Social Interaction and Academic Performance of Construction Management Students

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Article Information	ABSTRACT
	Social interaction between students is a crucial but under-researched part of the education realm. Understanding how connections form in university classes and their effects on learning outcomes may provide extraordinary knowledge for researchers, educators, and policy-makers. This paper collected data from the questionnaire survey and then processed them with Gephi software to produce visualization and measurement. Initial results seem to indicate a significant correlation between students' connectedness and academic performance in one class. However, in another class, the results show a contrasting situation as there is no evidence that social network attributes impact learning performance. Taken together, these results would seem to suggest that the characteristics of the network should be judged on a case-by-case basis, and large-scale SNA analyses have been rarely reported. This present study provides a springboard for a new way to shed some light on classmates' interconnection. Using a similar approach to this article, it is believed that there is ample opportunity to study the association between classmate connectedness and career success. Research techniques and approaches around Social Network Analysis are expected to evolve further in the foreseeable future.

INTRODUCTION

Social interaction between students is an essential but undiscovered part of the higher education field. Few researchers have addressed whether the social connection has any association with his/her academic performance. Understanding how learning relationships form in college classes and the effects on learning outcomes can provide practical information for educators in unique ways. It could conceivably lead to a foundation for policies and programs for educational innovation. Although this domain is interesting, it suffers from the lack of formal methods for detecting relational patterns. Social Network Analysis (SNA) offers an essential set of tools to explore relationships. Generally, SNA is genuinely a powerful toolkit for research using relational data in a wide range of domains. Particularly in the education sector, SNA has so far proved suitable for a context containing various complex interactions between actors, both human and non-human. This present study introduces the basic concepts in SNA and corresponding data collection, data processing, and data analysis.

SNA is generating considerable interest in terms of cross-disciplinary research collaboration. This practical method has been used successfully for testing and creating models in a wide variety of research fields. Very recently, for instance, food sharing (Harvey et al., 2020), bullying (Rambaran et al., 2020),

criminology (Sabon et al., 2021), digital games (Khajeheian and Kolli, 2020). Network analysis covers two significant hypotheses. First, hypotheses seek to understand what affects the formation of relationships in a given set. Second, hypotheses consider the effect of the relationship structure on outcome-shaping, either individually or collectively. More and more research on social connectivity in higher education is being conducted, testing the correlation with multiple variables such as academic performance, alcohol use, or career choices. SNA is a widely-used approach to describe the structure of the links between certain actors and apply quantitative processes to compute metrics to evaluate network-level and node-level properties. However, the social interaction and academic performance of Vietnamese students are still poorly understood. This paper will provide general and detailed perspectives on students' connectedness in two tertiary classrooms in a higher education institution in Hanoi. At the same time, the correlation between network measures and academic achievement will be elucidated.

Network measures in school settings

School is a social setting where young people interact with each other in their unique ways and rules. Usually, students feel comfortable in an environment of peers who empathize with their ideas and concerns (Ortiz et al., 2004). Having claimed that, connections with friends play an essential part in each student's social network and his/her tendency to get better or worse in career and life (Cairns et al., 1988, Farmer and Rodkin, 1996). In a seminal article, Grunspan et al. (2014) claim that SNA is the key to helping researchers uncover suspicions or implications for school environment interactions. In recent years, education researchers have put network measures concerning a variety of domains such as academic performance (Putnik et al., 2016, Saqr et al., 2018a), blog interaction (Lee and Bonk, 2016, Jimoyiannis et al., 2013), international friendship (Rienties and Nolan, 2014), online learning (Saqr et al., 2018b, Ouyang and Scharber, 2017). Indeed, the complex interactions between human and non-human actors in school settings require a sophisticated tool such as SNA.

Research in the context of construction management class

Construction management (CM), as dissimilar to other fields under the construction umbrella, construction management (CM) is a relatively recent branch of knowledge that embraces both the natural and social sciences (Dainty, 2008). That may be the reason why research on CM education has only flourished in recent decades. As a young field, it is not surprising that the research topics into CM teaching and learning are not diverse. The study of CM education mainly revolves around: curriculum improvement (Ahmed et al., 2014, Lee et al., 2011a), BIM integration (Ghosh et al., 2015, Shanbari et al., 2016, Wong et al., 2011), simulation (Jaeger and Adair, 2012, Glick et al., 2012, Lee et al., 2011b, Jaeger and Adair, 2010), sustainability integration (Lim et al., 2015, Wang, 2009).

The CM education studies that refer to a classroom setting or student-involved interaction are even infrequent. Maghiar et al. (2015) examined cognitive-content, affective-personal, and behavioral learning in CM students, analyzing the relationship between course valuing scores, Approaches to Study Inventory (ASI), and course performance. In a similar vein, Farrow and Wetzel (2020) provided an in-depth analysis of student experiences within the active learning environment, including a perceived impact on learning and engagement. Davis (2012) and Kim (2018) investigated the fit-for-purpose mobile devices and applications for the learning activity in CM classrooms to keep pace with industrial transformation. Likewise, by drawing on the technological aspect, (Kim et al., 2019) studied student perceptions of the learning experience and compared the two VR viewing options. What is known about CM education in classroom settings is primarily based on student learning experience and technical consideration. However, despite the enormous potential benefit of network study in education, very little is known about human and social relationships within CM classrooms. This lack of research leaves CM educators with insufficient empirical support for understanding their students and other stakeholders.

METHODS

The research aims to measure social interaction and investigate whether its pattern correlates with students' academic performance in the undergraduate construction management program. Understanding social interaction pattern among students helps to improve curricular and

extracurricular activities more effectively. On that basis, implications for instructors and staff at faculty and university levels arise and support the policy-making process towards integrating real-life student relationships. It was decided that the best method for this investigation was to map and measure the web of connections between students.

Social Network Analysis

According to Caulkins (1981), Eilert Sundt was the founder of social network research when conducting a survey of Norwegian farmers' social organizations in the community in 1856. Anthropologists, sociologists, and other famous social scientists such as Barnes, Mitchell, George Simmel, Jacobs Moreno continued to study social networks in depth. In recent decades, researchers in many fields such as economics, psychology, behavioral science, even natural fields such as natural disasters, health, ecology continue to research from more in-depth and interdisciplinary perspectives. Originally from graph theory, SNA was implemented to describe the structure of relationships (denoted by links) between certain entities (represented by nodes). SNA's distinctive feature is to compute measures for studying the characteristics of the overall network, group structure, and individual actors. It can be said that the three core concepts in SNA are "actor," "tie," and "network." Commenting on the application of SNA to school context, Williams et al. (2017) argue: "Since student interactions are inherently relational, it is natural to operationalize them with social network analysis."

"Density" and "Centrality" are essential indicators to evaluate the cohesion between the entities in a network. "Density" refers to the number of connections between the entities in the network. High thickness networks commonly lead to the fast and efficient exchange of information and resource mobilization (Meyer & Rowan, 1977). Some authors call this indicator 'coherence coefficient' instead of 'density.' When this index is larger, the degree of cohesion and the coherence of the relationships among the network actors are also greater. Therefore, the greater the mutual support among the actors, more efficiently, the more significant the modulation of the network over the actor's behavior is and vice versa. In addition, as the network density increases, the potential for coalition/cooperation increases, ensuring that common expectations for the exchange of resources are met so that the operations of the network institutions become more effective. Generally, this index is equal to the ratio between the sum of actual relationships in the network and its theoretical relationships (i.e., the sum of possible network links).

Network centrality refers to the relative position of an actor in the network relative to other actors. This index can be viewed to measure the popularity level of an actor in the network (Bocse, 2019). High centralization means that entity has the advantage of exploiting information and attracting resources. The centrality of a node is usually determined by the three leading indices: Degree of centrality, Closeness of centrality, and Betweenness of centrality (Freeman, 2017). Besides, this article also uses Eigenvector centrality. The degree of centrality (C_d) of a node is the number of its direct links to other nodes in the network (Shih, 2006). It corresponds to whether the entity is well connected or not in the local scope (John, 2000). The closeness of centrality (C_c) represents the distance between a node and other nodes in the network. This index is intended to estimate how information transmits from one node to another using the shortest paths in the network. The betweenness of centrality (C_b) quantifies the number of times a node acts as a bridge to create the shortest path connecting two nodes in the network (Freeman, 1978; Kirkley et al., 2018; Scott & Carrington, 2011). The centrality of a node is high when many interconnected nodes pass through this node with the shortest distance between them. Then, this node has the power to create control over resources and information among other entities in the network (Freeman, 1978). Eigenvector centrality (C_e) measures the node's importance while considering the importance of its neighbors (Golbeck, 2013). An entity with few connections can have a very high C_e index if its links are with actors with many associations (Hansen et al., 2020).

Actors with high centrality also have a separate term, 'gatekeeper,' which helps connect other actors with lower centrality, especially those around the network's edge. Actors with high centrality play an essential role in decision-making and are pivotal to the dissemination of ideas, information, and general operational decisions of the network (John & Cole, 1998; Urena et al., 2019). The clustering coefficient is an indicator that measures how well nodes tend to cluster together or measure the formation of triangles in the network (Liu et al., 2012). Assuming you have friends who most know each

other, you have a high cluster coefficient and vice versa. Gephi is open-source software for graph and network analysis that is used in this study. Gephi uses the 3D rendering engine to render large networks in real-time and speeds up data discovery. Gephi's flexible structure and multitasking allow users to work with complex data sets and produce visible results with high application value (Bastian et al., 2009). In the construction field, in addition to literature studies (Hosseini et al., 2018; Luo et al., 2018), many studies have used this tool; for instance, Wehbe et al. (2016) map the linkages between resilience and performance of building safety; Hosseini et al. (2020) explore features of corruption risks in Iranian construction projects; Xiong et al. (2018) seek the opinions of leaders regarding safety issues for construction workers; Akgul et al. (2017) examine SNA on Turkish construction companies operating in international markets.

Network connection and academic performance data collection

This study is conducted at a large public university (30,000-34,999 students) in downtown Hanoi. The two classrooms of interest are undergraduate construction management majors. There were 42 students (Class P) and 33 students (Class V) enrolled and finished the questionnaire survey. However, this article only analyzed 41 and 33 students because one student did not have recent semester results (deferment). The male/female distributions are 27 (65.9%)/14 (34.1%) and 22 (67.7%)/11 (33.3%) respectively. It is worth noting that although the credit system organizes the instruction, students remain within the academic year framework at the university. Generally, in class A, the academic-year-based basis is relatively stable unless a student of class A is enrolled in another class or a student of class B is enrolled in class A (due to re-study or personal preference).

Social networking data was collected using an online self-report survey developed by Qualtrics. The Vietnamese survey asks students to identify who they usually have information exchange in life and study subjects. A roster of all students enrolled in the course is included with the survey to assist students' reporting. An excerpt from the SNA survey is translated into English and illustrated in **Table 1**. The attached informed consent form made clear that the raw data would be handled by a member of the research team who was unattached to the course and that if a student did not sign or return the form, any data provided about them by others would not be used. It also asked them to agree to the researchers obtaining demographic and attainment information from university databases.

Table 1. An excerpt from the SNA survey that was given in the CM classroom

Please rate your closeness to all classmates. If you go to the line with your name, choose "Intimate friend" by default. You may need associations such as the following instructions:
An intimate friend is someone whom you have everyday information exchange with
A close friend is someone whom you weekly have at least 2-3 times of information exchange with
A casual friend is someone whom you monthly have at least 2-3 times of information exchange with
An acquaintance is someone whom you rarely have information exchange with
Information exchange could be done face to face or online.

	Intimate friend	Close friend	Casual friend	Acquaintance
Name 1				
Name 2				

Students' GPA represents students' academic performance data before the study, expressed on the typical 10.0 scale. Complete grades data set were downloaded from the university's electronic record system. Data management and analysis are carried out using Gephi and SPSS Statistics.

RESULTS AND DISCUSSION

Class P's resulting directed weighted network consists of 41 nodes and 1168 ties, where the closeness of friendship defines tie weight: Intimate friend = 3; Close friend = 2; Casual friend = 1 and Acquaintance = 0. Overall, the average degree is 28.488, and the average weighted degree is 49.585. Put another way, 28.488 is the average number of edges per node in the graph. 49.585 indicates how many times the edge is passed between a pair of nodes. Meanwhile, the network diameter is 3, meaning the

average graph distance between all pairs of nodes is 3. This figure will be one if every node is connected to every other node. The measure of how many ties between actors exist compared to how many ties between actors are possible – graph density – in this case, is 0.712. The visualization and measurement reveal that the network studied here is generally dense, well-tied without any isolates. At the same time, the web of Class V students embraces 33 nodes and 659 ties. The average degree is 19.97, and the average weighted degree is 33. To put in perspective, a student in Class P has more and stronger connections with fellow students.
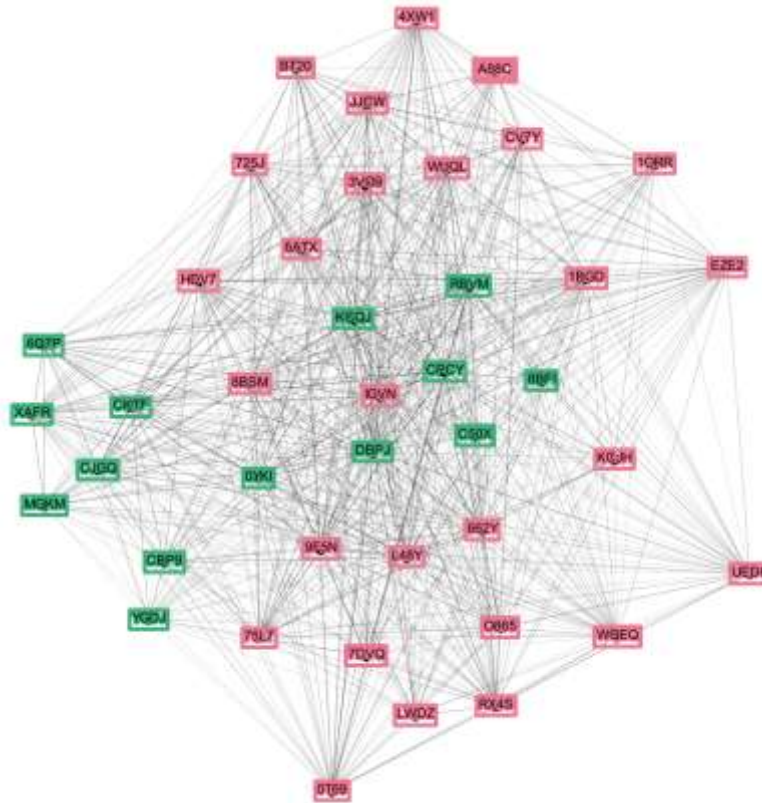

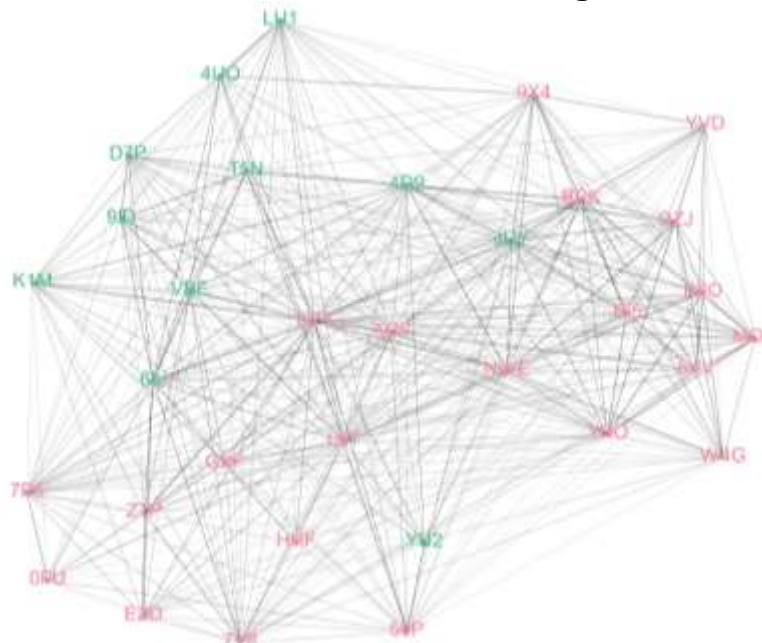**Figure 1. The whole network of Class P, female nodes in green and male ones in red**

Figure 2. The whole network of Class V, female nodes in green and male ones in red

Correlation between social connectedness and academic performance

For the Pearson r correlation, both variables should be normally distributed (normally distributed variables have a bell-shaped curve). After checking by drawing the histogram, the pairs of variables have a normal distribution with each other. Correlation analysis was performed using SPSS and the results obtained are shown in **Table 2** and **Table 3**

Table 2 Result of bivariate correlation analysis by SPSS for Class P

		indegree	outdegree	Degree	Weighted _indegree	Weighted _outdegree	Weighted _ degree
gpa	Pearson Correlation	.427**	0.039	0.176	.605**	0.188	.334*
	Sig. (2-tailed)	0.005	0.806	0.27	0	0.239	0.033
	N	41	41	41	41	41	41
		Eccentricity	Closeness centrality	Harmonic _CC	Betweenness centrality	clustering	Eigen centrality
gpa	Pearson Correlation	0.17	0.01	0.039	0.302	-0.081	.446**
	Sig. (2-tailed)	0.287	0.953	0.81	0.055	0.615	0.003
	N	41	41	41	41	41	41

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Academic achievement, as demonstrated in this paper by scores, is correlated with the following variables

- at a 99% confidence level: indegree, weighted indegree, eigencentrality;
- at a 95% confidence level: weighted degree.

Table 3. Result of bivariate correlation analysis by SPSS for Class V

		indegree	outdegree	Degree	Weighted _indegree	Weighted _outdegree	Weighted _ degree
gpa	Pearson Correlation	.170	-.177	-.085	.116	-.167	-.097
	Sig. (2-tailed)	.345	.323	.639	.521	.352	.592
	N	33	33	33	33	33	33
		Eccentricity	Closeness centrality	Harmonic _CC	Betweenness centrality	clustering	Eigen centrality
gpa	Pearson Correlation	.340	-.215	-.193	-.120	.149	.143
	Sig. (2-tailed)	.053	.229	.281	.507	.407	.427
	N	33	33	33	33	33	33

In the case of Class V, the results in Table 3 show that the Sig. Value is greater than 5%, meaning that there is no significant correlation between the independent variable (indicators measuring a student's connection in class) and the second variable (the student's learning outcomes). It means that the number of other peers' connections, whether high or low, a student's centrality is not correlated with academic performance. In other words, there is no evidence that a student's level of connection with classmates positively or negatively affects learning. This finding is similar to many case studies showing a small or moderate correlation between academic connection and achievement (Osterman, 2000). Time-length studies have also found a very modest correlation between school social connectivity and academic performance (Archambault et al., 2009; Wang & Holcombe, 2010).

On the contrary, many interesting and diverse results were obtained from Class P, as presented in **Table 2**. A student with many people who viewed him/her as a close friend appears to have good grades. According to Chen et al. (2002) and Sheskin (2020), this is demonstrated by the strong correlation, i.e., .605, between 'grade' and 'weighted indegree.' To a certain extent, this finding is in line with those reported by Samdal et al. (1999) and Wilkins et al. (2016) that students have good results if they are satisfied with their school, teachers, and fellow students. Surprisingly, the eigenvector centrality also seems to be the significant predictor of good grades. This finding substantiates previous literature on associations between student social networks and academic performance (Gomes Jr, 2019; Ortiz et al., 2004). Taken together, these results would seem to suggest that the characteristics of the network should be judged on a case-by-case basis, and large-scale SNA analyses have been rarely reported. Although the large sample size experiments provide generalizable outcomes, they may be time-consuming, error-prone, and expensive. Further work needs to be performed to improve the representativeness of the limited sample, to remain doable, and avoid excessive jargon.

CONCLUSION

This paper used a case study and questionnaire survey to measure and model the connections between members of two undergraduate classes and make relationships with learning outcomes. The two networks of interest were proved to be generally dense and well-tied through modeling and computing without any isolates. To test whether there is a correlation between score and intersection, the paper used the correlation analysis function in SPSS. The results show similarities with many previous studies that student centrality and connectedness positively affect scores in one class. In other words, the results show a contrasting situation as there is no evidence that students' connectedness attributes impact learning performance.

Given that the results obtained from the two cases are contradictory, the interpretations should be treated with caution. Educators can also use this research to generate ideas about classroom organization, group work improvement, and creating collaboration mechanisms. It is also hoped that this work will be constructive in solving the difficulty of revealing possible patterns of in-class social networks and academic performance. This study has few limitations. Some students had not participated in the survey, which caused the data to be incomplete in the 'real-life class' meaning. The data only reflects the state at the time of collection, while the network status and academic performance are more likely to change over time. Using a similar approach to this article, it is believed that there is ample opportunity to study the association between classmate connectedness and career success. Also, researchers can use the ego-centric network to study students' social connection with classmates and other schoolmates, teachers, and friends from other institutions. In general, the application range of SNA in examining relational data, including education, is very broad. Research techniques and approaches around SNA are expected to evolve further shortly, mainly as it is not limited to human-human relationships during the surge of multidisciplinary collaboration.

REFERENCES

Ahmed, S. M., Yaris, C. E. & Batie, D. L. 2014. Incorporating lean in CM education to improve the construction industry-proposing a model. *50th ASC Annual International Conference Proceedings.* Virginia Tech.

Akgul, B. K., Ozorhon, B., Dikmen, I., & Birgonul, M. T. (2017). Social network analysis of construction companies operating in international markets: case of Turkish contractors. *Journal of Civil Engineering and Management, 23*(3), 327-337. https://doi.org/10.3846/13923730.2015.1073617

Archambault, I., Janosz, M., Fallu, J.-S. & Pagani, L. S. 2009. Student engagement and its relationship with early high school dropout. *Journal of adolescence,* 32**,** 651-670.

Bastian, M., Heymann, S., & Jacomy, M. (2009, 03/19). Gephi: An Open Source Software for Exploring and Manipulating Networks. *Proceedings of the International AAAI Conference on Web and Social Media, 3*(1). https://ojs.aaai.org/index.php/ICWSM/article/view/13937

Bocse, A.-M. (2019). *Using Social Network Analysis to Study International Energy Policy Networks*. SAGE Publications Ltd.

Caulkins, D. (1981). The Norwegian connection: Eilert Sundt and the idea of social networks in 19th century ethnology. *Connections, 4*(2), 28-31. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.211.6067&rep=rep1&type=pdf#page=30

Cairns, R. B., Cairns, B. D., Neckerman, H. J., Gest, S. D. & Gariepy, J.-L. 1988. Social networks and aggressive behavior: Peer support or peer rejection? *Developmental psychology,* 24**,** 815.

Chen, P. Y., Smithson, M., & Popovich, P. M. (2002). *Correlation: Parametric and nonparametric measures*. Sage.

Dainty, A. 2008. Methodological pluralism in construction management research. *Advanced research methods in the built environment,* 1**,** 1-13.

Davis, K. A. Introducing Mobile Technology into the Construction Management Classroom. THE JOINT CIB INTERNATIONAL SYMPOSIUM OF W055, W065, W089, W118, TG76, TG78, TG81 AND TG84, 2012. 377.

Farmer, T. W. & Rodkin, P. C. 1996. Antisocial and prosocial correlates of classroom social positions: The social network centrality perspective. *Social Development,* 5**,** 174-188.

Farrow, C. B. & Wetzel, E. 2020. An Active Learning Classroom in Construction Management Education: Student Perceptions of Engagement and Learning. *International Journal of Construction Education and Research***,** 1-19.

Freeman, L. C. (1978). Centrality in social networks conceptual clarification. *Social networks, 1*(3), 215-239. https://www.bebr.ufl.edu/sites/default/files/Centrality%20in%20Social%20Networks.pdf

Freeman, L. C. (2017). *Research Methods in Social Network Analysis*. Taylor & Francis. https://books.google.com.au/books?id=jJ0uDwAAQBAJ

Golbeck, J. (2013). Chapter 3 - Network Structure and Measures. In J. Golbeck (Ed.), *Analyzing the Social Web* (pp. 25-44). Morgan Kaufmann. https://doi.org/https://doi.org/10.1016/B978-0-12-405531-5.00003-1

Gomes Jr, L. (2019). In-class social networks and academic performance: how good connections can improve grades. Anais do XXXIV Simpósio Brasileiro de Banco de Dados,

Ghosh, A., Parrish, K. & Chasey, A. D. 2015. Implementing a vertically integrated BIM curriculum in an undergraduate construction management program. *International Journal of Construction Education and Research,* 11**,** 121-139.

Glick, S., Porter, D. & Smith, C. 2012. Student visualization: Using 3-D models in undergraduate construction management education. *International Journal of Construction Education and Research,* 8**,** 26-46.

Grunspan, D. Z., Wiggins, B. L. & Goodreau, S. M. 2014. Understanding classrooms through social network analysis: A primer for social network analysis in education research. *CBE—Life Sciences Education,* 13**,** 167-178.

Hansen, D. L., Shneiderman, B., Smith, M. A., & Himelboim, I. (2020). Chapter 3 - Social network analysis: Measuring, mapping, and modeling collections of connections. In D. L. Hansen, B. Shneiderman, M. A. Smith, & I. Himelboim (Eds.), *Analyzing Social Media Networks with NodeXL (Second Edition)* (pp. 31-51). Morgan Kaufmann. https://doi.org/https://doi.org/10.1016/B978-0-12-817756-3.00003-0

Harvey, J., Smith, A., Goulding, J. & Illodo, I. B. 2020. Food sharing, redistribution, and waste reduction via mobile applications: A social network analysis. *Industrial Marketing Management,* 88**,** 437-448.

Hosseini, M. R., Martek, I., Banihashemi, S., Chan, A. P., Darko, A., & Tahmasebi, M. (2020). Distinguishing characteristics of corruption risks in Iranian construction projects: A weighted correlation network analysis. *Science and engineering ethics, 26*(1), 205-231. https://doi.org/10.1007/s11948-019-00089-0

Hosseini, M. R., Martek, I., Zavadskas, E. K., Aibinu, A. A., Arashpour, M., & Chileshe, N. (2018). Critical evaluation of off-site construction research: A Scientometric analysis. *Automation in Construction, 87*, 235-247. https://doi.org/10.1016/j.autcon.2017.12.002

Jaeger, M. & Adair, D. 2012. Communication simulation in construction management education: Evaluating learning effectiveness. *Australasian Journal of Engineering Education,* 18**,** 1-14.

Jimoyiannis, A., Tsiotakis, P. & Roussinos, D. 2013. Social network analysis of students' participation and presence in a community of educational blogging. *Interactive Technology and Smart Education*.

John, P., & Cole, A. (1998). Sociometric mapping techniques and the comparison of policy networks: economic decision making in Leeds and Lille. *Comparing policy networks*, 132-146.

John, S. (2000). Social network analysis: A handbook. *Contemporary Sociology, 22*(1), 128. https://doi.org/10.1177/0038038588022001007

Khajeheian, D. & Kolli, S. 2020. Digital games get viral on social media: A social network analysis of Pokémon Go on Twitter. *International Journal of Web Based Communities,* 16**,** 262-278.

Kim, J. & Irizarry, J. 2021. Evaluating the use of augmented reality technology to improve construction management student's spatial skills. *International Journal of Construction Education and Research,* 17**,** 99-116.

Kim, J. & Leathem, T. Virtual reality as a standard in the construction management curriculum. International Conference on Construction Futures, 2018.

Kirkley, A., Barbosa, H., Barthelemy, M., & Ghoshal, G. (2018). From the betweenness centrality in street networks to structural invariants in random planar graphs. *Nature communications, 9*(1), 1-12.

Lee, J. & Bonk, C. J. 2016. Social network analysis of peer relationships and online interactions in a blended class using blogs. *The Internet and Higher Education,* 28**,** 35-44.

Lee, N. & Dossick, C. S. AC 2012–4816: Leveraging Building Information Modeling Technology in Construction Engineering and Management Education. Proceedings of the Annual Conference of the American Society for Engineering Education, San Antonio, TX, USA, 2012. 10-13.

Lee, S., Nikolic, D., Messner, J. I. & Anumba, C. J. 2011. The development of the virtual construction simulator 3: an interactive simulation environment for construction management education. *Computing in Civil Engineering (2011).*

Lim, Y. S., Xia, B., Skitmore, M., Gray, J. & Bridge, A. 2015. Education for sustainability in construction management curricula. *International Journal of Construction Management,* 15**,** 321-331.

Liu, S., Li, C., Feng, Y., & Rong, G. (2012). Network Structure and Logistics Efficiency: A New Approach to Analyze Supply Chain System. In I. D. L. Bogle & M. Fairweather (Eds.), *Computer Aided Chemical Engineering* (Vol. 30, pp. 392-396). Elsevier. https://doi.org/https://doi.org/10.1016/B978-0-444-59519-5.50079-4

Luo, T., Xue, X., Tan, Y., Wang, Y., & Zhao, Z. (2018). *Mapping Global Research on the Construction Industrialization* ICCREM 2018: Innovative Technology and Intelligent Construction,

Maghiar, M., Sturges, D., Maurer, T. & Jackson, M. 2015. Exploration of student perceptions, behaviors and academic performance in construction management classes. *International Journal of Construction Education and Research,* 11**,** 241-256.

Meyer, J. W., & Rowan, B. (1977). Institutionalized organizations: Formal structure as myth and ceremony. *American journal of sociology, 83*(2), 340-363. https://doi.org/10.1086/226550

Ortiz, M. G. R., Hoyos, J. R. C., & López, M. G. R. (2004). The social networks of academic performance in a student context of poverty in Mexico. *Social networks, 26*(2), 175-188. https://doi.org/10.1016/j.socnet.2004.01.010

Ouyang, F. & Scharber, C. 2017. The influences of an experienced instructor's discussion design and facilitation on an online learning community development: A social network analysis study. *The Internet and Higher Education,* 35**,** 34-47.

Osterman, K. F. 2000. Students' need for belonging in the school community. *Review of educational research,* 70**,** 323-367.

Putnik, G., Costa, E., Alves, C., Castro, H., Varela, L. & Shah, V. 2016. Analysing the correlation between social network analysis measures and performance of students in social network-based engineering education. *International Journal of Technology and Design Education,* 26**,** 413-437.

Rambaran, J. A., Dijkstra, J. K. & Veenstra, R. 2020. Bullying as a group process in childhood: A longitudinal social network analysis. *Child development,* 91**,** 1336-1352.

Rienties, B. & Nolan, E.-M. 2014. Understanding friendship and learning networks of international and host students using longitudinal Social Network Analysis. *International Journal of Intercultural Relations,* 41**,** 165-180.

Sabon, L., Yang, S. & Zhang, Q. 2021. Social Network Analysis of a Latino Sex Trafficking Enterprise. *Journal of Human Trafficking***,** 1-17.

Samdal, O., Wold, B., & Bronis, M. (1999). Relationship between students' perceptions of school environment, their satisfaction with school and perceived academic achievement: An international study. *School Effectiveness and School Improvement, 10*(3), 296-320. https://doi.org/10.1076/sesi.10.3.296.3502

Saqr, M., Fors, U. & Nouri, J. 2018a. Using social network analysis to understand online Problem-Based Learning and predict performance. *PloS one,* 13**,** e0203590.

Saqr, M., Fors, U. & Tedre, M. 2018b. How the study of online collaborative learning can guide teachers and predict students' performance in a medical course. *BMC medical education,* 18**,** 1-14.

Scott, J., & Carrington, P. J. (2011). *The SAGE handbook of social network analysis*. SAGE publications.

Shanbari, H. A., Blinn, N. M. & Issa, R. R. 2016. Laser scanning technology and BIM in construction management education. *Journal of Information Technology in Construction (ITcon),* 21**,** 204-217.

Sheskin, D. J. (2020). *Handbook of parametric and nonparametric statistical procedures*. crc Press.

Shih, H.-Y. (2006). Network characteristics of drive tourism destinations: An application of network analysis in tourism. *Tourism Management, 27*(5), 1029-1039. https://doi.org/10.1016/j.tourman.2005.08.002

Urena, R., Kou, G., Dong, Y., Chiclana, F., & Herrera-Viedma, E. (2019). A review on trust propagation and opinion dynamics in social networks and group decision making frameworks. *Information sciences, 478*, 461-475.

Wang, M.-T. & Holcombe, R. 2010. Adolescents' perceptions of school environment, engagement, and academic achievement in middle school. *American educational research journal, 47***,** 633-662.

Wang, Y. 2009. Sustainability in construction education. *Journal of professional issues in engineering education and practice,* 135**,** 21-30.

Wehbe, F., Al Hattab, M., & Hamzeh, F. (2016). Exploring associations between resilience and construction safety performance in safety networks. *Safety science, 82*, 338-351. https://doi.org/10.1016/j.ssci.2015.10.006

Wilkins, S., Butt, M. M., Kratochvil, D., & Balakrishnan, M. S. (2016). The effects of social identification and organizational identification on student commitment, achievement and satisfaction in higher education. *Studies in higher education, 41*(12), 2232-2252.

Williams, E., Zwolak, J. P., Dou, R., & Brewe, E. (2017). Engagement, integration, involvement: supporting academic performance and developing a classroom social network. *arXiv: Physics Education*. https://www.researchgate.net/profile/Remy-Dou/publication/317576485_Engagement_integration_involvement_supporting_academic_performance_and_developing_a_classroom_social_network/links/596cc2f00f7e9b80919c4ad0/Engagement-integration-involvement-supporting-academic-performance-and-developing-a-classroom-social-network.pdf

Wong, K.-D. A., Wong, F. K. & Nadeem, A. 2011. Building information modelling for tertiary construction education in Hong Kong.

Xiong, C., Liang, K., Luo, H., & Fung, I. W. (2018). Identification of safety-related opinion leaders among construction workers: Evidence from scaffolders of metro construction in Wuhan, China. *International journal of environmental research and public health, 15*(10), 2176. https://doi.org/10.3390/ijerph15102176