



Structural Leadership Improves Student Engagement in Collaboration

Dong Zhao, Ph.D., M.ASCE¹; Zhiting Chen²; George Berghorn, Ph.D.³; Lei Shu, A.M.ASCE⁴; and Cornelia Asiedu-Kwakyewaa⁵

Abstract: In civil engineering and construction management programs, student collaboration is important for their skill building, but its relationship with student engagement remains elusive. This study explored this relationship by examining the structure and characteristics of student collaboration networks. The results underscore the significance of network diameter as a measure of reachability and communication efficiency—a smaller network diameter correlates with higher engagement and suggests quicker and more-efficient communication in student groups. Structural leadership is a key factor in reducing the diameter and enhancing engagement by facilitating communication and bridging structural connection holes. In this context, structural leaders (i.e., brokers or bridges) who connect disconnected students or isolates play a more crucial role than opinion leaders (i.e., influencers or hubs) who connect a larger number of students. The findings reflect the ideal dual-lead pattern observed in industry collaborations, in which a technical lead makes critical decisions and a coordination lead diffuses knowledge and information. Strategies to nurture structural leadership are proposed, including leveraging virtual collaboration such as BIM and focusing on cultivating bridge students and their coordination skills. Additionally, the study highlights the benefits of small-world networks and reveals that demographic factors have little significant influence on engagement levels. DOI: [10.1061/JCECD.EIENG-2027](https://doi.org/10.1061/JCECD.EIENG-2027). © 2024 American Society of Civil Engineers.

Author keywords: Engagement; Virtual collaboration; Construction management; Engineering education; Network analysis.

Introduction

Student engagement is associated with their university experience. Evidence shows that engagement is related positively to various educational outcomes such as academic achievement (Fredricks et al. 2004; Hughes et al. 2008; Kuh et al. 2011; Ladd and Dinella 2009), student satisfaction (Filak and Sheldon 2008; Zimmerman and Kitsantas 1997), student persistence in learning (Berger and Milem 1999; Fredricks et al. 2004; Kuh et al. 2011), and social capital (Harper 2008). In the learning process, interactivity is considered to be an essential component (Blasco-Arcas et al. 2013); it encourages students to participate actively in classroom activities, which is a foundation for collaborative learning (Guthrie and Carlin

2004; Thalheimer 2003). Sustained participation in learning activities therefore fosters the development of engagement (Erbaş et al. 2018; Taffere et al. 2024; Webb and Carnaghan 2006). The present study defines engagement in a collaborative project as active participation, contribution, commitment, interaction, involvement, and cooperation of individuals or groups in a particular task or activity (De Weger et al. 2018; Taffere et al. 2024). Research on student engagement helps evaluate educational systems and generate positive improvement. For example, Pascarella and Terenzini (1991) suggested that the best way to enhance student persistence is to focus on social and academic activities in which students are involved during college. Proactive student engagement and social interactions with peers are highly intertwined during the learning process (Tinto 1987; Wolf-Wendel et al. 2009).

Collaborations impact the academic performance, social engagement, and career development of college students. Although student engagement in collaborative learning has a significant positive correlation with their learning outcomes and academic success (Blasco-Arcas et al. 2013), the mechanisms of how collaborations influence engagement are not well established. Some studies emphasized social capital, which increases self-efficacy, achievement, retention, and other valuable abilities for future career (Ellison et al. 2007). Some studies encourage active classroom activities that increase the development of social networks, student interpersonal interaction, perception of social support, liking among students, friendship, and social learning relations (Algan et al. 2013; Chi and Wylie 2014; Johnson et al. 1998; Rienties and Nolan 2014). Overall, social networks built upon collaborations connect students, establishing social capital in college life and facilitating powerful means to maintain the social ties for future benefits—for example, job opportunities.

Most civil engineering and construction management programs highlight the importance of student collaboration. Assignments—for example, team projects—are used widely in construction-related

¹Associate Professor, School of Planning, Design, and Construction, Michigan State Univ., 552 W. Circle Dr., East Lansing, MI 48824; Associate Professor, Dept. of Civil and Environmental Engineering, Michigan State Univ., 552 W. Circle Dr., East Lansing, MI 48824 (corresponding author). ORCID: <https://orcid.org/0000-0002-2404-7669>. Email: dz@msu.edu

²Formerly, Graduate Assistant, School of Planning, Design, and Construction, Michigan State Univ., 552 W. Circle Dr., East Lansing, MI 48824. Email: chenzh38@msu.edu

³Assistant Professor, School of Planning, Design, and Construction, Michigan State Univ., 552 W. Circle Dr., East Lansing, MI 48824. Email: berghorn@msu.edu

⁴Ph.D. Student, School of Planning, Design, and Construction, Michigan State Univ., 552 W. Circle Dr., East Lansing, MI 48824. ORCID: <https://orcid.org/0009-0008-0086-4702>. Email: shulei1@msu.edu

⁵Ph.D. Student, School of Planning, Design, and Construction, Michigan State Univ., 552 W. Circle Dr., East Lansing, MI 48824. ORCID: <https://orcid.org/0000-0001-6458-0057>. Email: asiedukw@msu.edu

Note. This manuscript was submitted on May 31, 2023; approved on June 26, 2024; published online on September 14, 2024. Discussion period open until February 14, 2025; separate discussions must be submitted for individual papers. This paper is part of the *Journal of Civil Engineering Education*, © ASCE, ISSN 2643-9107.

courses to develop students' collaboration skills. In practice, collaborations occur throughout all stages of the architecture, engineering, and construction (AEC) project process. The assignments offer an excellent opportunity to enhance student engagement across the collaborative learning process. The social networks generated and/or maintained throughout the collaboration can be a potential predictor of student engagement (Zhao et al. 2019); however, the correlations have not been identified, at least in the engineering education area. Most researchers focus on instructional or pedagogical design to encourage active student engagement from the instructor's perspective (Peterson and Fennema 1985; Tanner 2013). There is a lack of studies that explore student interactions and student engagement from the student's perspective.

The objective of this study was to identify the relationship between student engagement and their collaborations through the lens of network theory. In other words, we sought to understand how student collaboration networks (e.g., network structure, density, and centrality) are associated with their engagement levels. In particular, we explored two research questions rooted in the engineering education field: (1) What collaboration groups are likely to have high engagement at the group level? (2) Who in a collaboration network is likely to have high engagement at the individual level? From the network perspective, the first research question focuses on the network structure, and the second research question focuses on the network nodes. We surveyed participants to collect data about their collaboration network and their levels of engagement. We performed social network analysis and regressions to analyze the relationships. The outcomes indicate the network characteristics that influence student engagement in collaborations. The understanding of engagement in collaborations also benefits construction project management—for example, fostering appropriate project planning to minimize expensive change orders and cost overruns.

Background

Student Engagement in Collaboration

Engagement is important for student success as well as teaching. Fredricks et al. (2004) framed student engagement in higher education using three dimensions: affect, cognition, and behavior. The affective dimension of engagement refers to a student's enthusiasm, interest, and sense of belonging in college. The cognitive dimension of engagement represents self-regulated learning and a deep learning approach. The behavioral dimension of engagement involves the evaluation of a student's time and effort, interaction, and participation. Social engagement has been studied widely regarding the influences in higher education such as motivation, learning outcomes, and academic success (Gordon et al. 2008; Zepke et al. 2010).

Learning through collaboration in AEC-related courses facilitates teamwork spirit and builds communication skills for future career development. Active engagement in such collaborative learning significantly affects the students' learning outcomes from project work. Instructors can advise students to develop relationships with peers and foster their social engagement to build social capital, which is vital to their academic and career success. Student disengagement in the behavioral dimension leads to a higher school dropout rate (Archambault et al. 2009). A study of gender found that there is a significant gender disparity in scientific collaboration; men tend to cooperate more, whereas women have greater commitment to egalitarian principles (Araújo et al. 2017). Although previous social capital research explained differences in school experience networks based on class, gender, and race and/or ethnicity

(Lin 2000), the impact of these factors on student engagement in a college classroom is confirmed. Peterson and Fennema (1985) identified sex-related impacts on student engagement in classroom activities. Zunzunegui et al. (2003) used hierarchical regression analysis to test the influence of gender on social engagement and the effects of age and level of education on cognitive function. Kelly (2009) proposed a framework to study the effect of social identity on student engagement.

Social engagement in college is highly associated with student collaboration and academic success. Ream and Rumberger (2008) suggested that active engagement and networking contributed to lower school dropout rates. Kahu (2013) interpreted student engagement as a dynamic network constructed by various correlated factors. Overall, social engagement and collaboration networks are used widely to examine social relations, but few have studies analyzed their correlations.

Network Approaches in Education Research

Social network analysis (SNA) is a reliable approach for visualizing network characteristics and structure, aligning with the fundamental principles of sociology. It enables the mathematical identification and representation of interactions between individuals and groups in a sociogram, thereby determining the significance of each individual at the organizational level. SNA-based approaches focus on various constructs, including individual interactivity, role, and position, as well as their influence on group cohesion (Saqr et al. 2018). At the individual level, centrality measures in social network analysis assess the importance of central nodes based on proximity and communication activity (Duva et al. 2024; Scott 1988). These measures provide insight into the influence of group members and illustrate their social relations within the group structure (Xie et al. 2018). Degree centrality focuses solely on direct interactions to indicate authority, whereas eigenvector centrality identifies hubs in the network that have strong connections to influential individuals. Betweenness centrality and closeness centrality assess an individual's overall influence within the network. Group-level SNA allows for a comprehensive examination of organizational social structure patterns by identifying network clusters based on dense interactions within the group (McCulloh et al. 2013). It aims to assess the effectiveness of group collaborations and information sharing. This study employed subgroup size, density, diameter, average degree, and centralization as measurements to analyze network patterns at the group level. Density, which is calculated using probability, represents the ratio of actual links to the total possible links within the network. Diameter refers to the longest geodesic in the network, and measures the overall network connectedness. Average degree indicates the average number of edges per node in the network. Network centralization is evaluated based on individual nodal centrality; degree centralization assesses the relative dominance of nodes in the network, betweenness centralization identifies potential gatekeepers, and closeness centralization indicates the proximity of a presiding node to all other nodes in the network.

The formation of social links is driven by social forces. For example, reciprocity reflects the tendency of individuals to maintain relationships with those who actively interact with them. Transitivity allows for the expansion of social connections to third parties, significantly promoting group collaborations and information sharing within the network. The ability to share information, such as knowledge and resources, through social interactions is referred to as social capital (McCulloh et al. 2013). Social capital is accumulated through social networks, but its measurement presents challenges (Shea et al. 2014). In a class setting, the instructor

(or, in a project team, the construction manager) often acts as a high-betweenness node, playing a critical role in facilitating information sharing and fostering the formation of social capital among members. Therefore, optimizing social connections at the nodal level can significantly enhance group cohesion and productivity.

The integration of SNA offers a reliable means to evaluate students' class participation by examining the influence of peer relations (Rabbany et al. 2011). Xie et al. (2018) utilized SNA to rank students' contributions in an online learning community, allowing for the assessment of leadership behaviors and an understanding of performed leadership roles based on centrality measures. Additionally, SNA provides a network perspective to assess the effectiveness of course design and enhance teaching instruments for interactive class activities (Ouyang and Scharber 2017). Saqr et al. (2018) proposed that appropriately designed interventions can enhance the existing social structure of online learning communities. Numerous studies have explored the relationship between complex communication and interaction behaviors and students' academic performance by analyzing their positions within social learning networks (Mansur and Yusof 2013; Zhao et al. 2019).

Methods

Participants

We recruited 132 students of construction and civil engineering to participate in this study. They were from two universities at distinct locations in the US. Both universities have distinguished civil and construction programs that emphasize project collaborations (Chiocchio et al. 2011). We adopted the selective sampling technique to reach out to the participants because the participating institutions are representative to suit the study objective. Overall, 111 valid respondents were finalized for data analysis after the detection of missing data. The final sample consisted of 77% male respondents and 23% female respondents. The respondents' ages ranged from 18 to 43, with a median age of 22. In terms of race and ethnicity, 69% of respondents self-identified as White, 21% self-identified as American Asian, 6% self-identified as Hispanic or Latino, 3% self-identified as black, and 1% self-identified as American Indian or Alaska Native. The majority of students were seniors (58%), and 40% were juniors; 44% of the respondents were

from University P, and 56% of the respondents were from University Q. The distribution was consistent with the department demographics: 82% of the students were ages 20–25; 78% of the students were male and 22% were female; and 75% of students were White. This indicates that our sample was a true reflection of the population.

Procedure

We surveyed the participants when they were collaborating on project assignments. The data collection included three components: the collaborative network attributes, the participant engagement level, and participant demographic information. First, participants were asked to report two to five close partners with whom they collaborated on activities such as homework, labs, studying for exams or quizzes, sharing notes, textbooks, and information on deadlines and online file repositories. The collaboration channels included face-to-face meetings, emails, text messaging, and video chats. The participants also were asked to provide the strength of the collaboration interactions, measured by frequency (i.e., the number of times they collaborate per week) and duration (i.e., the length of each collaborative activity). Second, participants were asked to answer 13 questions to measure their level of engagement, adapted from Hunsu et al. (2018). The measurement of engagement consisted of three constructs: trust, reciprocity, and sense of belonging. The questions were on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Third, participants were asked to report their age, gender, race and ethnicity, grade, and institution. The data were collected using Qualtrics. The project was reviewed under IRB#STUDY00007658 at Michigan State University.

Measures and Analysis

We conducted social network analysis to visualize network sociograms and calculate network attributes. Table 1 lists the network attributes that represented the network structure at the group level or the nodal position at the individual level. We also conducted descriptive analysis to report the collaboration networks.

We constructed two regression models to use network attributes to predict engagement. The first regression model was used to answer the first research question, i.e., to identify the relationship

Table 1. List of network attributes

Level	Network attribute	Description
Group	Network density	Ratio of observed edges to the number of possible edges. In networks with the same number of nodes, more observed edges lead to higher density and indicate more interactions among nodes.
	Network diameter	Length of the longest path between two nodes in the network. It indicates the separated of nodes from one another in a network.
	Degree centralization	Centralization describes the extent to which a subgroup is organized around the most central point. Degree centralization is the ratio of the actual sum of differences to the maximum possible sum of differences in degree centrality.
	Closeness centralization	Ratio of the actual sum of differences to the maximum possible sum of differences in closeness centrality
	Betweenness centralization	Ratio of the actual sum of differences to the maximum possible sum of differences in betweenness centrality
Individual	Degree centrality	Total number of connections linked to a node. Higher degree centrality indicates that the node is more central.
	Clustering coefficient	Ratio of the number of edges connecting a node's neighbors to the total number of possible edges between the node's neighbors. When a node's neighbors have dense connections, the node's clustering coefficient is high.
	Eigenvector centrality	A measure of the transitive influence of nodes. Connections originating from high-scoring nodes contribute more to the score of a node than do connections from low-scoring nodes.
	Closeness centrality	Average of the shortest path length from the node to every other node. Closeness centrality indicates how close a node is to all other nodes in the network.
	Betweenness centrality	Number of shortest paths between two other nodes that pass through the node. A node that has a high betweenness centrality appears in many shortest paths.

between network structure and student engagement at the group level [Eq. (1)]. The dependent variable was the aggregate engagement for each group; the independent variables were the attributes of network structure in Table 1 (i.e., network density). The second regression model was used to answer the second research question, i.e., to identify the relationship between nodal position and engagement at the individual level [Eq. (2)]. The dependent variable was the engagement of each individual member; the independent variables were the attributes of each member's nodal position listed in Table 1 (i.e., degree centrality). Additionally, we controlled demographic factors such as age, gender, years in college, and ethnicity

$$Y = \Sigma\beta_1X_1 + \Sigma\beta_2C_1 + \sigma \quad (1)$$

where Y = student engagement; X_1 = group-level network attributes; C_1 = group-level control variables; β = impact of predictors X_1 on Y ; and σ = variability in Y that cannot be explained by predictors and control variables

$$Y = \Sigma\beta_1X_2 + \Sigma\beta_2C_2 + \sigma \quad (2)$$

where Y = student engagement; X_2 = individual-level network attributes; and C_2 = individual-level control variables; β = impact of predictor, i.e., individual-level network attributes X_2 on student engagement Y ; and σ = unexplained variability in Y that cannot be explained by predictors and control variable.

Results

Group-Level Engagement

Fig. 1 displays the sociogram of the whole academic network that visualizes students (nodes) and their collaborations (ties). A total of 13 student groups were determined by network modularity through social network analysis. Modularity is a measure of network structure, which determines the strength of division of a network into groups (also called subgroups, clusters or communities). Networks with high modularity have dense within-group connections and sparse cross-group connections between the nodes. Some subgroups were larger, with many students, and they were well connected, whereas some subgroups were smaller, with few students, and they were isolated.

Table 2 lists the results of network attributes. The results indicate the following network characteristics for student collaboration:

1. Student groups generally were not dense, and had sparse connections [mean density = 0.106 (10.6%)]. Sparse networks imply simple connections for student collaboration which lacks a certain pattern or extensive connectivity.
2. Student groups were not quick and efficient in communication; a student has to go through at least four students (mean diameter = 4.462) to reach another member.
3. Student groups had a moderately centralized network structure, and were not dominated heavily by a few highly central nodes.

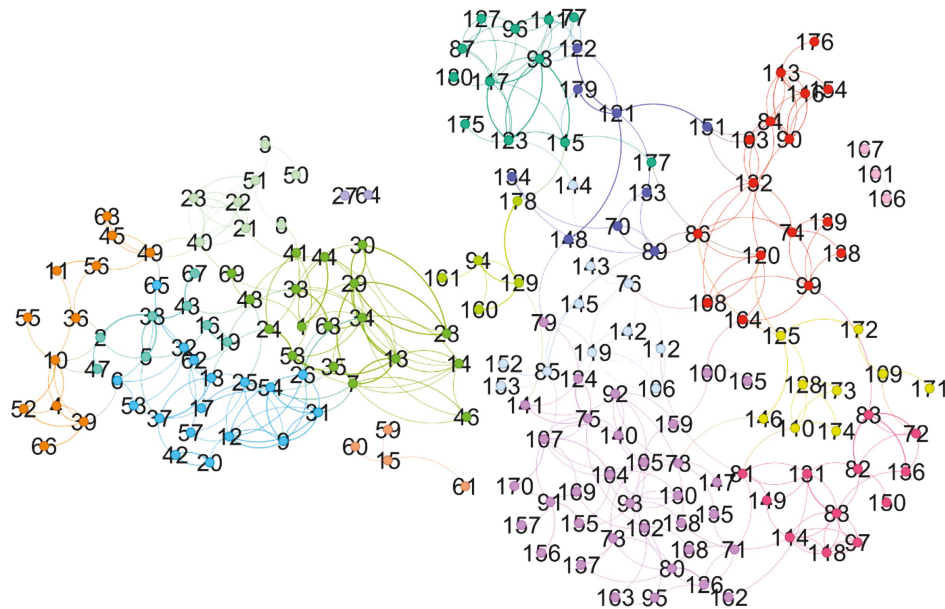


Fig. 1. Sociogram of student academic networks and groups.

Table 2. Network measures at group level

Variable	Mean	Standard deviation	Median	Min	Max
Network density	0.106	0.053	0.085	0.054	0.233
Network diameter	4.462	1.898	4.000	2.000	9.000
Degree centralization	0.380	0.254	0.302	0.111	0.985
Closeness centralization	0.365	0.096	0.396	0.171	0.471
Betweenness centralization	0.460	0.199	0.489	0.057	0.823
Engagement	4.134	0.144	4.123	3.924	4.318
Age	22.903	1.394	23.000	20.857	25.909
Gender	0.811	0.160	0.800	0.429	1.000
Years in college	3.938	0.776	4.400	2.933	5.000

Table 3. Means, standard deviations, and correlations for independent and control variables

Variable	Mean	Standard deviation	1	2	3	4	5	6	7	8	9	10	11
Independent variables													
1. In-degree centrality	4.78	4.41	1	—	—	—	—	—	—	—	—	—	—
2. Out-degree centrality	7.19	4.43	0.44 ^a	1	—	—	—	—	—	—	—	—	—
3. Degree centrality	11.96	7.51	0.85 ^a	0.85 ^a	1	—	—	—	—	—	—	—	—
4. Local clustering coefficient	0.24	0.25	0.25 ^a	−0.03	0.13	1	—	—	—	—	—	—	—
5. Eigenvector centrality	0.19	0.21	0.82 ^a	0.46 ^a	0.75 ^a	0.44 ^a	1	—	—	—	—	—	—
6. Closeness centrality	0.45	0.26	0.06	−0.06	0.01	−0.10	0.03	1	—	—	—	—	—
7. Betweenness centrality	0.002	0.003	0.16	0.21 ^b	0.22 ^b	−0.23 ^b	0.11	−0.30 ^a	1	—	—	—	—
Control variables													
8. Age	2.99	1.34	−0.21	−0.15	−0.22 ^b	0.00	−0.13	−0.17	0.22 ^b	1	—	—	—
9. Gender	0.77	0.42	−0.05	−0.12	−0.10	0.10	−0.01	−0.19	−0.07	0.10	1	—	—
10. Years in college	3.84	0.86	−0.19 ^b	−0.09	−0.16	0.02	−0.03	−0.21 ^b	0.32 ^a	0.64 ^a	0.18	1	—
11. Race or ethnicity	0.37	0.62	−0.07	−0.03	−0.06	−0.18	−0.14	0.13	−0.19	−0.08	0.05	−0.08	1

^aCorrelation is significant at 0.01 level (two-tailed).^bCorrelation is significant at 0.05 level (two-tailed).

The networks had a mix of central and less-central nodes, allowing for a certain level of redundancy and decentralized connectivity [mean degree centralization = 0.380 (38.0%), closeness centralization = 0.365 (36.5%), and betweenness centralization = 0.460 (46.0%)].

- Student groups had a good quality of data sample with normal distributions; the mean and median values of engagement and control variables (e.g., age, gender) were very close.

The regression results identify three significant relationships from the possible predictors (Table 1)

- The results indicate a negative relationship between student engagement and network diameter ($t = -2.610$, $p < 0.05$). Diameter is the maximum eccentricity of any node in a network, and represents the linear size of a network. In other words, diameter shows the longest of all the shortest paths (geodesic) between any pair of nodes. A network with a shorter diameter suggests that a student can reach information in academic collaboration in fewer steps (faster). The negative relationship identified in the regression shows that students often have a higher level of engagement when information can spread more quickly in their group.
- The results indicate a negative relationship between student engagement and student group size ($t = -2.541$, $p < 0.05$). The finding is well aligned with the existing literature which indicates that students often enjoy the learning environment in a smaller group.
- The results indicate a positive relationship between student engagement and network betweenness centralization ($t = 3.115$, $p < 0.01$). A higher betweenness-centralization value suggests that a few nodes in the network act as critical intermediaries or bottlenecks for information flow, communication, or resource transfer. The positive relationship demonstrates that students are better engaged when some students play a crucial role in maintaining the connectivity and efficient functioning of the network. Additionally, the coefficients for the other four predictors were network density = 0.860 ($p = 0.40$), network diameter = 2.610 ($p < 0.05$), degree centralization = 0.575 ($p = 0.61$), and closeness centralization = 1.355 ($p = 0.20$).

Overall, the findings highlight the importance of communication efficiency in student collaborations. Fast information flow (i.e., shorter diameter) and key intermediary roles (i.e., higher betweenness) were found to be associated with greater engagement. In other words, a student leader is desired to play a critical bridge role to enable quick and efficient information diffusion and exchange.

Individual-Level Engagement

Table 3 lists the correlations of the variables at the individual level. The results indicate the following nodal characteristics for student collaboration:

- Senior (or older) students frequently assume the role of a bridge in collaborative endeavors, whether purposely or inadvertently. This finding is evident from the positive correlations between betweenness centrality and age (correlation = 0.22, $p < 0.01$) or years in college (correlation = 0.32, $p < 0.01$). That is, older students often function as a bridge to improve information exchange in group collaboration. This finding is consistent with common observations that students often place trust in senior peers due to additional years of learning, experience, and exposure to the subject matter, or due to higher social status in the student community, such as being role models or key opinion leaders (Kinzie and Kilgo 2022).
- Senior (or older) students do not serve as a hub in collaborative learning. For example, student age had a negative correlation with degree centrality (correlation = -0.22 , $p < 0.05$), and the student's years in college had a negative correlation with their closeness centrality (correlation = -0.21 , $p < 0.05$). That is, older students do not want to connect with many peers and they hesitate to be the hub. Instead, they would rather complete their work by themselves, possibly due to their greater experience or capabilities.
- The students who serve as hubs in the network often are not the ones who fulfill the role of a bridge. The data analysis shows that a student's betweenness centrality is negatively related to their closeness centrality (correlation = -0.30 , $p < 0.01$). The negative correlation demonstrates that nodes that are closer to others in terms of the shortest paths have a lesser role as intermediaries or bridges. This observation is consistent with the preceding two findings that senior students often are bridges rather than hubs in collaboration.
- Outgoing connections are more important for establishing a bridge role in facilitating efficient information flow. The nodal betweenness centrality is positively related to out-degree centrality (correlation = 0.21, $p < 0.05$). This finding suggests a vital function of proactive outreach and sending information when serving as a bridge, rather than receiving information.
- The demographics of gender, race, or ethnicity did not differentiate the student's role in collaboration. The results show that the control variables of age and race or ethnicity were not related significantly to any network attributes.

The regression results indicate a positive relationship between student engagement and degree centrality ($t = 1.999$, $p < 0.05$). Degree centrality measures the number of direct connections—for example, the number of classmates with whom a student directly talks or collaborates. The positive relationship suggests that students are more engaged when they collaborate with a higher number of other students. One possible explanation for this is that team members are more likely to experience a strong sense of belonging when they hold a hub position, which connects them to immediate partners (Zhao et al. 2021b). Furthermore, we examined the subcentrality measures—in-degree centrality and out-degree centrality—to investigate the nature of student collaboration. The results show that student engagement is related positively to the out-degree centrality ($t = 2.013$, $p < 0.05$) but not to in-degree centrality ($t = 1.412$, $p = 0.16$). This finding suggests that students who take the initiative in initiating communications and sharing information exhibit a higher level of engagement in collaborative learning. They demonstrate a greater willingness to interact with classmates, and these social connections contribute to their active participation and fulfillment within the academic learning environment.

Overall, the findings underscore the distinction between the hub role and the bridge role in student collaboration. Interestingly, students who intend to take a proactive approach to initiating collaboration with more students demonstrate a higher level of engagement, despite the fact that they often assume the hub role rather than the bridge role that senior students typically prefer.

Discussion

Network Structures for Efficient Information Flows

The data analysis findings suggest that highly engaged collaboration networks should have small diameters, which facilitates efficient and rapid communication between any pair of nodes. Based on network theories, these networks should have low eccentricity, which is the distance from a given starting node to its farthest node. The presence of low eccentricity optimizes information exchange within the network, which contributes to the maintenance and enhancement of high-level student engagement among group members. Furthermore, considering the nature of student collaboration, the desired networks also should have sparse connectivity, because students tend to collaborate on an equal basis without strict hierarchical structures. Two types of network structures meet these requirements: small-world networks, and scale-free networks (Fig. 2).

Small-world networks have high clustering, indicating that nodes in the network are connected to their immediate neighbors (Uzzi et al. 2007). These networks also have a small number of long-range connections that enable short paths between any two nodes (Fig. 2). The interplay between local clustering and a limited number of long-range connections gives rise to sparse connections throughout the network. Small-world networks have small diameters and enable efficient communication and facilitate the exchange of information across the network. Hence, we propose two approaches to enabling small-world structure for student collaboration

1. Information technologies help establish long-range connections to improve internal communication. Du et al. (2020) found that the construction projects that apply building information modeling (BIM) technology have a higher small-worldness and their project communication networks opt for a small-world network structure. BIM largely enables efficient information exchange, especially to reach the long-range nodes.

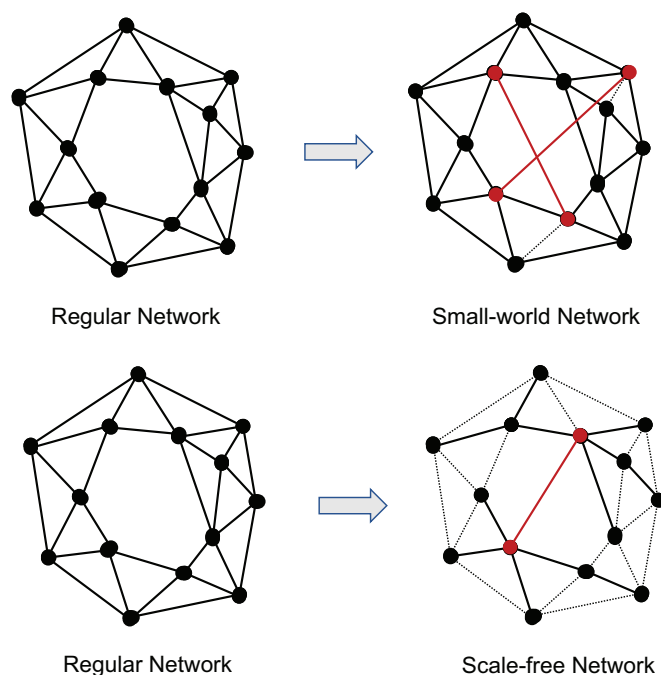


Fig. 2. Illustrations of regular network, small-world network, and scale-free network. Dashed lines denote the disappearance.

2. Network brokers can build long-range connections and help close the gap between long-distance nodes. They function as bridges in the collaboration network. The establishment of those broker nodes (students) reduces the average path length between other students and facilitates the exchange of information across the network.

Scale-free networks have a power-law distribution of node degrees. That is, the degrees of nodes in a scale-free network follow a mathematical pattern called a power law, in which a few nodes have a significantly higher number of connections than most remaining nodes. These networks have small diameters owing to the preferential attachment, i.e., the rich-get-richer phenomenon. According to this mechanism, new nodes joining the network are more likely to connect to well-connected or highly connected nodes that already exist. This preferential attachment leads to the formation of hubs, which are nodes with a disproportionately large number of connections. In other words, scale-free networks rely on hubs to play a crucial role in providing shortcuts and facilitating efficient information flows across the whole network. However, this network structure does not fit the characteristics of student collaboration because it is not highly centralized and degree centrality is often evenly distributed.

Structural Leadership to Close Connection Holes

The data analysis findings reveal a paradox wherein different students tend to represent hubs and bridges in their collaboration (Fig. 3). Bridges are expected because they reduce the network diameter and enhance group engagement. Hubs often receive higher levels of engagement. We consider individuals in a bridge role to be structural leaders, and those in a hub role to be opinion leaders. In social network theories, the term structural leadership (or network brokerage) is used to refer to those brokers that serve as intermediaries between different groups or clusters within a network. The brokers play a crucial role in facilitating communication,

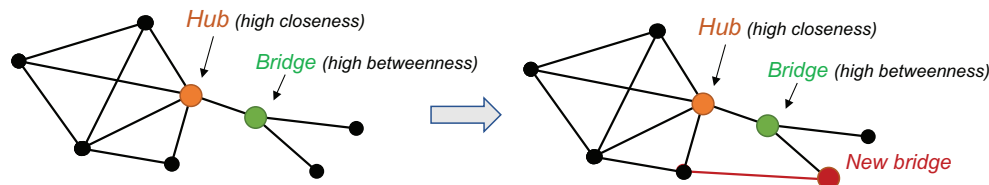


Fig. 3. Discrepancy of hub and bridge roles in collaboration network.

information flow, and coordination between otherwise disconnected parts of the network.

In a network, the key function of structural leaders (i.e., brokers) is to bridge gaps and connect disparate students. Structural leaders close connection holes and thus increase group engagement. They have connections to students who are not connected to each other directly, and effectively act as bridges or conduits for information exchange and interaction. Recent studies prove that network brokers are perceived to be the team leader because they have access to connection holes and their brokerage behaviors enable information flows across the holes (Burt et al. 2021). This also reflects the industry practices in which a dual core structure (a technical lead and a coordination lead) improves collaboration across interorganizational organizations (Zhao et al. 2021a). That is, structural leaders may not be the hubs (i.e., technical lead) with a large number of connections, but they act as information conduits (i.e., coordination lead) to facilitate the dissemination of information across different parts of the network. They can help overcome information barriers and ensure that knowledge reaches students who otherwise would have limited access to it. Moreover, the structural leaders control the flow of information, mediate conflicts, and shape the decision-making processes within the network, using their brokerage positions. Therefore, establishing structural leadership in collaboration can be an effective strategy to reduce the network diameter and thus enhance overall student engagement. By introducing more brokers strategically (Fig. 3), new shortcuts and alternative pathways are created to bypass longer routes among students who previously were distant from each other. This increased connectivity can lead to a decrease in the average path length and, in turn, in the network diameter.

Overall, structural leadership has the potential to foster sustainable cross-disciplinary engagement in collaborative learning. It is crucial to incorporate a leadership-based academic network structure to promote high levels of student engagement in higher education. Previous research by Crumpton (2018) established a strong correlation between instructional leadership behaviors and student engagement, emphasizing the importance of developing student leadership skills in collaborative learning environments. Despite the leadership, the engagement of followers also is important. Without responsive followers, the impact of leadership skills on student engagement becomes questionable. Burch and Guarana (2014) found that a high-exchange relationship between followers and leaders is essential for fostering follower engagement. Additionally, Yang et al. (2017) suggested that proactive personalities of both followers and leaders, aligned with goal congruence, contribute to sustained follower engagement and the achievement of maximum outcomes.

Student Leadership Development

This research provides valuable insights into the debate on the significant roles of structural leadership, instructional behaviors, and follower engagement in collaborative learning environments. The findings underscore the importance of adopting a comprehensive

approach that integrates leadership development and active involvement of followers to effectively enhance student engagement.

From the perspective of college students, leadership development requires self-discovery learning through real-life scenarios (Morrison et al. 2003). Zhao et al. (2015) emphasized four skills for effective project collaboration among AEC students (4C development): a common goal, communication, coordination, and cooperation. Specially, the coordination skill refers to abilities and responsibilities to connect distant individuals and solve potential conflicts among them—which is very similar to the structural leadership discussed previously. It is recommended that instructors incorporate instructional strategies in collaboration-based course designs that involve leadership-building activities such as role-play to foster personal skill growth (Jenkins 2013). Assigning and rotating the coordinator role (structural leadership) within project teams is suggested to encourage group members to interact with other partners in a systematic manner.

Empirical research indicates that leader assignment may be less effective due to the dynamic nature of emergent leadership behaviors (Xie et al. 2018). College students also express a preference for personalized leadership development rather than group-oriented approaches (Allen and Hartman 2009). Effective discussion-based instructional strategies also were recommended by Jenkins (2013) to facilitate leadership development. Leadership development is a reciprocal process that requires efforts from both leaders and followers. The goal is to transform coordinators into leaders who can perform multiple leadership roles and establish emergent and sustainable leadership within collaboration groups. This, in turn, promotes proactive student engagement in collaborative learning.

Conclusions

This study used social network analysis to explore how student project collaboration influences student engagement. The findings demonstrate that collaboration networks with a smaller diameter are associated with higher overall engagement, indicating the importance of communication efficiency. The network diameter is an important metric because it provides insights into the overall reachability and efficiency of communication within the network. A smaller diameter implies that students in the network can communicate more quickly and efficiently, because the maximum number of hops required to reach any other student is relatively small. Conversely, a larger diameter may indicate increased communication delays or limitations in reaching distant students. In other words, the quickness and efficiency of information exchange within student teams is highly related to student engagement.

The findings emphasized the importance of structural leadership in reducing network diameter and increasing student engagement. Structural leaders are the network brokers who serve as intermediaries between disconnected students within a network. They play a crucial bridge role in facilitating communication, closing connection holes, and controlling information flow. Therefore, the development of structural leadership in collaboration is an effective

strategy to enhance student engagement in project collaboration. This study discussed possible approaches to develop such leadership, for example, enabling virtual collaboration via digital technology (e.g., BIM), or enriching more bridge students (structural leaders or brokers) than hub students (influencers). In addition, typical network structures that help achieve short diameters were discussed, for example, small-world networks.

In addition, this study uncovered the patterns of student collaboration in networks that are neither dense nor centralized. Senior students (e.g., by age) often play the bridge role in collaboration; demographic factors of gender, race, and ethnicity do not affect the engagement in collaboration.

It is important to acknowledge the limitations of this study. Firstly, this study did not produce guidelines and instructions for higher education instructors and course designers to proactively intervene and optimize collaborative learning engagement among students. Future research could establish feasible intervention guidelines for emergent academic network structures by aggregating the effects of network interventions at both the group and individual levels. The goal should be to establish a strong connection between student engagement development and leadership development, with practical implications. Secondly, the undifferentiated effects of demographic factors in subgroups might occur during the data pretreatment stage. Consequently, the findings may not be applicable to extreme cases, such as project teams consisting solely of female students. Future empirical research is needed to validate the proposed pedagogical strategy and address these limitations.

Data Availability Statement

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

Acknowledgments

This study was partially supported by the National Science Foundation (NSF) through Grant No. 2204959. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the researchers and do not necessarily reflect the views of NSF.

References

- Algan, Y., P. Cahuc, and A. Shleifer. 2013. "Teaching practices and social capital." *Am. Econ. J.: Appl. Econ.* 5 (3): 189–210. <https://doi.org/10.1257/app.5.3.189>.
- Allen, S. J., and N. S. Hartman. 2009. "Sources of learning in student leadership development programming." *J. Leadersh. Stud.* 3 (3): 6–16. <https://doi.org/10.1002/jls.20119>.
- Araújo, E. B., N. A. M. Araújo, A. A. Moreira, H. J. Herrmann, and J. S. Andrade Jr. 2017. "Gender differences in scientific collaborations: Women are more egalitarian than men." *PLoS One* 12 (5): e0176791. <https://doi.org/10.1371/journal.pone.0176791>.
- Archambault, I., M. Janosz, J.-S. Fallu, and L. S. Pagani. 2009. "Student engagement and its relationship with early high school dropout." *J. Adolescence* 32 (3): 651–670. <https://doi.org/10.1016/j.adolescence.2008.06.007>.
- Berger, J. B., and J. F. Milem. 1999. "The role of student involvement and perceptions of integration in a causal model of student persistence." *Res. Higher Educ.* 40 (6): 641–664. <https://doi.org/10.1023/A:1018708813711>.
- Blasco-Arcas, L., I. Buil, B. Hernández-Ortega, and F. J. Sese. 2013. "Using clickers in class. The role of interactivity, active collaborative learning and engagement in learning performance." *Comput. Educ.* 62 (Mar): 102–110. <https://doi.org/10.1016/j.compedu.2012.10.019>.
- Burch, T. C., and C. L. Guarana. 2014. "The comparative influences of transformational leadership and leader-member exchange on follower engagement." *J. Leadersh. Stud.* 8 (3): 6–25. <https://doi.org/10.1002/jls.21334>.
- Burt, R. S., R. E. Reagans, and H. C. Volvovsky. 2021. "Network brokerage and the perception of leadership." *Social Networks* 65 (May): 33–50. <https://doi.org/10.1016/j.socnet.2020.09.002>.
- Chi, M. T., and R. Wylie. 2014. "The ICAP framework: Linking cognitive engagement to active learning outcomes." *Educ. Psychologist* 49 (4): 219–243. <https://doi.org/10.1080/00461520.2014.965823>.
- Chiochio, F., D. Forgues, D. Paradis, and I. Iordanova. 2011. "Teamwork in integrated design projects: Understanding the effects of trust, conflict, and collaboration on performance." *Project Manage. J.* 42 (6): 78–91. <https://doi.org/10.1002/pmj.20268>.
- Crumpton, D. J. 2018. *Instructional behavior and its impact on student engagement*. Minneapolis: Walden Univ.
- De Weger, E., N. Van Vooren, K. G. Luijckx, C. A. Baan, and H. W. Drewes. 2018. "Achieving successful community engagement: A rapid realist review." *BMC Health Serv. Res.* 18 (1): 285. <https://doi.org/10.1186/s12913-018-3090-1>.
- Du, J., D. Zhao, R. R. A. Issa, and N. Singh. 2020. "BIM for improved project communication networks: Empirical evidence from email logs." *J. Comput. Civ. Eng.* 34 (5): 04020027. [https://doi.org/10.1061/\(ASCE\)CP.1943-5487.0000912](https://doi.org/10.1061/(ASCE)CP.1943-5487.0000912).
- Duva, M., S. Mollaoglu, D. Zhao, and K. A. Frank. 2024. "A framework for social network interventions in AEC teams: Strategies and implications." *J. Constr. Eng. Manage.* 150 (2): 05023016. <https://doi.org/10.1061/JCEMD4.COENG-13475>.
- Ellison, N. B., C. Steinfield, and C. Lampe. 2007. "The benefits of Facebook 'friends': Social capital and college students' use of online social network sites." *J. Comput.-Mediated Commun.* 12 (4): 1143–1168. <https://doi.org/10.1111/j.1083-6101.2007.00367.x>.
- Erbas, M., M. Kabak, E. Özceylan, and C. Çetinkaya. 2018. "Optimal siting of electric vehicle charging stations: A GIS-based fuzzy multi-criteria decision analysis." *Energy* 163 (Jun): 1017–1031. <https://doi.org/10.1016/j.energy.2018.08.140>.
- Filak, V. F., and K. M. Sheldon. 2008. "Teacher support, student motivation, student need satisfaction, and college teacher course evaluations: Testing a sequential path model." *Educ. Psychol.* 28 (6): 711–724. <https://doi.org/10.1080/01443410802337794>.
- Fredricks, J. A., P. C. Blumenfeld, and A. H. Paris. 2004. "School engagement: Potential of the concept, state of the evidence." *Rev. Educ. Res.* 74 (1): 59–109. <https://doi.org/10.3102/00346543074001059>.
- Gordon, J., J. Ludlum, and J. J. Hoey. 2008. "Validating NSSE against student outcomes: Are they related?" *Res. Higher Educ.* 49 (1): 19–39. <https://doi.org/10.1007/s1162-007-9061-8>.
- Guthrie, R. W., and A. Carlin. 2004. "Waking the dead: Using interactive technology to engage passive listeners in the classroom." In *Proc., 10th Americas Conf. on Information Systems, AMCIS 2004*, 2952–2958. Atlanta: Association for Information Systems.
- Harper, S. R. 2008. "Realizing the intended outcomes of Brown: High-achieving African American male undergraduates and social capital." *Am. Behav. Sci.* 51 (7): 1030–1053. <https://doi.org/10.1177/0002764207312004>.
- Hughes, J. N., W. Luo, O.-M. Kwok, and L. K. Loyd. 2008. "Teacher-student support, effortful engagement, and achievement: A 3-year longitudinal study." *J. Educ. Psychol.* 100 (1): 1. <https://doi.org/10.1037/0022-0663.100.1.1>.
- Hunsu, N., D. R. Simmons, S. A. Brown, and O. Adesope. 2018. "Developing an instrument of classroom social engagement." In *Proc., 2018 ASEE Annual Conf. & Exposition*. Washington, DC: American Society for Engineering Education.
- Jenkins, D. M. 2013. "Exploring instructional strategies in student leadership development programming." *J. Leadersh. Stud.* 6 (4): 48–62. <https://doi.org/10.1002/jls.21266>.
- Johnson, D. W., R. T. Johnson, and K. A. Smith. 1998. "Cooperative learning returns to college: What evidence is there that it works?" *Change*:

- Mag. Higher Learn.* 30 (4): 26–35. <https://doi.org/10.1080/00091389809602629>.
- Kahu, E. R. 2013. “Framing student engagement in higher education.” *Stud. Higher Educ.* 38 (5): 758–773. <https://doi.org/10.1080/03075079.2011.598505>.
- Kelly, S. 2009. “Social identity theories and educational engagement.” *Br. J. Sociol. Educ.* 30 (4): 449–462. <https://doi.org/10.1080/01425690902954620>.
- Kinzie, J., and C. A. Kilgo. 2022. “Engagement insights: Survey findings on the quality of undergraduate education.” In *The national survey of student engagement*. Bloomington, IN: National Survey of Student Engagement.
- Kuh, G. D., J. Kinzie, J. A. Buckley, B. K. Bridges, and J. C. Hayek. 2011. *Piecing together the student success puzzle: Research, propositions, and recommendations: ASHE higher education report*. New York: Wiley.
- Ladd, G. W., and L. M. Dinella. 2009. “Continuity and change in early school engagement: Predictive of children’s achievement trajectories from first to eighth grade?” *J. Educ. Psychol.* 101 (1): 190. <https://doi.org/10.1037/a0013153>.
- Lin, N. 2000. “Inequality in social capital.” *Contemp. Sociol.* 29 (6): 785–795. <https://doi.org/10.2307/2654086>.
- Mansur, A. B. F., and N. Yusof. 2013. “Social learning network analysis model to identify learning patterns using ontology clustering techniques and meaningful learning.” *Comput. Educ.* 63 (5): 73–86. <https://doi.org/10.1016/j.compedu.2012.11.011>.
- McCulloh, I., H. Armstrong, and A. Johnson. 2013. *Social network analysis with applications*. New York: Wiley.
- Morrison, J. L., J. Rha, and A. Helfman. 2003. “Learning awareness, student engagement, and change: A transformation in leadership development.” *J. Educ. Bus.* 79 (1): 11–17. <https://doi.org/10.1080/08832320309599081>.
- Ouyang, F., and C. Scharber. 2017. “The influences of an experienced instructor’s discussion design and facilitation on an online learning community development: A social network analysis study.” *Internet Higher Educ.* 35 (Jun): 34–47. <https://doi.org/10.1016/j.iheduc.2017.07.002>.
- Pascarella, E. T., and P. T. Terenzini. 1991. *How college affects students: Findings and insights from twenty years of research*. San-Francisco: Jossey-Bass.
- Peterson, P. L., and E. Fennema. 1985. “Effective teaching, student engagement in classroom activities, and sex-related differences in learning mathematics.” *Am. Educ. Res. J.* 22 (3): 309–335. <https://doi.org/10.3102/00028312022003309>.
- Rabbany, R., M. Takaffoli, and O. R. Zaïane. 2011. “Analyzing participation of students in online courses using social network analysis techniques.” In *Proc., Educational Data Mining*. Princeton, NJ: Citeseer.
- Ream, R. K., and R. W. Rumberger. 2008. “Student engagement, peer social capital, and school dropout among Mexican American and non-Latino white students.” *Sociol. Educ.* 81 (2): 109–139. <https://doi.org/10.1177/003804070808100201>.
- Rienties, B., and E.-M. Nolan. 2014. “Understanding friendship and learning networks of international and host students using longitudinal social network analysis.” *Int. J. Intercultural Relations* 41 (Dec): 165–180. <https://doi.org/10.1016/j.ijintrel.2013.12.003>.
- Saqr, M., U. Fors, M. Tedre, and J. Nouri. 2018. “How social network analysis can be used to monitor online collaborative learning and guide an informed intervention.” *PloS One* 13 (3): e0194777. <https://doi.org/10.1371/journal.pone.0194777>.
- Scott, J. 1988. “Social network analysis.” *Sociology* 22 (1): 109–127. <https://doi.org/10.1177/0038038588022001007>.
- Shea, P., S. Hayes, S. Uzuner-Smith, M. Gozza-Cohen, J. Vickers, and T. Bidjerano. 2014. “Reconceptualizing the community of inquiry framework: An exploratory analysis.” *Internet Higher Educ.* 23 (5): 9–17. <https://doi.org/10.1016/j.iheduc.2014.05.002>.
- Taffere, G. R., H. T. Abebe, Z. Zerihun, C. Mallen, H. P. Price, and A. Mulugeta. 2024. “Systematic review of community engagement approach in research: Describing partnership approaches, challenges and benefits.” *J. Public Health* 32 (2): 185–205. <https://doi.org/10.1007/s10389-022-01799-9>.
- Tanner, K. D. 2013. “Structure matters: Twenty-one teaching strategies to promote student engagement and cultivate classroom equity.” *CBE—Life Sci. Educ.* 12 (3): 322–331. <https://doi.org/10.1187/cbe.13-06-0115>.
- Thalheimer, W. 2003. “The learning benefits of questions.” In *Work-learning research*, 1–37. Somerville, MA: Work-Learning Research.
- Tinto, V. 1987. *Leaving college: Rethinking the causes and cures of student attrition*. Chicago: University of Chicago Press.
- Uzzi, B., L. A. N. Amaral, and F. Reed-Tsochas. 2007. “Small-world networks and management science research: A review.” *Eur. Manage. Rev.* 4 (2): 77–91. <https://doi.org/10.1057/palgrave.emr.1500078>.
- Webb, A., and C. Carnaghan. 2006. *Investigating the effects of group response systems on student satisfaction, learning and engagement in accounting education*. Rochester, NY: Social Science Research Network.
- Wolf-Wendel, L., K. Ward, and J. Kinzie. 2009. “A tangled web of terms: The overlap and unique contribution of involvement, engagement, and integration to understanding college student success.” *J. College Student Dev.* 50 (4): 407–428. <https://doi.org/10.1353/csd.0.0077>.
- Xie, K., G. Di Tosto, L. Lu, and Y. S. Cho. 2018. “Detecting leadership in peer-moderated online collaborative learning through text mining and social network analysis.” *Internet Higher Educ.* 38 (Jun): 9–17. <https://doi.org/10.1016/j.iheduc.2018.04.002>.
- Yang, K., X. Yan, J. Fan, and Z. Luo. 2017. “Leader-follower congruence in proactive personality and work engagement: A polynomial regression analysis.” *Personality Individual Differ.* 105 (Apr): 43–46. <https://doi.org/10.1016/j.paid.2016.09.033>.
- Zepke, N., L. Leach, and P. Butler. 2010. “Engagement in post-compulsory education: Students’ motivation and action.” *Res. Post-Compulsory Educ.* 15 (1): 1–17. <https://doi.org/10.1080/13596740903565269>.
- Zhao, D., M. Duva, S. Mollaoglu, K. Frank, A. Garcia, and J. Tait. 2021a. “Integrative collaboration in fragmented project organizations: Network perspective.” *J. Constr. Eng. Manage.* 147 (10): 04021115. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0002149](https://doi.org/10.1061/(ASCE)CO.1943-7862.0002149).
- Zhao, D., A. P. McCoy, T. Bulbul, C. Fiori, and P. Nikkhoo. 2015. “Building collaborative construction skills through BIM-integrated learning environment.” *Int. J. Constr. Educ. Res.* 11 (2): 97–120. <https://doi.org/10.1080/15578771.2014.986251>.
- Zhao, D., D. Simmons, and Z. Chen. 2021b. “Interconnectivity in collaboration networks impact on member belongingness.” *J. Constr. Eng. Manage.* 147 (8): 04021078. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0002114](https://doi.org/10.1061/(ASCE)CO.1943-7862.0002114).
- Zhao, D., D. R. Simmons, and M. Duva. 2019. “Measuring students’ class-level sense of belonging: A social-network-based approach.” In *Proc., ASCE Conf. Washington, DC: American Society for Engineering Education*.
- Zimmerman, B. J., and A. Kitsantas. 1997. “Developmental phases in self-regulation: Shifting from process goals to outcome goals.” *J. Educ. Psychol.* 89 (1): 29. <https://doi.org/10.1037/0022-0663.89.1.29>.
- Zunzunegui, M.-V., B. E. Alvarado, T. Del Ser, and A. Otero. 2003. “Social networks, social integration, and social engagement determine cognitive decline in community-dwelling Spanish older adults.” *J. Gerontology Ser. B: Psychol. Sci. Social Sci.* 58 (2): 93–100. <https://doi.org/10.1093/geronb/58.2.S93>.