Interaction between Project- and Group-Level Knowledge Transfer in Project Team Networks: A Social Influence Analysis

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Abstract: Collaboration is challenging for complex project teams that have many subteams with diverse and complementary skills that are working toward shared goals. Knowledge transfer among subteams (i.e., project-level knowledge transfer) enhances integrative collaboration and results in behavioral changes within subteams (i.e., group-level knowledge transfer). However, there is a lack of quantitative evidence about how such project-level knowledge transfer influences group-level knowledge transfer behaviors. This study examined the change in knowledge transfer behaviors along with project progress, using the energy-efficiency subteam as an example. To achieve the goal, the authors collected longitudinal email exchanges and archival project data during the delivery of a complex construction project in the state of Michigan. Social network analysis and social influence models were utilized to analyze the change of knowledge-transfer networks over time. The results confirmed that exposure to project-level knowledge transfer positively predicts the subsequent group-level knowledge transfer behaviors during project delivery, measured by eigenvector centrality. The findings provide quantitative evidence explaining the importance of knowledge transfer behaviors in project communication: project-level knowledge transfers change members' attitudes and behaviors and subsequently improve individuals' influences in their respective project subteams. In addition, opinion leaders demonstrate a certain extent of resistance to the change. **DOI: 10.1061/JMENEA.MEENG-5718.** *© 2024 American Society of Civil Engineers.*

Author keywords: Social influence; Social contagion; Knowledge transfer; Team collaboration; Sustainability.

Introduction

Architectural, engineering, and construction (AEC) projects are complex, because of the involvement of diverse stakeholders, individuals, and tiers of organizational assignments (Koolwijk et al. 2020; Mollaoglu-Korkmaz et al. 2014). Individuals with different and complementary expertise, motivations, and backgrounds are expected to collaborate to accomplish project goals (Fong and Lung 2007). Based on the project needs, project teams are divided into different subteams, which are nested in a project team, and transfer knowledge to achieve specific project tasks (i.e., group-level knowledge transfer) (Poleacovschi and Javernick-Will 2016). To address the challenges of complexity and ensure project efficiency, these subteams need to practice integrative collaboration with other subteams in the project team by engaging in knowledge transfers across organizational and disciplinary boundaries. (i.e., project-level knowledge transfer) (Garcia et al. 2021). For example, an electrical subcontractor collaborates with other subcontractors to coordinate the sequence of tasks while doing rough-in, or the general contractor works with the design team to properly execute the project.

In the organizational sciences literature, knowledge transfer refers to the behavior of sending and receiving knowledge, disseminating ideas, and providing inputs acquired in one situation to another for problem-solving (Singley and Anderson 1989; Szulanski 1996). Knowledge transfer involves continuing social interactions among project members, triggers certain behavior patterns (Nonaka 1994), and results in social influence. Social influence theory explains the social mechanisms of how individuals alter their attitudes, emotions, beliefs, and behaviors when exposed to knowledge or emotions during social interactions (Kaufer and Carley 2012; Kelman 1953). However, it is not clear how social interactions at the project level influence the way individuals transfer knowledge at the group level within projects, and vice versa. Without this information, it would be challenging for project managers to understand whether cross-level, multidisciplinary knowledge transfer or domain-specific knowledge transfer should be facilitated to achieve higher project performance.

To address this problem, this study identified the social influence regarding knowledge transfer behaviors across project and group levels of project collaboration. Specifically, the study determined how project-level knowledge transfer, including all team

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Note. This manuscript was submitted on June 5, 2023; approved on October 20, 2023; published online on January 5, 2024. Discussion period open until June 5, 2024; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Management in Engineering***, © ASCE, ISSN 0742-597X.

members from all groups, influences group-level knowledge transfer behaviors in complex project collaborations. Methodologically, we used social network analysis (SNA) bolstered with mixed methods to analyze project networks and examine the structural properties relating to social interactions (Hanneman and Riddle 2005). We then established social influence models to gain quantitative evidence of the relationship between project-level and group-level knowledge transfer behaviors.

In this study, we examined the energy-efficiency subteam and their group-level knowledge transfer to test the research question. Sustainability is a core value for organizations and construction projects to address the energy crisis and climate change (Korkmaz et al. 2010). Buildings consume 55% of global electricity and 40% of global resources (UNEP 2020), and under the current scenario, the upward trend in global energy consumption and energy-related carbon dioxide emissions will continue through 2050 (US Energy Information Administration 2021). Due to the increasing depletion of energy and resources, construction projects are required to be energy efficient.

Literature Review

Knowledge Transfer in Project Networks

Knowledge transfer, exchange, or sharing does not have an agreed-upon definition, and the terms are often used interchangeably with different connotations such as information transfer (Foss et al. 2010). Nonaka (1994) stated that even though there is a difference between information and knowledge, knowledge is formed as a result of information flows. In AEC teams, knowledge gained through experience can be codified and shared as information, and therefore the terms are interrelated (Garcia et al. 2021).

New knowledge and solutions are generated as a result of social interactions (Nonaka 1994). Therefore, after the initiation of a project, team members first start interacting according to the project protocols and contracts, and form the project communication networks to achieve project goals (Franz et al. 2018). Subsequently, project networks evolve dynamically to address project needs, changing the way in which knowledge is transferred (Garcia et al. 2021). Therefore, examining formal organizational structures and depending on traditional project management tools are not sufficient to understand knowledge transfers and achieve high performance (Chinowsky et al. 2008; Cross et al. 2014). As a result, social network analysis has gained importance as a robust tool to examine the dynamic nature of knowledge transfers in AEC teams (Kereri and Harper 2018).

SNA is a method of assessing and calculating relational and social structures (Butts 2008). It is a robust approach because it translates social interactions, communications, and knowledge transfers into a mathematical foundation by using network properties such as degree, distance, or centrality (Chinowsky et al. 2011; Hanneman and Riddle 2005). Network properties are important for characterizing network topology, and understanding how and why things happen in a network (Golbeck 2013). The smallest network is formed by two individuals (referred to as nodes hereafter) and one relationship (referred to as ties hereafter) linking them, which is called a dyad. Larger networks can be studied through sociograms, in which interaction schemes of individuals in a network are visualized.

Understanding knowledge transfers is crucial to project success. Therefore, the AEC management literature addresses different aspects of knowledge transfer using SNA, particularly the dynamic and informal features of knowledge transfer networks (Garcia et al. 2021; Poleacovschi et al. 2017), motivations necessary for knowledge transfers (Chinowsky et al. 2008; Javernick-Will 2012), how boundary spanners facilitate knowledge transfers across different project entities and improve performance (Di Marco et al. 2010; Poleacovschi and Javernick-Will 2016), transferring organizational knowledge across projects (Wei and Miraglia 2017), and individual and organizational factors impacting knowledge transfer in interorganizational teams (Garcia and Mollaoglu 2020b; Ni et al. 2018). In an important study, Javernick-Will (2012) examined the knowledge-sharing motivations of project team members and found that social motivations, including conformity to organizational culture and reciprocation of others, were the most frequently mentioned reasons for knowledge transfer.

Although it has a great impact on knowledge transfer and subsequent project performance, few studies have examined the way individuals influence each other in terms of knowledge transfer in complex project teams (Javernick-Will 2012). This research fills this gap by establishing a social influence model to quantitatively determine the social influence occurring regarding knowledge transfer behaviors across project and group levels of project collaboration.

Social Influence in Knowledge Transfer Networks

Social influence theory explains how individuals change their beliefs, attitudes, or behaviors to conform to the norms of their social environment (Li et al. 2018). Conformity can occur in normative form (i.e., when a person changes their behavior with the expectation of being liked) or informational form (i.e., when a person lacks knowledge and acquires it from a group) (Deutsch and Gerard 1955). In this paper, we define social influence as attitude and behavioral changes through exposure to information and social interactions (Frank et al. 2018a; Marsden and Friedkin 1993), as dissemination of information is followed by influence flow (Li et al. 2018).

In project collaboration, individuals begin interactions with certain opinions, and as the project proceeds, they alter their beliefs, attitudes, or actions as a result of their interactions with others. Influence starts at the individual level when two individuals attempt to solve a problem by collaborating and creating new knowledge (Poleacovschi et al. 2017). Understanding the microlevel connections among individuals may explain knowledge transfer and behavior patterns at the group and project levels because these connections form macrolevel networks (Foss et al. 2010; Frank and Fahrbach 1999; Javernick-Will 2012). Although the individuals participating in group-level networks also are involved in project-level interactions, the network attributes measured using network metrics at the two levels are different due to the network size and composition. Therefore, in the context of this study, we developed the influence model using individuals' interactions to examine knowledge transfer at different levels to gain insight into how project networks function.

Structural properties of project networks are appropriate to use for examining influence (Brass 1984), because network properties of surrounding nodes affect the attitudinal and behavioral responses of the actors (Pauget and Wald 2013). In particular, the centrality of an actor in a network reflects an individual's power, status, or importance (Brass 1984), and the importance of nodes in a network spreads to the nodes to which they are connected as a behavior (Golbeck 2013).

In a network, the nodes with the highest centrality can control knowledge flows and affect the diffusion of information. Central nodes in a network participate in knowledge-sharing activities more actively (Baek and Bae 2019). For example, outdegree centrality is the number of ties that a node builds with other actors in a network, and it indicates the level of engagement (Freeman 1978). In other words, it can be used to determine the individuals who directly influence others in a social network (Das et al. 2018). Although outdegree centrality is useful for capturing influence (Duva et al. 2022), it accounts for the connections from a single person and indicates immediate influence (Borgatti 2005). Therefore, it is a measure of an egocentric network, and it gives less importance to the complete network. However, eigenvector centrality assigns relative scores to individuals based on the pattern of ties across the whole network, and calculates the centrality of a node based on the links from important nodes and their centralities (Bonacich 1972). Eigenvector centrality measures strategic and long-term direct and indirect influence, whereas outdegree centrality is a measure of immediate influence (Borgatti 2005). Therefore, eigenvector centrality is an ideal measure to use as an indicator for social influence processes and changes in knowledge transfer behaviors. The relationship between eigenvector centrality and knowledge transfer behaviors is discussed further in the "Methodology" section.

Froehlich and Carbonell (2022) discussed social influences in the context of team learning at three levels [i.e., the macrolevel (organizational network), mesolevel (team), and microlevel (team members)] to achieve project goals, and proposed using SNA and relational data to identify patterns, structures, and positions. They also stated that team learning at different levels is interrelated, and learning at each level influences learning at other levels. Peters et al. (2017) examined social influence via two construction projects to determine how diffusion of knowledge and network learning occur in interorganizational project networks. They stated that face-to-face negotiation, such as friendship ties; socialization, such as humor and informal communication; and utilization of artifacts trigger attitude change through influence mechanisms.

Network Boundaries and Social Influence

When evaluating social influence in networks, organizational and individual characteristics also should be taken into account (Frank et al. 2018b). Roles impact the influence processes because certain behavior patterns and expectations are attributed to different roles (Marsden and Friedkin 1993). Influence also is contingent on individuals' attitudes (Penuel et al. 2013). Overlooking individual characteristics might lead to uncoordinated practices and impair an organization's effectiveness in implementing innovations (Frank et al. 2018b).

Project collaboration networks might not always follow the organizational assignments, and there might be a misalignment among them (Fig. 1) (Hossain 2009; Zhao et al. 2021). Therefore, this study grouped individuals based on their comparative level of activity in collaboration networks (i.e., core–periphery status) (Borgatti and Everett 2000) as well as on their organizational assignments in the project network (Mollaoglu-Korkmaz et al. 2014). In core–periphery structures, the core consists of a small number of members who interact frequently, whereas the periphery is the members who are connected to the core sparsely (Borgatti and Everett 2000). Based on contractual relations and decision-making power, there are tiers and roles in a project organization network (Mollaoglu-Korkmaz et al. 2014): Tier 1 includes project managers; Tier 2 represents individuals from home organizations of Tier 1 members; and Tier 3 represents all other individuals, including subcontractors, vendors, and consultants. Roles [i.e., designer, owner, and general contractor (GC) in the context of this study] and tiers are based on organizational assignments, but anyone can be in the core team in a core–periphery collaboration network at any given time during project delivery despite their formal organizational role, tier, and expertise area.

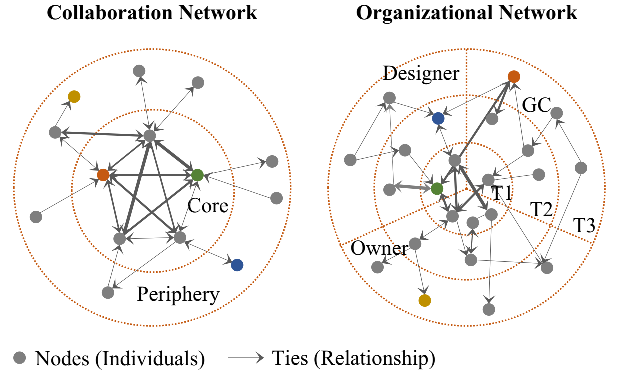

Fig. 1. Project networks according to communication behaviors and organizational assignments. Although organizational network is based on assigned roles, anyone can be in the core regardless of role, tier, or expertise area. Nodes with different shades represent a subgroup of individuals with different expertise. Arrows indicate the direction of the relationship. T1 = Tier 1, T2 = Tier 2, and T3 = Tier 3.

Determining core and Tier 1 members of the networks is important because those people might be opinion leaders and therefore have different influence patterns than the rest of the team (Valente 2010). This research also established a social influence model to quantitatively determine the differences in social influence occurring regarding the knowledge transfer behaviors of core and Tier 1 members.

Methodology

Data

We longitudinally collected data from a Leadership in Energy and Environmental Design (LEED)-certifiable expansion and renovation project that ran between 2018 and 2021. The project was budgeted at $22 million and was delivered via Construction Management at Risk. The data collection phase spanned the design (i.e., schematic design, design development, and construction documents) and construction phases throughout the project delivery.

The data included archival data (i.e., documents shared using online project management software and meeting minutes) and email exchange logs, and were collected in collaboration with the project owner, contractor, and designer. The archival data aided the creation of a timeline for data analyses and determining node characteristics (Tier 1 and the energy-efficiency group members). Email exchange logs consisting of email headers (i.e., sender, receiver, time, and subject line) were the main source to generate knowledge transfer networks and examine influence occurring, because influence does not occur merely as a result of face-to-face interaction, and the only precondition for influence is exposure to information (Marsden and Friedkin 1993). Using email exchange data eliminates self-reporting bias because it leaves a record, allows working on a large data set, and helps understand actual communication flows (Kadushin 2012; Quintane and Kleinbaum 2011). Moreover, email exchange is a convenient and common way of studying knowledge transfer in settings in which actors are geographically dispersed, as in the AEC industry (Du et al. 2020; Garcia and Mollaoglu 2020a; Jasimuddin 2007). Similarly, email exchange data represents different methods of knowledge transfer in the case study project, because team members were required to send follow-up emails for documentation purposes when they used a different medium for communication (e.g., face-to-face interaction or phone calls). The research team created Excel macros to discard irrelevant data (i.e., based on email subject and by eliminating emails from senders that were not related to the project, such as promotion, organizational, or personal emails) and conducted manual checks for nonrelevant emails that the algorithm could not catch. In addition, to verify whether the email exchange data were representative of all project communication, we (1) identified the 10 most frequently communicated individuals for team leaders, (2) showed them sociograms drawn using emails, and (3) asked them to give feedback and verify the sociograms based on their perceived team communication within the project. The team leaders verified that email data and communication patterns illustrated in the networks reflect overall project-specific team interactions.

Social Network Analysis

Fig. 2 summarizes the research framework. To examine the influence occurring between two time points, the first step was to use the archival data to determine the project episodes which showed the progress of the project (i.e., schematic design, design development, construction documents, and construction) (Garcia et al. 2014; Marks et al. 2001). Different episodes have different goals, changing the way team members interact with each other. Therefore, using project episodes as the key time points of reference, this study evaluated social influence processes longitudinally to understand the dynamic nature of knowledge transfer networks. Frank and Xu (2020) showed that influence models from cross-sectional data can be extremely biased due to uncontrolled selection based on prior behaviors. Models based on longitudinal data can directly control for these prior behaviors.

Second, we performed SNA to understand the knowledge transfer behaviors of individuals at the project level and group level for each project episode using email logs in Gephi software version 0.9.5. We determined the strength of the ties between nodes in the networks based on email exchange frequency and assigned 3, 2, and 1 as weights for daily, weekly, and monthly communication, respectively. We used core–periphery analysis for each episode to identify the core members of the networks by using UciNet version 6.773 (Borgatti and Everett 2000). We also determined Tier 1 members based on the archival data (e.g., team rosters, and weekly or biweekly project team meeting minutes).

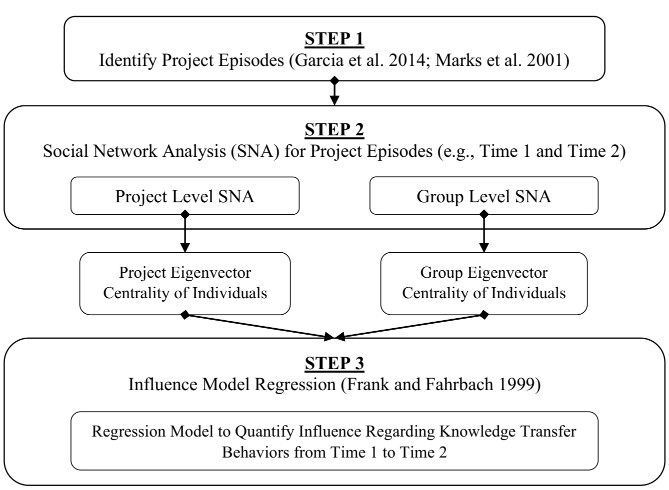

Fig. 2. Summary of the research framework.

We initially conducted project-level SNA including all team members from all groups, and calculated network metrics using Gephi for each episode. Then we identified energy-efficiency group members based on their node characteristics (i.e., expertise, roles, and tiers). Expertise areas and roles that should be collaborating in construction project teams for improved energy-efficiency outcomes include owner, commissioning authority, building manager, lighting designer, contractor, occupants, and mechanical engineer (USGBC 2020). Additionally, we scanned the email logs to determine the individuals working on the project's energy-efficiency issues such as the selection and commissioning of building energy systems to enable data triangulation. After determining the energy-efficiency group members, we conducted group-level SNA for the energy-efficiency subteam which involved the experts collaborating toward energy efficiency goals for each episode, and calculated network metrics. The last step was evaluating the influence regarding knowledge transfer behaviors by using the network metrics (i.e., eigenvector centrality) in the project-level network and the group-level network.

Eigenvector centrality was selected to calculate influence, based on the theory and previous work as discussed in the literature review. Additionally, we conducted supplemental analyses using knowledge transfer behaviors in face-to-face meetings to determine if the eigenvector centrality from email communication networks can be a proxy for knowledge transfer behaviors. To calculate knowledge transfer behaviors, two members of our team observed the weekly project team meetings and systematically recorded the number of times information was given by each individual in the meetings for each episode (the average correlation coefficient for intercoder reliability was $r = 0.89$). The average correlation coefficient between eigenvector centrality and information sharing behaviors of individuals in the meetings was $r = 0.75$ for all episodes. Because the number of meeting attendees was lower than the number of all project members in the project networks, we used eigenvector centrality to evaluate holistically the influence processes in project teams.

Social Influence Modeling

We used the following social influence model adopted from Frank and Fahrbach (1999) and Marsden and Friedkin (1993), in which the influence is a function of exposure of i to the attributes of j through interaction:

$$y_{it1} = \rho \sum_{j=1}^{n} [w_{ij(t0\rightarrow t1)} z_{j(t0)}] + \gamma y_{it0} + e_{it} \tag{1}$$

where y_{it1} = group-level eigenvector centrality of node i at time t_1, denoting the subsequent potential knowledge transfer behavior of member i within the energy efficiency group network; y_{it0} = group-level eigenvector centrality of node i at time t_0, denoting the original potential knowledge transfer behavior of member i within the energy-efficiency group network; $w_{ij(t0\rightarrow t1)}$ = project-level interactions received by i from j during period t_0–t_1; z_{jt0} = project-level eigenvector centrality of node j at time t_0, denoting the original potential knowledge transfer behavior of member j in the project network; $\sum_j^n w_{ij(t0\rightarrow t1)} z_{j(t0)}$ = project-level exposure, indicating potential influence of project member j on group member i during period t_0–t; ρ = degree of influence; γ = extent to which people repeat prior behaviors; and e_{it} is an error term.

According to the social influence model, the knowledge transfer behavior of an actor i at the group level at t_1 (y_{it1}) depends on the knowledge exposure that the actor obtains from the whole project network and the actor's previous knowledge transfer behavior at t_0

at the group level (y_{it0}). Exposure is calculated as the summation of interactions with individuals multiplied by the knowledge transfer behaviors of those individuals interacted in the project network ($\sum_j^n w_{ij(t0\rightarrow t1)} z_{j(t0)}$).

We used the social influence model to analyze the social influence regarding knowledge transfer at three different time points, namely schematic design–design development (Analysis 1), design development–construction documents (Analysis 2), and construction documents–construction (Analysis 3). We estimated the analyses for the energy-efficiency group members who were present in two successive episodes. For example, for Analysis 1, new energy efficiency group-level knowledge transfer (y_{it1}) was calculated as the eigenvector centrality in the energy-efficiency group network in the design development episode, which was a function of the exposure occurring during the schematic design phase in the project network (t_0–t_1) and the knowledge transfer at the schematic design episode in the energy-efficiency group network (y_{it0}).

Because the robustness of these three analyses varied but showed evidence of influence, we also estimated a single influence model by stacking the data from three time points to understand how influence occurred throughout the project delivery. To do so, we added dummy variables for the different analyses [Eq. (2)]. Because of stacking data from three time points, some nodes were repeated in the data set more than once. Therefore, to account for the dependence of the observations, we included the nodes as fixed effects and ran mixed analysis

$$y_{it1} = \rho \sum_{j=1}^{n} [w_{ij(t0\rightarrow t1)} z_{j(t0)}] + \gamma y_{it0} + \text{Dummy1} + \text{Dummy2} + e_{it} \tag{2}$$

We also estimated the influence regarding knowledge transfer behaviors of core members using stacked data [Eq. (3)]. Because of concerns about collinearity and as indicated by increased standard errors from the fixed effects added, the reported results of these models are without the fixed effects. We repeated the same analysis with the stacked data for Tier 1 team members as well

$$y_{it1} = \rho \sum_{j=1}^{n} [w_{ij(t0\rightarrow t1)} z_{j(t0)}] + \gamma y_{it0} + \text{Dummy1} + \text{Dummy2} + \text{Core} + [\text{CE}] + e_{it} \tag{3}$$

where y_{it1} = group-level eigenvector centrality of node i at time t_1, denoting the subsequent potential knowledge transfer of member i within the group network; y_{it0} = group-level eigenvector centrality of node i at time t_0, denoting the original potential knowledge transfer of member i within the group network; $w_{ij(t0\rightarrow t1)}$ = project-level interactions received by i from j during period t_0–t_1; z_{jt0} = project-level eigenvector centrality of node j at time t_0, denoting the original potential knowledge transfer of member j in the project network; $\sum_j^n w_{ij(t0\rightarrow t1)} z_{j(t0)}$ = project-level exposure, indicating potential influence of project member j on group member i during period t_0–t_1; Core $= 1$ for core members, and 0 for periphery members; CE $=$ (Exposure of $i -$ Mean_Exposure) $\times$ (Coreness of $i -$ Mean_Core); ρ = degree of influence; γ = extent to which people repeat prior behaviors; and e_{it} = error.

Results

Table 1 presents the number of nodes in the project-level network and group-level network for each episode, and an example of project-level and group-level networks is demonstrated in Fig. 3. The number of individuals (i.e., observation number) for Analysis 1 was 34 and 39, and 48 for the successive analyses. The exposure calculated for energy-efficiency group members was based on their interactions at the project level, as mentioned in section "Methodology." Tier 1 (representing assigned leads in the project organization) and core member (representing emerged leads in the communication network) numbers in the project network also are identified in the table.

Table 1. Numbers of network members

Network	Sch des	Des dev	Cons docs	Cons
Project-level	178	183	244	875
Energy-efficiency group-level	43	44	62	65
Core members in analysis	12	11	9	—[a]
Tier 1 members in analysis	7	7	7	5

Note: Sch des = schematic design, Des dev = design development, Cons docs = construction documents, and Cons = construction.
[a]Core–periphery structure is rejected, and thus no core members are listed.

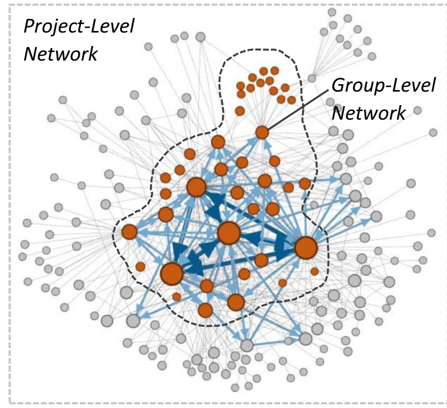

Fig. 3. Sociogram showing the project-level and group-level knowledge transfer networks in the schematic design episode. Group-level network denotes the energy efficiency subteam members. Node size denotes eigenvector centrality.

Table 2 lists the regression results of the three social influence analyses. The results show that the fits of all analyses were significant ($p < 0.001$), indicating the existence of a relationship between the original and subsequent knowledge transfer. The results also show that project-level exposure was a significant predictor of subsequent group-level knowledge transfer for Analyses 2 and 3 ($p < 0.05$). In addition, project-level exposure positively influenced group-level knowledge transfer in project teams (coefficients ranged between 0.447 and 1.184).

The strongest counterexplanation to our inference of influence on knowledge transfer is based on the selection of network members. Specifically, those who already had high levels of engagement may have chosen to interact to interact with similar others, negating our interpretation of the influence occurring. Our first response is that we controlled for the prior rate of behaviors. Frank and Xu (2020) showed that if selection occurs based only on prior behaviors, then controlling for prior behaviors, as we did, removes the bias. Furthermore, we recognize that there still may be concerns about selection bias that cannot be attributed solely to the prior behaviors for which we controlled. Therefore, we performed sensitivity analysis using KonFound-It causal inference robustness tool (Rosenberg et al. 2022) and quantified how much of the

Table 2. Regression results of influence model

Analysis	N	R^2	p-Value	Variable	Coefficient	Standard error	p-value
Analysis 1	34	0.646	<0.001	Y_{it0}	0.240	0.426	0.577
				Exposure	0.447	0.425	0.302
Analysis 2	39	0.719	<0.001	Y_{it0}	−0.322	0.347	0.360
				Exposure	1.184	0.358	0.002
Analysis 3	48	0.668	<0.001	Y_{it0}	0.144	0.310	0.644
				Exposure	0.677	0.313	0.035

Table 3. Regression results of stacked influence model with nodes as fixed effects

						95% confidence interval	
Parameter	Estimate	Standard error	df	t	p-value	Lower bound	Upper bound
Intercept	0.155	0.080	63	1.938	0.057	−0.005	0.315
Exposure	0.844	0.290	63	2.912	0.005	0.265	1.424
Y_{it0}	−0.524	0.265	63	−1.979	0.052	−1.053	0.005
Dummy1	−0.032	0.028	63	−1.170	0.246	−0.088	0.023
Dummy2	−0.037	0.026	63	−1.409	0.164	−0.089	0.015

Table 4. Regression results of stacked influence model for core members

Analysis	N	R^2	p-value	Variable	Coefficient	Standard error	p-value
1. Stacked core	121	0.668	<0.001	Y_{it0}	−0.213	0.265	0.424
				Exposure	1.045	0.336	0.002
				Dummy 1	−0.047	0.031	0.133
				Dummy 2	−0.028	0.030	0.345
				Core	0.056	0.047	0.238
				CE	−0.296	0.227	0.196

estimated effect of exposure must be due to uncontrolled bias to invalidate the inference (Frank et al. 2013). For Analysis 2, to invalidate our inference, 38.787% of the estimate would have to be due to bias. Following Frank et al. (2013), this can be interpreted as meaning that in order to invalidate an inference, 15 observations would have to be replaced with cases for which the effect is 0 [robustness of inference to replacement (RIR) = 15]. Within the context of this study, the findings suggest that an individual's exposure to the overall project collaboration has a positive impact on their sharing, disseminating, and inputting of energy-efficiency–related knowledge for problem solving. An exception is Analysis 1, in which the exposure's impact was not observed early in project delivery between the periods of schematic design and design development.

Because the robustness of these three analyses varied but showed evidence of influence, we also estimated a single influence model by stacking the data from three times points. The influence model with the stacked data showed that the exposure had a positive effect (coefficient $= 0.844$; $p = 0.005$) on the subsequent group-level knowledge transfer, controlling for nodes with fixed effects (Table 3). We also used random effects with the nodes, and the estimate and interpretation were very similar (exposure coefficient $= 0.840$; $p < 0.001$), with a smaller standard error (0.215). The coefficient for Y_{it0} was negative (−0.524), because it was collinear with the nodes as fixed effects. When we repeated the same analysis by removing the nodes as fixed effects, Y_{it0} was positive, with a coefficient of 0.036.

We also performed sensitivity analysis using KonFound-It for the stacked model and we quantified how much of the estimated effect of exposure must be due to uncontrolled bias (Frank et al. 2013). For the analysis in which the nodes were fixed effects, to invalidate our inference, 38.358% of the estimate would have to be due to bias. That is, to invalidate an inference, 38 observations would have to be replaced with cases for which the effect is 0 (RIR $= 38$) (Frank 2000).

We also estimated the influence regarding knowledge transfer behaviors of core members using stacked data. The result of the analysis showed that influence may be weaker for the members of the core (Table 4). The core members of the networks were the outliers of the social influence model, and their behavior change was less than that for the rest of the team. They were influenced less by being exposed to less-extreme people. When we controlled for the core members, the estimated influence of team members was stronger (coefficient $= 1.045$).

We performed the same analysis with the stacked data to test whether exposure also was weaker for members of Tier 1, and the results indicated that influence may be weaker for Tier 1 members (Table 5). Most Tier 1 members were involved in the core throughout the project delivery, and additional members entered and exited the core based on the project needs.

Discussion

By using social influence mechanisms, diffusion of necessary practices and behaviors can be enabled for better project performance, but few studies have examined the concept in project teams. Therefore, this study investigated changes in knowledge transfer behaviors of team members that occur through social influence mechanisms as a result of information exchanges between different levels of project

Table 5. Regression results of stacked influence model for Tier 1 members

Analysis	N	R^2	p-value	Variable	Coefficient	Standard error	p-value
1. Stacked Tier 1	121	0.668	<0.001	Y_{it0}	−0.070	0.238	0.771
				Exposure	0.912	0.279	0.001
				Dummy 1	−0.046	0.032	0.151
				Dummy 2	−0.026	0.030	0.380
				Tier 1	0.003	0.055	0.964
				TE	−0.136	0.167	0.416

Note: Tier 1 = 1 for Tier 1 members, and 0 for others; TE = (Exposure of i − Mean Exposure) × (Tier 1 status of i − Mean Tier 1 status).

collaboration. This research found quantitative evidence that exposure to project-level knowledge transfer exerts a causal influence on group-level knowledge transfer of individuals within project collaborations. The outcomes of this research provide theoretical and practical implications to better understand and implement collaboration and influence mechanisms, especially in complex project organizations.

Theoretical Implications

First, this study quantitatively confirmed that knowledge transfer behavior is dynamic, and individuals' knowledge transfer behaviors in their subteam changes as a result of their project-level knowledge transfer interactions. In other words, exposure to diverse information from different subteams at the project-level is a significant predictor of the subsequent group-level knowledge-transfer behaviors. In this paper's context, we found that interacting with influential and central members of the project network positively impacted the knowledge transfer of an individual in the energy efficiency subteam network and made them more influential by increasing their centrality in the following episode. The results indicate that being connected to individuals from different social circles and obtaining novel and diverse expertise promote sustainability knowledge transfer (Granovetter 1973; Henry and Vollan 2014). The results support the idea that every relationship in a network creates an opportunity for the actors to access knowledge and achieve creative outputs (Froehlich and Carbonell 2022; Kratzer et al. 2010). We also observed that during the early stages of the projects, the influence might not occur due to a lack of deep knowledge transfer (Garcia et al. 2021).

Second, this study suggests from a quantitative standpoint that team members reciprocate knowledge transfer behaviors of their colleagues and the action of receiving knowledge by giving in the future as a result of influence mechanisms (Froehlich and Carbonell 2022; Javernick-Will 2012). However, we found that opinion leaders (i.e., Tier 1 or core members) received weaker influence and their knowledge transfer changed little over project delivery. This reflects a paradox that team leaders often have strong exposure, but they are difficult to be influenced during the information exchange with many others in their networks. They are good at influencing others but cautious about changing their beliefs so as not to lose their positions in the network (Kadushin 2012; Valente 2010). The results support the idea that opinion leaders do not embrace an idea before the majority does and they exercise their influence (Valente and Pumpuang 2007).

Third, this study used eigenvector centrality as a proxy for knowledge transfer behaviors, and suggests that eigenvector centrality can be used as a measure of attitude (Brass 1984). To the best of our knowledge, few prior studies in the project management literature used network properties to evaluate social influence regarding knowledge transfer behaviors quantitatively and longitudinally. The study findings suggest that individuals with high eigenvector centrality spread it as an attitude to their connections (Golbeck 2013).

Practical Implications

The findings provide practical implications for complex AEC project teams. Understanding how network structure and the social dynamics of a network mutually inform each other can help project managers develop practical and managerial strategies for successful project delivery.

First, project managers should promote project-level knowledge transfer at early stages in project delivery [e.g., preferably no later than design development (Swarup et al. 2011), as allowable by the selected delivery methods] so that team members' subsequent group-level knowledge transfer behaviors can be enhanced by social influences. To further catalyze influence mechanisms over time in project delivery for improved performance outputs, project managers should facilitate opportunities, such as meetings or charettes, for key subteam leaders corresponding to the priority issues and project goals early in design phases to promote a cohesive team with goal alignment and achieve higher knowledge integration (Franz et al. 2017; Mollaoglu-Korkmaz et al. 2013).

Second, subteam leaders should encourage and empower their team members to interact with other subteams by crossing group boundaries when needed. Cross-team knowledge transfer is not a waste of time or effort when strategically coordinated by subteam leaders. Instead, cross-team interactions can facilitate the flow of novel ideas and knowledge transfers at the group level (Kadushin 2012; Di Marco et al. 2010). Therefore, subteam members can attend project-level events or meetings for targeted discussions. For example, a mechanical or electrical engineer can provide the designer with tremendous insight into the details of interior design, which might minimize the project cost and duration.

Third, project managers should promote knowledge transfer between opinion leaders and peripheral members to accelerate the diffusion of the necessary information and behaviors from opinion leaders to all project members to implement innovation (Lee et al. 2018). Opinion leaders with a higher influence and central position spread their attitudes and centrality to the people with whom they interact and help propagate innovations (Henry and Vollan 2014), because increased centrality has a positive effect on performance (Sanchez et al. 2017).

Fourth, project managers and opinion leaders should recognize peripheral members who bring innovative ideas. The findings show lower attitude change for opinion leaders. Although this can give stability to the system during project delivery, it also might reduce the project team's innovative capacity. Therefore, project managers should involve key peripheral members in collaboration networks proactively and early in project delivery (e.g., early involvement of a mechanical engineer during the design phase) to ensure influence. Involvement might include copying key peripheral members in relevant emails, inviting them to face-to-face meetings for targeted discussions, and increasing their access to project information (Duva et al. 2020; Zhao et al. 2021).

Conclusion

Complex project teams often include professional subteams with distinct backgrounds and competencies. Project members should collaborate efficiently, within and across subteams, to fulfill project expectations and diffuse desired practices. Cross-level knowledge transfer (i.e., social interactions to send and receive knowledge) becomes difficult due to the increased number of subteams, requirements, and technical components in complex project teams. In particular, there is a lack of quantitative evidence explaining the mechanism by which project-level social interactions impact subteam (group-level) knowledge transfers. Therefore, this study mathematically explored the relationships between project-level and group-level knowledge transfers longitudinally during project delivery, using the approaches of social network analysis and social influence modeling.

The findings mathematically confirmed that the exposure to project-level knowledge transfer is a positive predictor of the subsequent group-level knowledge transfer. Knowledge transfer in this study was measured by eigenvector centrality, which is a measure of the influence of members in team communication networks. In addition, being exposed to individuals from different social circles with different expertise and high eigenvector centrality positively impacts the eigenvector value of an individual in the group-level network and makes them more influential subsequently. Opinion leaders in the networks change their attitudes less than the rest of the team, and they exercise their influence on others. Moreover, the network properties can be used to evaluate behavioral changes such as eigenvector centrality.

Limitations exist in this study, which can be addressed in future research. The scope and generalizability of the findings might be limited due to the use of a single, medium-sized case study delivered using Construction Management at Risk. Although we identified a causal relationship between project-level and group-level knowledge transfer, we acknowledge that there might be other confounders for our causal estimates. Although we validated that email exchange data represent project team communication, influence was estimated using the email exchange data without examining the impact of other communication methods such as face-to-face interactions, online meetings, or text messages. Future research can extend this work and explore the influence mechanisms in larger or smaller project networks. Nevertheless, this study provides a foundation for future applications in industries in which temporary interorganizational and interdisciplinary project teams exist by (1) providing quantitative evidence of how influence mechanisms impact knowledge transfer behaviors, and (2) showing how email network metrics can be used as a proxy for knowledge transfer behaviors.

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.

Acknowledgments

This research was supported by the National Science Foundation through Grant No. 1825678. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the researchers and do not necessarily reflect the views of the National Science Foundation.

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