3) other (e.g., "Let's get [the meeting] started"). We calculated the interrater reliability for each of 21 meetings across all pairs of coders with a range of 6 to 14 team members per meeting. The average correlation between coders was high $r = 0.89$ ($n = 21$) (Cohen and Cohen 1983). This implies an 80% overlap in the variance of the rankings of any two coders, leaving very little residual differences. Given the large correlation of 0.89 [with standard error of $1/(n-3)^5 = 0.23$, with $n = 21$ meetings], it was not necessary to pursue stronger evidence for intercoder reliability.

Project Intervals

We determined the study project's intervals based on project progress toward key project goals (Garcia et al. 2014; Marks et al. 2001). Based on the aforementioned project meetings, documents, and observations, we used scope, budget, and schedule as the key project goals. We identified three project intervals ranging between 4 and 4.5 weeks during the schematic design based on the following milestones which highlighted the progress accomplished toward the key project goals: Initial concept estimate based on design and scope changes (Interval 1), design efforts on hold for owner and general contractor to consolidate estimates (Interval 2), and owner's approval of scope, budget, and continuation to design development phase (Interval 3).

Project intervals can help detect those stages where project teams emphasize either coordination or deep knowledge transfers based on the progress made to fulfill project goals and, consequently, where the project team's knowledge-transfer network might display different structures. Therefore, we ran our network and qualitative analyses considering these three project intervals.

Knowledge-Transfer Network

We used email exchange data among team members to capture the network ties, namely, the knowledge-transfer network.

Knowledge-transfer network herein refer to flows of project-related understanding that can help individuals develop their tasks. Knowledge can be either tacit or explicit; whereas the former is frequently referred to as knowledge that is intuitive, proceeds from experience and is hard to codify, the latter is typically referred to as information because it can be easily codified with words or algebraic symbols in books or manuals (Nonaka and Takeuchi 1995; Smith 2001).

However, knowledge and information are interrelated because knowledge can somehow be expressed with information (Nonaka 1991). For example, a project estimator can send an email with the subject "Project duration to take 15 months." The email subject is information because it is codified; however, it reflects the knowledge of the estimator because it knows the project duration based on its experience. Because every AEC project is complex, unique, and not codified in any manual or book, we considered the email exchange data as representative of knowledge transfers.

The data proceeded from owner, general contractor (GC), and designer representatives and consisted of email headers including sender, receiver, time, and subject. The weight of the network ties was determined based on the frequency of email exchanges (i.e., 3 = daily, 2 = weekly, and 1 = monthly). Although a single and unofficial channel of communication among many other mediums (e.g., in person, phone calls, text messages, and web-based platforms), email data allows researchers to model team collaboration and examine complex AEC networks (Albino et al. 2002; Dogan et al. 2015; Durugbo et al. 2011; Franz et al. 2018), providing a representative and reliable data source in comparison with retrospectively collected and self-reported data (Kadushin 2012). To ensure that our study captured a representative reflection of team knowledge-transfer networks, we interviewed core team members at multiple intervals during project delivery and verified our network findings.

Team Member (Node) Characteristics

Five main characteristics were considered:

- Main roles in the project (i.e., owner, designer, or contractor). These were determined using the project team roster and organizational charts.
- Tiers of decision-making in project operations. Tiers were also determined using the project team roster and organizational charts (i.e., Tier 1 includes lead representatives from each main role, Tier 2 members are those in Tier 1 members' home organizations, and Tier 3 includes subcontractors, vendors, consultants, and other stakeholders) (Mollaoglu-Korkmaz et al. 2014; Garcia et al. 2020).
- Expertise areas such as project management, architectural design, construction, and various engineering fields. These were determined via online or paper-based surveys and complemented with web searches whenever possible.
- Years working in the AEC industry. These were also determined via online or paper-based surveys and complemented with web searches whenever possible.
- Meeting participation data (i.e., measured through provide input as explained previously). These data were collected and coded by two coders who attended and observed the weekly project team meetings.

Data Analysis

In the light of the literature, because core-periphery configurations are likely to emerge first in project teams, we tested for the presence of a core-periphery structure at each interval starting with Interval 1. If it was present, then we tested whether the network had a significant probability to display triangular patterns and subgroups at that interval and develop them in the following interval around specific nodes or dyads within/across the core and periphery subnetworks. At the following intervals, we examined evidence for how subsequent structures emerged out of individual action embedded in the previous network. If a core-periphery network was not present, then we tested the tendency for triadic patterns and subgroups around all nodes and dyads. After this quantitative analysis, we qualitatively examined the activities that the study project team developed at each interval to match them with the adopted structures.

Core-Periphery Networks

We used Borgatti and Everett's (2000) algorithm in the UCINET version 6.675 software (Borgatti et al. 2002) to examine the presence of core-periphery structures in the observed networks of the study project team. The algorithm finds the highest correlation between the observed network matrix and an ideal core-periphery matrix partitioned into four blocks: a1-block at the top left of the ideal core-periphery matrix represents a core subnetwork with all members connected to each other; another 0-block at the bottom right represents a peripheral subnetwork with all members disconnected; two additional blocks representing interactions between core and peripheral members complete the ideal core-periphery matrix at the top right and bottom left. The last two blocks are treated as missing data to allow the algorithm to focus on maximizing densities within core and minimizing densities in peripheral subnetworks. In summary, the algorithm maximizes the following unnormalized Pearson correlation coefficient between the observed and ideal core-periphery network matrices (Borgatti and Everett 2000):

$$R = \sum_{ij} y_{ij}\rho_{ij} \tag{1a}$$

$$\rho_{ij} = \{1 \text{ if } (i,j) \in \text{core; } 0 \text{ if } (i,j) \in \text{ periphery; } \text{"missing" otherwise}\} \tag{1b}$$

where R = correlation between the observed and ideal core-periphery networks (i.e., the extent to which the observed network of the study project team resembles an ideal or perfect core-periphery network); i and j = network nodes (i.e., team members in the observed network); y_{ij} = weight of the tie from i to j in the observed network (i.e., frequency of knowledge transfer from a team member to another one); and ρ_{ij} = presence of a tie from i to j in the ideal core-periphery network (i.e., 1 if there should be a tie in an ideal core-periphery structure between two team members of the observed network, and 0 otherwise).

Fig. 2 shows an example of an ideal core-periphery network with the highest correlation with a hypothetical observed network based on the algorithm in Eqs. (1*a*) and (1*b*). The networks are expressed as matrices where each cell in row i and column j contains the value of the network tie from node i to j. Lastly, we used team members' characteristics as explained previously to qualitatively examine the composition of the core and periphery subnetworks.

Triangular Network Patterns

To examine the presence of triangular patterns within the observed network of the study project team and whether they are related to dyad and node characteristics (Broekel and Hartog 2013), we used exponential random graph models (ERGMs), which express the conditional probability of a network tie with the following stochastic model (Butts et al. 2014):

$$\log \frac{P(y_{ij} = 1 | Y_{ij}^c)}{P(y_{ij} = 0 | Y_{ij}^c)} = \boldsymbol{\theta}^T \Delta[\boldsymbol{g}(\boldsymbol{y})]_{ij} \tag{2}$$

	1	2	3	4	5	6	7	8
1		1	1	-	-	-	-	-
2	1		1	-	-	-	-	-
3	1	1		-	-	-	-	-
4	-	-	-		0	0	0	0
5	-	-	-	0		0	0	0
6	-	-	-	0	0		0	0
7	-	-	-	0	0	0		0
8	-	-	-	0	0	0	0	

(a)

	1	2	3	4	5	6	7	8
1		2	3	0	3	2	0	0
2	1		1	0	0	0	1	0
3	2	1		0	0	0	1	0
4	0	2	0		0	0	0	0
5	0	0	0	0		0	0	0
6	0	0	0	1	0		0	1
7	0	0	0	0	0	0		0
8	0	1	0	0	0	0	0	

(b)

Fig. 2. Example of correlation between ideal and observed core-periphery networks: ideal core-periphery network (a) with highest correlation with an observed network (b) based on Borgatti and Everett's (2000) algorithm (R = 0.83). Block at top left = core subnetwork; and and block at bottom right = peripheral subnetwork.

where Y^c_{ij} = observed network of the study project team without a tie between team members (network nodes) i and j; and y_{ij} = tie between i and j (i.e., 1 if there is a tie, 0 otherwise), so therefore, $\mathrm{P}(y_{ij} = 1|Y^c_{ij})$ and $\mathrm{P}(y_{ij} = 0|Y^c_{ij})$ are the probabilities of the presence or absence of a tie between i and j given the observed network Y^c_{ij} ; and $\boldsymbol{g}(\boldsymbol{y})$ is a vector containing the network statistics that are potential predictors of the probability of a tie between team members i and j. We developed $\boldsymbol{g}(\boldsymbol{y})$ using Morris et al.'s (2008) ERGM terms:

$$\boldsymbol{g}(\boldsymbol{y})^{\mathrm{T}} = (gwesp,\ dyadcov,\ nodefactor,\ gwesp \times dyadcov,\ gwesp \times nodefactor,\ edges) \quad (3)$$

where $\mathbf{g}(\boldsymbol{y})$ includes the following network statistics: *gwesp* (geometrically weighted edgewise shared partner) at the network configuration level represents the number of triads that would be closed if a network tie between nodes or team members i and j occurs. This term applies a discount for each additional shared partner via a decay parameter α (Hunter and Handcock 2006; Hunter 2007; Broekel and Hartog 2013). The statistic *dyadcov* at the dyad level relates to a pair of team members i and j and represents their expertise similarity and their type of relation based on their network position [i.e., core-to-core (CC), periphery-to-periphery (PP), and core-to-periphery (CP) dyads]. The statistic *nodefactor* at the node level represents team members' characteristics explained previously (i.e., main role, tiers, expertise areas, years working in the AEC industry, and project team meeting participation). The interaction term *gwesp* × *dyadcov* at the network configuration and dyad levels allows us to estimate whether the effect of *gwesp* (associated with closed triads in the network) is greater for certain dyadic covariates (e.g., CC dyads). The interaction term *gwesp* × *nodefactor* allows us to estimate whether the effect of *gwesp* is greater for certain types of actors (e.g., a team member of the owner role). Finally, *edges* is a control variable, with the corresponding model coefficient representing the overall density of network ties.

Overall, Eq. (2) expresses the changes in the log odds of a tie between team members i and j given a one unit increase in the network statistics in $\boldsymbol{g}(\boldsymbol{y})$. In Eq. (2), the vector $\boldsymbol{\theta}$ contains the model coefficients, six in total (i.e., θ_1, θ_2, θ_3, θ_4, θ_5, and θ_6), one for each of the six network statistics within the vector $\Delta[\boldsymbol{g}(\boldsymbol{y})]_{ij}$, which refers to the increment of the network statistics in $\boldsymbol{g}(\boldsymbol{y})$ when the tie y_{ij} in the network y switches from 0 (no tie) to 1 (tie between i and j). Thus, for example, θ_1 is associated with the increment of the network statistic *gwesp* [Eq. (3)], meaning that if θ_1 turns out to be positive and significant in the ERGM analysis, then the statistic *gwesp* significantly influences the probability of occurrence of network ties; that is, network ties between team members are more likely to emerge if they close network triangles.

Conversely, if θ_1 is negative, it means that team members avoid engaging in closed triangles for knowledge transfers. We estimated the ERGM parameters in vector $\boldsymbol{\theta}$ [Eq. (3)] with RStudio version 1.2.1335 software using the Markov chain Monte Carlo maximum likelihood estimation (MCMLE) method (Hunter et al. 2008). For the analysis, we used the unweighted and undirected network of the study project team because members in network triangles can collaborate under a set of social norms regardless of the directionality and weight of knowledge flows (Coleman 1988; Reagans and McEvily 2003).

Cohesive Subgroups

To examine the presence of cohesive subgroups within the observed network of the study project team, we used Frank's (1995) selection model (with KliqueFinder version 0.15 software), which expresses the probability of network ties based on their membership to a cohesive subgroup:

$$\log\frac{P(y_{ij}=1)}{1-P(y_{ij}=1)} = \theta_0 + \theta_1 SG_{ij} \quad (4a)$$

$$SG_{ij} = \{1 \text{ if } (i,j) \in \text{ same subgroup; } 0 \text{ otherwise}\} \quad (4b)$$

where $P(y_{ij} = 1)$ = probability of a tie between team members (network nodes) i and j; and SG_{ij} = whether i and j belong to a common cohesive subgroup in the observed network (1 if yes, 0 otherwise). Thus, Eq. (4*a*) represents the changes in the log odds of a tie between team members i and j given the fact that they belong to the same subgroup. Thus, if θ_1 is positive and significant, it means that team members are more likely to interact if they belong to the same cohesive subgroup, whereas they tend to remain disconnected if they belong to different subgroups. Larger values of θ_1 indicate a higher concentration of ties within subgroups of the observed network.

The estimation of θ_1 consists of iteratively reassigning nodes to subgroups until finding a set of subgroups within the observed network that maximizes θ_1. Frank (1995) showed how a Monte Carlo sampling distribution for θ_1 can be generated by repeatedly applying the KliqueFinder algorithm to data simulated from the degree distribution of the observed data. This provides a p-value for the parameter θ_1 of the observed network. We also used the study team's unweighted and undirected network in this analysis because the subgroups are based on network cohesion, which promotes the creation of social norms for collaboration regardless of the direction and weight of knowledge flows (Coleman 1988; Reagans and McEvily 2003). Finally, based on team members' characteristics explained previously, we qualitatively evaluated the composition of the subgroups.

Project Team Activities

Using the study project's meeting minutes and documents (i.e., archival data), and observations in the weekly team meetings, we qualitatively examined the project activities under Coordination and/or Deep Knowledge Transfer categories. The Coordination category included statements related to project goals and team collaboration such as "We're doing things differently [. . .]. Cost control items should be eliminated, and [the] total reduction [of project cost] would be [$X] million." The Deep Knowledge Transfer category included discussions where team members gain a deeper knowledge about a specific topic such as the following among three team members (i.e., M1, M2, and M3) regarding site utilities:

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- M1: "Send us whatever you have, a more formal utility map;"
- M2: "There's an existing telecom duct bank under the sidewalk, they said there is no way you will be able to go under there. We would go under the green space, patch it;"
- M3: "They want cover on top of it;" M1: "[. . .] we put in a manhole, but we need to make sure there is no conflict between that and the telecom."

Lastly, we overlaid the activities and their categories with the network structure adopted at the same interval to gain further insights.

Results

Network Findings

During the schematic design phase, 179 individuals in total participated in the knowledge-transfer network during at least one interval (i.e., 79, 101, and 102 members at Intervals 1, 2, and 3 respectively) from more than 15 expertise areas and 20 different organizations. Those individuals included but were not limited to owner representatives, architects, engineers, contractors, subcontractors, consultants, and vendors.

The observed network was highly correlated with an ideal core-periphery network throughout all three intervals. The correlations between the observed and ideal networks were $r_1 = 0.75$, $r_2 = 0.74$, and $r_3 = 0.73$ at Intervals 1, 2, and 3, respectively. Table 1 presents the composition of the observed core-periphery networks.

The core included between 8 and 10 team members (network nodes) mainly with primary expertise in project management and architecture under owner and designer roles, and Tiers 1 and 2. Nodes carrying other primary areas of expertise (e.g., mechanical and civil engineering), and roles (i.e., contractor) moved in and out of the core during these intervals. The peripheral subnetwork contained mostly members from Tier 2 and 3 from all roles and expertise areas (e.g., architecture, project planning, strategic management, final user needs, mechanical and civil engineering, and construction).

We tested multiple ERGMs to examine the tendency to form triangles within different areas of the core-periphery structure. We used as an indicator of model fit the MCMLE and generalized linear models' convergence to a solution when combining the *gwesp* network statistic at the network configuration level with other network statistics at the node and dyad levels. Table 2 presents the results of the ERGM analysis.

The parameter estimates for the interaction term *gwesp* × *CC-Tie* were positive and significant at each interval ($\theta_1 = 6.03$, $p = 0.001$; $\theta_2 = 5.55$, $p = 0.001$; and $\theta_3 = 11.19$, $p = 0.001$). Therefore, network members showed a tendency to develop core-to-core ties closing triangles during all the intervals. Conversely, the estimates for *gwesp* × *PP-Tie* were negative and significant across the three intervals, suggesting that network members avoided periphery-to-periphery ties that would form triangles at any interval. Finally, the estimate for *gwesp* × *CP-Tie* was positive and significant only at Interval 3 ($\theta_3 = 3.33$ and $p = 0.001$), indicating the emergence of team members' tendency to establish core-to-periphery ties closing network triangles during Interval 3. All the models excluded dyads' expertise similarity, and nodes' main roles, tiers, expertise areas, years working in the AEC industry, and meeting participation because, otherwise, they were not convergent.

Table 1. Descriptive analysis of core-periphery networks and cohesive subgroups

		Core-periphery networks						Cohesive subgroups								
		SD Int. 1		SD Int. 2		SD Int. 3		SD Int. 3								
Network attributes		Core	Peri.	Core	Peri.	Core	Peri.	SG.1	SG.2	SG.3	SG.4	SG.5	SG.6	SG.7	SG.8	SG.9
Total number of members		8	71	10	91	8	94	15	25	10	18	4	4	7	16	3
Aver. eigenv. ($\times 10^{-3}$)		286	48	259	32	295	36	86	84	71	69	63	11	11	2	0
Density ($\times 10^{-2}$)		150	1	147	1	153	1	20	17	27	18	50	33	38	13	67
Members per tier	Tier 1	6	1	4	3	7	—	2	3	1	1	—	—	—	—	—
	Tier 2	2	49	3	57	1	62	12	12	4	14	2	3	2	11	3
	Tier 3	—	21	3	31	—	32	1	10	5	3	2	1	5	5	—
Members per role	Owner	1	27	2	48	2	56	5	2	9	16	—	3	7	16	—
	Designer	4	32	8	32	3	30	—	23	1	2	4	—	—	—	3
	Contractor	3	12	—	11	3	8	10	—	—	—	—	1	—	—	—
Members per expertise area	Architecture	3	11	4	12	2	15	—	10	—	2	1	1	—	—	3
	Project planning	1	15	—	12	1	14	7	5	—	1	—	—	—	2	—
	Strategic manage.	—	6	—	8	—	20	—	3	1	6	—	2	2	6	—
	Final user needs	—	8	—	8	1	14	2	—	6	1	—	—	5	1	—
	Mechanical eng.	—	5	2	14	—	7	2	3	—	—	—	—	—	2	—
	Construction	—	7	—	9	—	4	1	—	—	—	—	1	—	2	—
	Civil engineering	—	7	1	5	—	5	—	—	—	3	2	—	—	—	—
	Information tech.	—	4	—	6	—	4	—	—	1	—	—	—	—	3	—
	Project manage.	4	—	2	2	4	—	2	1	—	1	—	—	—	—	—
	Electrical eng.	—	2	1	2	—	4	1	3	—	—	—	—	—	—	—
	Landscape	—	2	—	2	—	4	—	—	—	3	1	—	—	—	—
	Specialty design	—	—	—	6	—	1	—	—	1	—	—	—	—	—	—
	Vendor	—	3	—	2	—	1	—	—	1	—	—	—	—	—	—
	Interior design	—	1	—	2	—	1	—	—	—	1	—	—	—	—	—
	Subcontractors	—	—	—	1	—	—	—	—	—	—	—	—	—	—	—

Note: SD Int. = schematic design interval; Core = core subnetwork; Peri. = periphery subnetwork; SG = subgroup; Aver. eigenv. = average eigenvector centrality per member; Manage. = management; Eng. = engineering; and Tech. = technology.

Table 2. Results of the ERGM analysis

Model	Network statistics	ERGM estimates								
		SD Interval 1			SD Interval 2			SD Interval 3		
		θ_1	SE	p	θ_2	SE	p	θ_3	SE	p
1	*gwesp* ($\alpha = 0.5$)	1.76	0.14	0.001*	1.58	0.11	0.001*	1.61	0.12	0.001*
	CC-Tie	−8.63	0.89	0.001*	−6.19	0.79	0.001*	−17.39	1.00	0.001*
	gwesp × CC-Tie	6.03	0.79	0.001*	5.55	0.59	0.001*	11.19	0.90	0.001*
	Edges	−5.40	0.23	0.001*	−5.21	0.17	0.001*	−5.65	0.20	0.001*
2	*gwesp* ($\alpha = 0.5$)	1.71	0.12	0.001*	1.72	0.11	0.001*	1.46	0.11	0.001*
	PP-Tie	0.13	0.40	0.730*	−0.72	0.55	0.180*	−4.46	0.51	0.001*
	gwesp × PP-Tie	−1.26	0.41	0.001*	−2.22	0.38	0.001*	−6.61	0.46	0.001*
	Edges	−5.06	0.19	0.001*	−5.19	0.15	0.001*	−5.21	0.17	0.001*
3	*gwesp* ($\alpha = 0.5$)	1.74	0.12	0.001*	1.70	0.10	0.001*	1.59	0.10	0.001*
	CP-Tie	0.58	0.46	0.200*	−0.28	0.41	0.490*	2.03	0.44	0.001*
	gwesp × CP-Tie	−1.80	0.44	0.001*	−1.01	0.30	0.001*	3.33	0.31	0.001*
	Edges	−5.14	0.18	0.001*	−5.23	0.16	0.001*	−5.13	0.15	0.001*

Note: *gwesp* = geometrically weighted edgewise shared partner (to test the presence of network triangles); α = decay parameter; CC-Tie = core-to-core tie; PP-Tie = periphery-to-periphery tie; CP-Tie = core-to-periphery tie; edges = number of ties in the network; SD = schematic design; θ_i = parameter estimate of the effect of a network statistic at interval i, meaning the change in the log-odds of the probability of a tie occurring when the tie increases the network statistic by a unit; SE = standard error; p = p-value; and $^*p < 0.01$.

Although some standard errors were high, there are not strong concerns about multicollinearity because the number of endogenous variables was close to three (e.g., *gwesp, CC-Tie, gwesp × CC-Tie*, and *edges* in Model 1) and the density of the observed networks was low at the three intervals ($\rho_1 = 0.05$, $\rho_2 = 0.04$, and $\rho_3 = 0.03 < 0.3$) (Duxbury 2018).

In summary, based on the ERGM results, the study network developed triangles (i.e., closed triads for communication) connecting only core members at Intervals 1 and 2, indicating a tendency to increase or keep network cohesion in the core while maintaining the peripheral members sparsely connected. Only at Interval 3, the triangles involved both core and peripheral members.

At Interval 3, when the triangles emerged involving core and peripheral members, cohesive subgroups also emerged within the core-periphery structure ($\theta_3 = 0.30$ and $p < 0.001$) without eliminating it. Thus, triangles and subgroups emerged simultaneously. The results suggested nine subgroups (SGs) where the four most central ones had one to three members from the core subnetwork (i.e., SG.1 to SG.4) (Fig. 3). On average, the core members participated in more network triangles than peripheral members (46.8 triangles per core member versus 3.3 per peripheral member) (Table 3). Therefore, the accumulation of network triangles around members in the core subnetwork supported the emergence of the cohesive subgroups at Interval 3. Table 1 indicates that the subgroups had between 3 to 25 members, and they were interdisciplinary with 4.4 different areas of expertise on average. The expertise area that was present across more subgroups was strategic management (six subgroups) followed by architecture, and final user needs (five subgroups), project planning (four subgroups), and mechanical and civil engineering, and construction (three subgroups). Members from the owner role participated in almost all the subgroups, whereas those from the GC role were concentrated in the most central subgroup (i.e., SG.1). Members from Tier 1 only participated in the subgroups with higher centrality (SG.1 to SG.4) whereas those from Tiers 2 and 3 were distributed across all the subgroups.

The study network size varied between 79 and 102 members across the intervals with 179 in total involved at some interval at least. Thus, some members came in and out during network evolution. However, only 14 members participated in the core subnetwork at some point, and all of them were present in the network permanently. Moreover, the triangles and subgroups emerged primarily them; therefore, the variation in team size did not affect substantially the emergence and changes of the team network structures.

Qualitative Findings

Project representatives reported satisfactory project progress at the observed team meetings and during study interviews, signaling the presence of a preferable network structure during the study period. Qualitative analysis of the network data (i.e., examination of node characteristics such as expertise and role), observational, and archival data complemented our understanding of the functions of the core and periphery subnetworks and showed that members in the core subnetwork had the potential to diffuse project goals to coordinate the whole project team and that the network structure can evolve in parallel to the changing project needs.

More specifically, we observed that project team discussions involved coordination intentions during all three intervals while the team gradually shifted the emphasis of the discussions toward deep knowledge transfers by the end in the last interval. At Interval 1, the core subnetwork was mostly composed of project management and architectural design experts to create and transmit design expectations (e.g., systems and layout) based on the budget. For example, at a team meeting, core members of project management and architectural design, respectively, stated "What the programming is showing does not fit into [the] budget. Once we have a conceptual estimate, then we can have a better understanding of the budget drivers so we can make decisions based [on the project priorities]" and "I am recommending reducing 19 m^2 (200 square ft) and reducing the [. . .] scope but the answer is no, therefore recommending eliminating the patio, but it is not cost saving."

At Interval 2, design expectations were further detailed with assistance from mechanical, electrical, and civil engineers that moved from the peripheral to the core subnetwork. For example, one stated, "Two options for mechanical are no rooftop unit with two chiller units or rooftop unit and a big unit." Another stated, ". . . Every door on the exterior will be electrified. Panic holds will be electrified . . . ." Finally, another stated, "We might end up getting new pumps . . . for backflow precaution."

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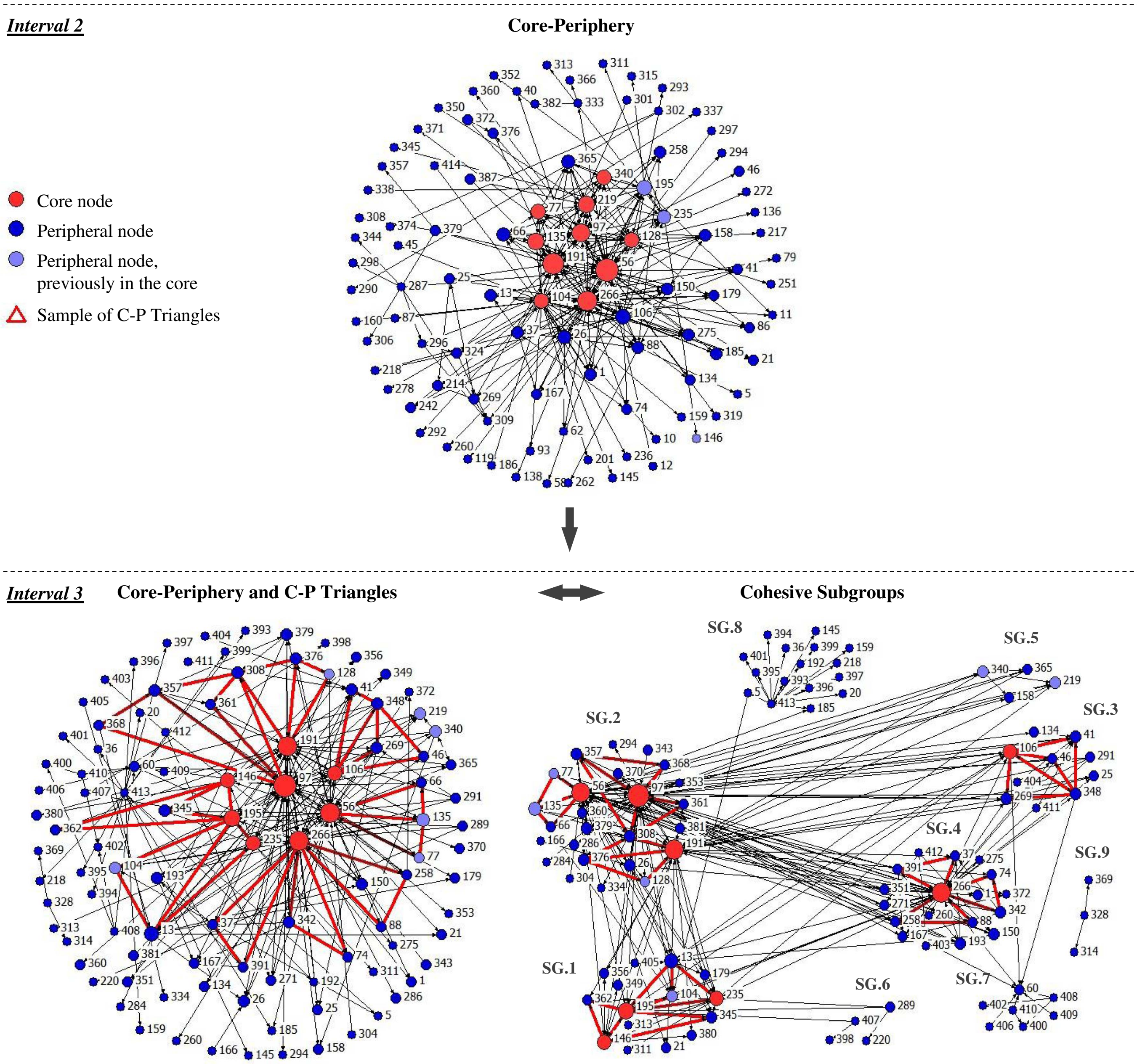

Fig. 3. Evolution of network structures in the study project team during schematic design's intervals. Members of the core subnetwork at Interval 2 generated triangles at Interval 3 that supported the emergence of cohesive subgroups. Presence of network structures in the study project team over the schematic design intervals based on statistical analyses. SD Int. = schematic design interval; C-P Triangles = triangles with core and periphery members; SG = subgroup; nodes are sized based on their eigenvector centrality; and distances among nodes in the core-periphery structures are approximately based on metric multidimensional scaling in UCINET (Borgatti et al. 2002).

At Interval 3, specialists in project planning and experts in final user needs replaced the engineers in the core subnetwork to initiate and coordinate a value engineering process to finalize project design expectations, scope, and budget. For example, a final user needs specialist stated regarding one item of the interior design: "What's the number for [room with specific purpose]? Oh! That's a big number. I will talk to the director and take this out [of the scope]." Meeting minutes also showed a cost control log attached to the project design for team coordination. Interestingly, although staying within a core-periphery network structure in all three intervals (supporting team coordination), the network gradually evolved into developing triangles (i.e., closed triads) and subgroups for deep knowledge transfers in Interval 3 (Fig. 3).

Network analysis in Interval 3, studied in the light of node characteristics (expertise area, roles, tiers, among others) and analysis of email headers (i.e., sample keywords reported subsequently in italics), showed that the project team network's structure evolved into subgroups for deep knowledge transfers at this stage following core subnetwork leads to maintain team coordination in the larger project network (Fig. 3): Subgroup 1 coalesced around three core members from the GC role (e.g., cost control logs, value engineering, and estimate); Subgroup 2 coalesced around three core members from the Designer role (e.g., REVIT model, gross square footage, and site design); and Subgroups 3 and 4 coalesced around two members from the Owner role, representing different functional departments including final user needs (e.g., flooring, and

Table 3. Descriptive statistics of network triangles

	No. of triangles					
	SD Interval 1		SD Interval 2		SD Interval 3	
Triangles' attributes	Total	Percent (%)	Total	Percent (%)	Total	Percent (%)
All	335.0	—	395.0	—	280.0	—
Only core members	56.0	16.7	99.0	25.1	45.0	16.1
Only periphery members	21.0	6.3	19.0	4.8	4.0	1.4
Core and periphery members	258.0	77.0	277.0	70.1	231.0	82.5
2 core and 1 periphery	152.0	58.9	171.0	61.7	144.0	62.3
1 core and 2 periphery	106.0	41.1	106.0	38.3	87.0	37.7
Average triangles per member	4.2	—	3.9	—	2.7	—
Per core member	51.2	—	44.8	—	46.8	—
Per periphery member	5.1	—	4.2	—	3.3	—

Note: SD = schematic design phase.

equipment room) and project management (e.g., budget sheet, and civil design review), respectively. The remaining five subgroups (i.e., SG.5 to SG.9) were satellite (i.e., less central in the network) and did not include members from the core subnetwork. They connected with the most central subgroups (i.e., SG.1-4) through core members. The satellite subgroups either provided resources to the main subgroups (e.g., SG.6 to SG.1) or functioned as bridges to help coordinate other subgroups (e.g., SG.7 between SG.2 and SG.3).

Discussion

AEC project teams are complex systems composed of members from multiple disciplines and organizations. These members must develop proper knowledge-transfer networks to transfer and integrate their expertise and deliver a unique built-environment product. Otherwise, AEC project team networks might break up into subgroups specialized in different building systems and whose actions and outcomes are incompatible (Chinowsky et al. 2008, 2011; Kereri and Harper 2019). This in-depth analysis of an AEC project team illustrates how dynamic networks emerge and evolve for facilitating coordination and deep knowledge transfers in project-related activities in early stages of project delivery. The study's findings bring insights into how project managers can improve collaboration and performance of complex interorganizational AEC project teams via informed network interventions.

At the earliest stages of delivery, projects may benefit from a core subnetwork that coordinates the whole project team toward common project goals because the scope is likely to be variable. The core subnetwork should be flexible to accommodate experts from all roles (i.e., owner, designer, and general contractor) based on project demands. Therefore, managers should consider optimal timing of key participants' involvement in project delivery such as contractor's involvement before the design development phase (Mollaoglu-Korkmaz et al. 2013), and the adoption of integrative project delivery methods and practices (e.g., design-build and partnering) that facilitate the creation of shared goals (Lahdenperä 2012; Franz et al. 2016). Core subnetworks involving owner representatives can catalyze their contribution to team goal alignment and, therefore, help avoid team members' opportunistic behaviors (Hetemi et al. 2020). The composition of the core subnetwork in our study varied between 8 and 10 members, adapting to project needs. Although the core-periphery structure proved effective for the study project, managers should consider that the higher the size of the core subnetwork, the harder to coordinate all team members (Csermely et al. 2013); thus, there is a need to carefully select the key areas of expertise that should participate in the core subnetwork.

The study's findings suggest that project managers can create and preserve core subnetworks by promoting network triangles for knowledge transfers among designated core members. Inclusions of peripheral members in these network triangles may lead to the emergence of cohesive subgroups. The subgroups bring together core and peripheral members from diverse disciplines (e.g., strategic management, architecture, and mechanical engineering) and roles (e.g., owner, designer, and contractors). Subgroup members carry out complex activities requiring deep knowledge transfers such as those in value engineering processes. Because the core members are highly knowledgeable of the project goals, they can ensure that the subgroups in which they participate gather adequate experts and work in alignment with project goals. Therefore, project managers should consider being proactive rather than reactive in the creation of cohesive subgroups. They should keep core members responsible in leading their formation and coordination. As subgroups' coordinators, core members can have their performance enhanced if they possess multidisciplinary expertise (Laurent and Leicht 2019).

In summary, project managers can promote core-periphery structures that help coordinate project teams at the earliest delivery stages (e.g., schematic design phase or earlier), whereas later, they can support cohesive subgroups for deep knowledge transfers (e.g., detailed design phase or later). However, based on our findings, project managers do not need to disassemble an established core-periphery structure when moving on to delivery stages that require cohesive subgroups. Instead, they can encourage team members in the core subnetwork to create triangular patterns with peripheral members for collaboration (e.g., designer and contractor representatives in the core subnetwork start collaborating with a structural engineer in the periphery to further develop the scope and estimate of the building's superstructure). In doing so, project teams can preserve the core-periphery structure that supports team members' coordination while generating multiple cohesive subgroups for deep knowledge transfers and efficiently adapt to changing project needs. In addition, network triangles can help improve team members' trust (Henry and Vollan 2014) and avoid network fragmentation due to staff turnovers (Franz et al. 2018).

Lastly, the study's findings suggest that core-periphery and subgroups are not mutually exclusive structures and can cohabit as distinct dimensions of the same network structure. As Rombach et al. (2017) suggested, network structures can exhibit cohesive subgroups, each containing its own core-periphery structure or, the other way around, a core-periphery structure can contain cohesive subgroups. We found in our study that the subgroups can emerge via network triangles involving core and peripheral members from a preexisting core-periphery structure. The findings were drawn from a network structure deployed during the schematic design phase of an AEC project.

At later stages, AEC project networks might evolve following the inverse process described herein; that is, networks might transition back from a clustered structure (e.g., subgroups) into a more centralized one (e.g., core-periphery alone or with subgroups) to fully integrate and complete the final product (Parraguez et al. 2015). Researchers should examine this transition and explain if and how a core-periphery structure can emerge from cohesive subgroups. As suggested by the study findings, the network structures are expected to be interdependent across all project delivery phases.

Conclusion

This study explored the emergence and evolution of knowledge-transfer networks in an AEC project team. It contributes to the body of knowledge by expanding our understanding of the dynamic nature of knowledge-transfer networks in complex interorganizational and interdisciplinary AEC project teams. These networks can adopt a succession of structures that are interdependent, and each of them is suitable for a specific function. They can adopt core-periphery structures in which multiple cohesive subgroups can emerge via network triangles. The cohesive subgroups can coexist with core-periphery structures if triangles involve core and peripheral members. Whereas core-periphery structures emphasize team coordination, cohesive subgroups support deep knowledge transfers. Via social network interventions, project managers can shape knowledge-transfer networks that improve team and project performance.

The study's main limitation is that the network structures were explored in a single medium-size project team, and therefore, the scope and generalizability of the findings might be limited. The findings might not be applicable to especially small project teams, where everyone can easily interact with each other. In addition, although the literature and our participant verifications provide validity to our methods, it is important to point out that the weight of network ties in this study was drawn from the frequency of knowledge transfers among team members based on email exchanges and did not consider other modalities of interactions (e.g., in-person, text messing via cell phone, or telephone communication), which might entail different interaction frequencies for transmitting similar knowledge or the quality of interactions (e.g., high-quality knowledge might require fewer transfer interactions).

Thus, future researchers should explore dynamics of networks in complex interorganizational engineering project teams considering other modalities and qualities of interactions, and project delivery methods (e.g., design-bid-build, or design-build) and phases (e.g., construction) that this study could not account for and that would further improve management of complex interorganizational engineering project teams.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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