

Impact on team performance of interaction with BIM

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ABSTRACT: Building information modelling (BIM) is a methodology that is increasingly gaining strength in the architecture, engineering and construction industry. Building information modelling is focused on the effective collaboration and interaction of teams. It is for this reason that many classrooms around the world have decided to teach BIM to engineering and architecture students, where team-based learning and project-based learning are the main teaching methods. However, although students may work in teams, it is unknown how this interaction impacts on performance. The objective of this work was to understand how interaction impacts the performance of teams adopting BIM. A case study was carried out with 25 students in their final year of civil engineering and taking a Virtual Design and Construction course. The students were organised into six groups, who then developed a project over 12 weeks. It was concluded that there is a strong correlation between the interaction of the teams and their performance, which was shown by the evaluation scores and the variability of the scores.

INTRODUCTION

Building information modelling (BIM) methodology is a new industry standard for architecture, engineering and construction (AEC), which improves the low productivity traditionally observed in infrastructure and building projects [1]. The adoption of BIM has the result of promoting collaborative and integrated work among all agents in a project, throughout the life cycle, optimising cost and duration through interconnected digital parametric models, along with employing virtual construction processes [2]. In addition, BIM is able to incorporate environmental variables, facility management, interference management and project co-ordination into the simulations, optimising design and construction processes of architecture, structure and engineering, construction and maintenance [3].

Business information modelling counters fragmentation of the AEC industry through collaborative digital practices and tools, in effect demanding that professionals work in a collaborative and interdisciplinary way throughout a project. Faced with this new standard, the industry is now looking for professionals with training in BIM for various positions in projects, with it becoming a basic requirement for recruitment [4].

This new professional should have not only the technical skills of the particular discipline and the use of BIM tools, but also extensive interdisciplinary teamwork, communication and integration skills. There has been a shift from technical assessment to collaborative practices [5]. Faced with these requirements, universities should promptly incorporate the teaching of BIM into their curricula, to train professionals who can solve the challenges that the industry presents [6].

In recent years, many universities and training institutions have expanded training in BIM, focusing on teaching computer modelling and simulation tools, through individual learning and without mixing disciplines [7]. Training in BIM should not be considered only as *learning a computer program*, but as an integrated process of modelling and management of the life cycle of a project, deepening the methodological aspects that underpin the collaborative work [8].

A gradual systematic approach is required for the teaching of BIM, which starts with initial training in three-dimensional parametric modelling, then moves on to planning and control, and then to aspects of collaboration and integral management, always guided by a methodological vision over the strictly technological one [9].

Thus, the teaching of BIM requires methodologies that promote and form interdisciplinary collaborative work, applied to real projects that allow the developing of a broad vision of the life cycle and the application of BIM [10]. Team-based learning (TBL) allows students to simulate real-work environments, assuming collaborative roles and interactions. In this way, the student not only learns BIM, but also the learning process generates in parallel the adoption of collaborative practices [11].

At present teamwork is considered a lever for achieving expected results in organisations. At the same time, teamwork is the product of interactions among its members. However, finding synergies can be difficult in the face of the nature of human relationships, individual differences and conflicts [12].

Interaction can be considered as the flows of information or instances of collaboration between people participating in an organisation or project team. In the AEC industry, interactions have been evaluated through social network analysis (SNA) [13]. For example, work interaction has been evaluated in architectural offices [14] or construction teams [15].

A team of researchers simulated the interaction in a project team when BIM was used, and represented the interaction with different SNA metrics [16]. Social network analysis is a method for studying interactions and relationships among people; it provides both visual and quantitative analyses of human associations [17].

Generally, in university and engineering education, research activity has a higher priority than teaching, thus generating an imbalance between these two [18]. This gap is widened by the prevalence of a traditional teacher model that prevails in the classrooms of engineering schools, as opposed to a collaborative model. It is, therefore, interesting to demonstrate the benefits of the application of this latter model, to promote it as a lever for better results.

Therefore, the objective of this research is to understand how interaction impacts the performance of different teams in the context of BIM work. In this article, the following questions are addressed:

1) Does collaborative interaction in work teams have an impact on their performance?
2) Does the level of collaboration between students impact their performance?

RESEARCH METHOD

To achieve the objective, a case study was carried out with students who, in their final year of civil engineering, participated in the Virtual Design and Construction course at the Pontificia Universidad Católica de Valparaíso. The 25 students were placed into six groups of four or five participants, to develop a project (divided into four-part deliverables) over a 12-week period. The project consisted of BIM modelling, co-ordination of specialties, 4D modelling; and the analysis and structural design of a building. Project-based and team-based learning were applied as teaching-learning strategies. All this was in a classroom with the technological infrastructure to support collaborative learning [19].

Performance of the teams was evaluated by assessments of the different deliverables based on appropriate rubrics. Some deliverables were group-based and others individual. Each student obtained a percentage achievement score independently of the team to whom they belonged. The achievement percentage ranged from 0% to 100%, with the minimum approval level being 60%. For the individual analysis, the average percentage of achievement of a student was applied to all the tasks and deliverables. For team analysis, the average of all team members was applied, and the standard deviation of the achievement percentage of each student in the team.

To assess the interaction, each course participant was asked with whom did they collaboratively interact during the 12 weeks. With this information, social network analysis was conducted: first, collaborative interactions were graphed throughout the course; then, metrics were analysed by project team; and finally, metrics were analysed by student. In the team analysis, the following SNA metrics were used [13]:

1) Density: ratio between number of real connections and number of possible connections in each team.
2) Average degree: average number of connections for each team member.
3) Diameter: minimum distance between the two farthest team members.

In the individual analysis, the following SNA metrics were used:

1) Indegree: the number of people who claim to have had a collaborative interaction with each node (student/professor) [20];
2) Authority: an iterative algorithm to rank the nodes by number of in-links connections [21], i.e. the students other students look for with whom to collaborate;
3) Page rank: an iterative algorithm that measures the importance of each node within the network; this metric is normalised, therefore, the sum of the page rank is 1 [22];
4) Eigenvector centrality: a measure of the extent to which a node is connected to influential other nodes, therefore it represents an informal power in the network [22].

Then, in the team analysis, the Spearman correlation between the indices of each team and the performance indices (average and standard deviation) were calculated to define the strength and direction of the correlation. In addition, the significance (*p*-value) was calculated to define whether, with the available data, the correlation was significant defined as a p-value < 0.05. Finally, a similar analysis was made between the network indices and the percentage achievement of each student.

DISCUSSION OF RESULTS

To visualise collaborative interactions, the free software, Gephi, was adopted to model the networks. Each node is a person and each edge is a connection between people (nodes). In addition, each team was represented by a different colour (Figure 1). In the graph, the team of professors is central and, in a position, to collaborate with all the teams of students. The T1, T5, T3 and T6 teams seem compact, i.e. the collaboration focused on other team members during the 12 weeks of the course. Teams T2 and T4 do not seem compact; in the case of team 2, it is possible to imagine how a student leaves the team as a result of the team's poor academic performance. Team 4 never really managed to work as a team and seemed to have had a traditional system of partitioning tasks among the members of the group.

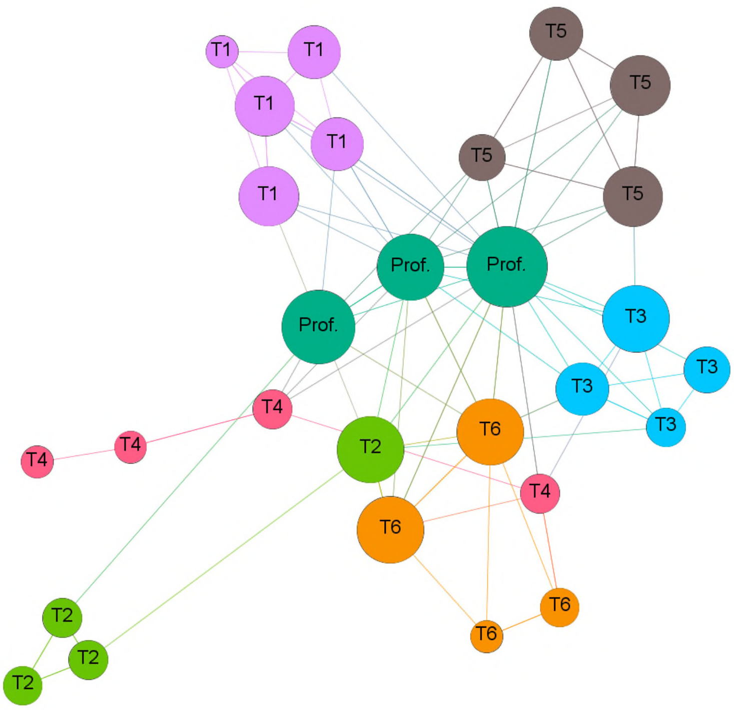

Figure 1: Collaboration network: a case study.

For each team of n participants, calculated were the density, average degree and diameter. In a small team a density (0 to 1) closer to one will imply a more connected network; the average degree (0 to n-1), if closer to n-1 would demonstrate a more collaborative team; and the diameter (1 to n-1), if closer to 1 would imply a team with more connections without intermediaries.

Table 1 shows Spearman's correlation and *p*-value between each team's network and achievement indices. Density and average degree have a positive correlation with average student achievement and a negative correlation with standard deviation; therefore, as there is greater collaboration, students improve their average performance and there are fewer divergences among team members. Something similar can be concluded from the negative correlation between diameter and average achievement, and positive correlation between diameter and standard deviation; that is, as fewer intermediaries exist in a team, their performance will be higher, and their variability will be lower.

Table 1: Spearman correlation - team analysis.

Network index	Achievement index (%)	Spearman	*p*-value	Decision
Density	Average	0.754	0.084	Strong positive correlation, but non-significant
Density	Std. deviation	-0.319	0.538	Weak negative correlation and non-significant
Average degree	Average	0.812	0.048	Very strong positive correlation and significant
Average degree	Std. deviation	-0.667	0.148	Strong negative correlation, but non-significant
Diameter	Average	-0.617	0.192	Strong negative correlation, but non-significant
Diameter	Std. deviation	0.648	0.164	Strong positive correlation, but non-significant

While all correlations calculated are strong or very strong, only the correlation between the network average degree and the average achievement has a significant correlation (*p*-value < 0.050). Figure 2 shows the average degree of each team versus the achievement percentage (left axis) and standard deviation (right axis). The circles with a blue border represent the achievement percentage and the circles with a red border represent the deviation within each team, which is represented by the same colour as in Figure 1. The positive and negative trends of the correlations presented in Table 1 can be clearly seen in Figure 2.

It is important to highlight the differences with respect to the achievement between the T2 team (green) and the T6 (orange), given they have similar levels of connectivity. The T6 team is more aligned, while the T2 team has a lower average performance and a high variability, which is due to the separation of one of the members of the team not conforming to the team performance and this student had a much higher achievement than did peers.

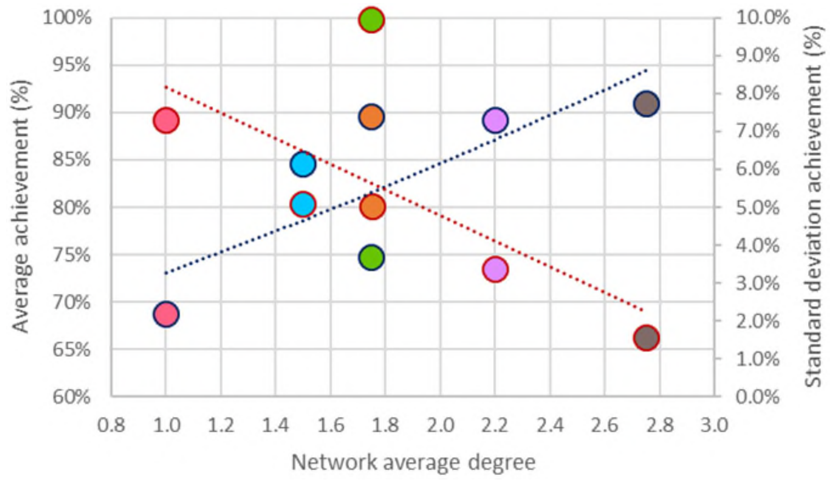

Figure 2: Relation between network average degree and achievement percentage.

For each student, the following metrics were calculated: indegree, authority, page ranks and eigenvalue centrality. All of these indicators are higher for students who are regarded as an informal authority among their peers. Therefore, they are sought out for collaboration and consultation. Table 2 shows Spearman's correlation and *p*-value between each student index and the achievement percentage of those students. In all cases, strong positive correlations were found with a high level of significance (p-value < 0.05), i.e. the students with the highest performance are the most consulted and with whom the rest of the students most seek to collaborate.

Table 2: Spearman's correlation: individual analysis.

Network index	Performance index (%)	Spearman	*p*-value	Decision
Indegree	Achievement	0.800	0.000	Very strong positive correlation and significant
Authority	Achievement	0.646	0.000	Strong positive correlation and significant
Page-ranks	Achievement	0.599	0.002	Strong positive correlation and significant
Eigenvalue centrality	Achievement	0.811	0.000	Very strong positive correlation and significant

The correlations in Table 2 are shown graphically in Figure 3, where the horizontal axis represents the achievement percentage of each student, the vertical left axis represents the degree of entry of each node, and the vertical right the authority and the eigenvector centrality.

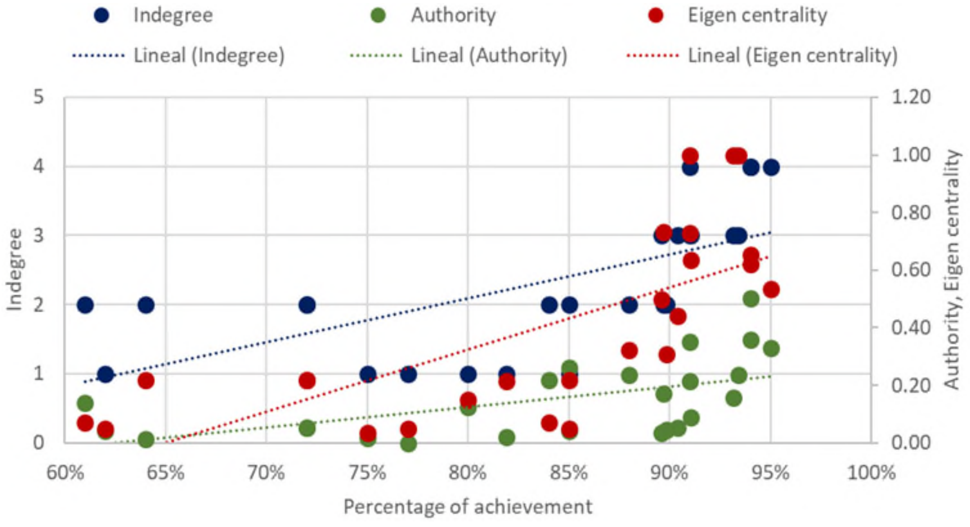

Figure 3: Relation between achievement and individual networks indices.

CONCLUSIONS

The results of the evaluation of the collaborative work of an advanced civil engineering course are presented. The selected course was an elective course Virtual Design and Construction, which allowed the introduction of students to technologies in business information modelling.

The results produced interesting findings, among which is the relationship between the level of collaboration and the average performance of students. Likewise, it was possible to corroborate that, to the extent that the level of collaboration between the members of a team is increased, the gaps in performance of the participants are reduced.

From the analysis of the indicators according to the *p*-value of Spearman's correlation, only a significant correlation was detected between the average degree of a network and the average achievement of each team, which reinforces the positive evaluation of collaborative work.

Finally, the methodology has made it possible to detect the positive influence of the achievement percentage, confirming that the participants with the greatest interaction (connection number) not only with the members of their own team, but with the rest of the participants, including the professors of the course, had better achievements.

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