Analytics for WhatsApp chats: tracking and visualising students' collaboration in project teams

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Abstract: COVID-19 and remote learning have accelerated online collaboration. Capturing online collaboration in terms of quantitative and qualitative description of students' interaction to achieve learning outcomes remains a challenge. We introduce a framework for describing and visualising students' interactions in WhatsApp group chat. We present five studies (N = 123, N = 64, N = 106, N = 55, N = 46) in courses taken by mathematics and business students. We found that mathematics students wrote more messages and shorter messages than business students. We also found that average number of words per message correlated with the project mark positively in mathematics but negatively in business courses. We suggest a way to visualise a WhatsApp chat as a network and tested the hypothesis that the centralisation coefficient of this network correlated negatively with the project score. The hypothesis was not confirmed. Implications and suggestions for further study are presented.

Keywords: learning analytics; collaboration visualisation; network science; student collaboration; WhatsApp chats.

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1 Introduction

The World Economic Forum identified 16 skills students require for the 21st century, among them collaboration (Schwab and Sala-i Martín, 2016). The same report highlighted the gap between the skills people need and the skills people learn. As the world enters the Fourth Industrial Revolution, and the new economic landscape ushers in new jobs, graduates will need to possess collaboration skills that are increasingly valued in the workplace of the future. Collaboration, as a critical non-cognitive skill, needs to be examined in the context of how students learn. How students learn and how they collaborate have been disrupted by the COVID-19 pandemic as educational institutions around the world shut their campuses and pivoted to online mode, unleashing new challenges and opportunities. Learning, whether it happens online or in the traditional classroom, is embedded in groups and social networks. How learning happens in groups, and the group processes as well as learning outcomes are important for both educators and learners. There is a need to "unlock the black box of collaboration in learning" (Kent and Cukurova, 2020). To unlock this "black box of collaboration in learning", we turn to learning analytics and collaborative visualisation.

Learning analytics is defined by the Society for Learning Analytics Research (SOLAR) as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" – 1st International Conference on Learning Analytics and Knowledge 2011 (Siemens and Gasevic, 2012). Datasets collected can be analysed to generate learning analytics that reveal patterns and associations on collaboration as well as improve student engagement and performance (Martin and Ndoye, 2016; Drachsler and Greller, 2012; Siemens, 2013). These learning analytics–driven insights can ultimately help to improve students' learning outcomes.

The emergence of collaboration visualisation (Isenberg et al., 2011) has been enabled by the almost ubiquitous use of mobile devices and online collaboration platforms in diverse education settings (Coleman and O'Connor, 2019; Nortcliffe and Middleton, 2013). These ubiquitous and mobile devices, sometimes referred to as mLearning (or mobile learning), have created unprecedented opportunities for collaboration (Xiao et al., 2020). Collaboration is highly desirable in mobile learning as mobile devices enable and augment collaboration among learners (Karacapilidis, 2011). Collaborative learning can help students become more active learners as it can promote more interaction.

The ease of connecting and collaborating with one another across mobile devices and the visual displays of messages and postings allow users to share, view and respond to information in real-time or near real-time. Collaboration data can be valuable if it can be visualised and thus visualisation of collaboration can provide a new set of lenses for understanding collaboration in educational settings. Collaboration that can be visualised can shed light on how learners collaborate in terms of their interaction and communication, generating valuable and practical insights for educators and learners on how to enhance collaborative learning (Mac Callum, 2008).

The context for this study was driven primarily by the motivation to understand how to generate collaboration visualisation that can spark deep and meaningful insights for both educators and learners on how students collaborate. According to Selwyn (2019), an important concern with learning analytics is inaccurate and incomplete representation of learning by educational data. This agrees with our experience (which may be different from that of the reader) – students in our classes simply do not use online forums linked to learning management systems.

The almost ubiquitous availability and use of smartphones by students have sparked interest among educators to explore how smartphones can be used as an educational platform. Almost all students with smartphones take their devices with them wherever they go and see them as a necessary part of their lives. With the pivot to online and remote mode of learning, the COVID-19 pandemic can be said to be the catalyst for greater use of smartphones in online collaboration in educational settings.

In Singapore, as in many other countries, students with smartphones are active users of WhatsApp, one of the most popular mobile applications in the world. WhatsApp is an instant messaging (IM) app for smartphones created in 2009 by two former Yahoo employees, Brian Acton and Jan Koum. Here are a few facts about WhatsApp:

- Current statistics show that WhatsApp has more than 2 billion active users in over 180 countries – (WhatsApp, 2021).
- In the USA, 50% of WhatsApp users are daily users and WhatsApp usage is the highest among younger adults, between 18 and 24 – (Business of Apps, 2021).
- WhatsApp has seen a 40% increase in usage due to COVID-19 pandemic – (Tech Crunch, 2020).

It is therefore not surprising that WhatsApp has been adopted by educators, and its use is gaining momentum (Aharony, 2015; Giordano et al., 2015; Johnston et al., 2015; Allagui, 2014; Rambe and Chipunza, 2013; Yeboah and Ewur, 2014). Educators view WhatsApp as having the potential to support the learning process and have started exploring its impact on student behaviour and performance (Appiah, 2016), for example, investigated the influence of WhatsApp with 200 university students in Ghana. The study found that students were keen to use WhatsApp for group discussion and sharing content. WhatsApp can be an effective and efficient platform for group collaboration as it promotes interaction and sharing within groups and this can lead to students having a stronger sense of community and belonging (Nicholson, 2002). WhatsApp allows communication within a group and keeps a record of the communication for further use as instructional content (Giordano et al., 2015; Johnston et al., 2015). Although one study found that IM (instant messenger)-based online discourse was inferior to classroom-based face-to-face discourse, it still concluded that IM-based online discourse platform has the potential to be an important learning tool due to its accessibility, convenience and multiformity (Cheng and Jiang, 2015). In today's learning environment, students are encouraged to be collaborative in the learning process (Egizii, 2015; Tao et al., 2015), and more studies are needed to examine how students use WhatsApp to interact, communicate and collaborate in groups.

Making sense of WhatsApp chats is similar to making sense of other types of online chats and forums. Different methods have been used to study the content of WhatsApp chats. One study employed thematic analysis and identified three themes: organisational, educational and social (Raiman et al., 2017). Another study (Siebert-Evenstone et al., 2017) manually labelled 3,824 student chat messages to produce a network representation of team communication and to compare three different approaches to visualise communication as a network. Pursuing understanding of student collaboration, some researchers transcribe actual conversations (Oshima et al., 2018). However, such laborious manual processing is hardly feasible for WhatsApp data because of its sheer volume, and we turn to network science to address this.

Network science is widely applied in various disciplines (Lewis, 2009). In education settings, student position in a network is related to academic performance (Gardner et al., 2018). In studying students' interactions in online collaboration, social network analysis is generally considered to be effective (Saqr et al., 2018). Network centrality and its correlation with team performance has shown mixed findings so far, both positive and negative correlations have been reported. One study has reported that students who not only collaborate often, but also collaborate significantly with many different people tend to achieve higher grades (Vargas et al., 2018). Another study (Grund, 2012), has found a negative correlation between football team performance and centralisation of the pass network in the team. This clearly shows more research is needed on examining the relationship between network centrality and team performance.

In this study, we attempt to address the following research questions:

1. How do we visualise how students interact and collaborate on WhatsApp group chat in working in their team project?
2. Is there any correlation between students' collaboration on WhatsApp group chat with team project performance?

2 Research method

To address both research questions, we draw on past research on collaborative learning, collaboration visualisation and social network analysis.

Past research on collaborative learning has shown that collaboration data and patterns can provide educators with revealing insights into the collaborative learning process (Hrastinski, 2008, 2009). Recent research, for example (Echeverria et al., 2019), has come up with new conceptualisations of collaboration such as "collaboration or social translucence", which refers to "computer-mediated systems that provide social cues that compensate for the loss of visibility (of socially significant information), awareness (of others' presence or actions) and accountability (of people's own visible actions) as a result of moving away from interaction in physical spaces into the digital realm (Echeverria et al., 2019). Social network analysis and network visualisations are commonly used for exploring social interactions between learners (Jin, 2017). Visualising collaboration is considered to be a 'frontline challenge' as quantitative collaboration data has to be able to generate qualitative insights that has learning value for both educators and learners (Knight and Shum, 2017; Milligan and Griffin, 2016). Network visualisation and more specifically, network visualisation tools, can motivate student participation in collaborative online learning (Jin, 2017). However, some network visualisations can be too complex for educators to use. In this study, we propose a simple network visualisation that can capture important collaboration data and generate valuable insights.

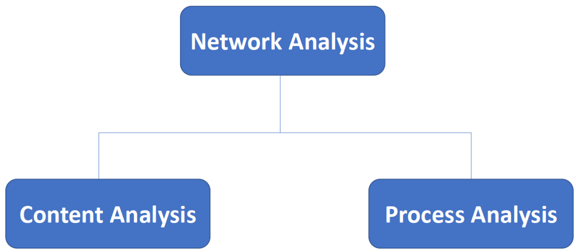
Following Hoppe (2017), we adopted a three-pronged approach in our visualisation of collaboration in students' group chats in their team project:

1 content-oriented analysis

2 process-oriented analysis

3 network analysis.

Figure 1 Collaboration visualisation – 3-pronged approach (see online version for colours)



In *content-oriented analysis*, we present text analytics visualisation of the content in group chats using word cloud. A word cloud helps us to interpret text and is useful in gaining insight into the most prominent items in a text, by visualising the word frequency in the text as a weighted list. We also analysed the number of messages and the length of messages.

Table 1 Summary of statistics by course. A and B are math courses; C, D, and E are business courses

Course	*No. of students*	*No. of teams*	*No. of messages*	*Word count, mean*	*Word count, std. dev.*
A	123	23	15,119	6.4	11.5
B	64	12	4,583	6	11
C	106	24	4,373	7.9	14.4
D	55	10	1,226	35.1	85.4
E	46	10	463	10.7	26.5

Note: The number of students, the number of teams, the total number of messages, the mean word count in a message and the standard deviation of the word count in a message are reported for each course.

In *process-oriented analysis*, we performed a temporal sequence analysis of communication and interaction activities in group chats over the duration of the group project. Activity threads of postings and messages and responses were analysed.

In *network analysis*, we analysed the social relations and interactions among group members on group chat. We wanted to find out how group members collaborated and interacted with each other. Key constructs relating to team collaboration like network centrality and team cohesion were examined.

3 Data

Data on student interaction in WhatsApp chats was collected in five courses on mathematics and business taught by the authors. We call these courses ‘A’, ‘B’, ‘C’, ‘D’, and ‘E’ here, to protect students’ privacy. All the courses were taught over a semester of 13 weeks. The team projects spanned 8 to 10 weeks. The summary of statistics by course is shown in Table 1 and by team in Table 7. The difference in the number of messages across courses can be explained by the difference in subjects and duration of the project.

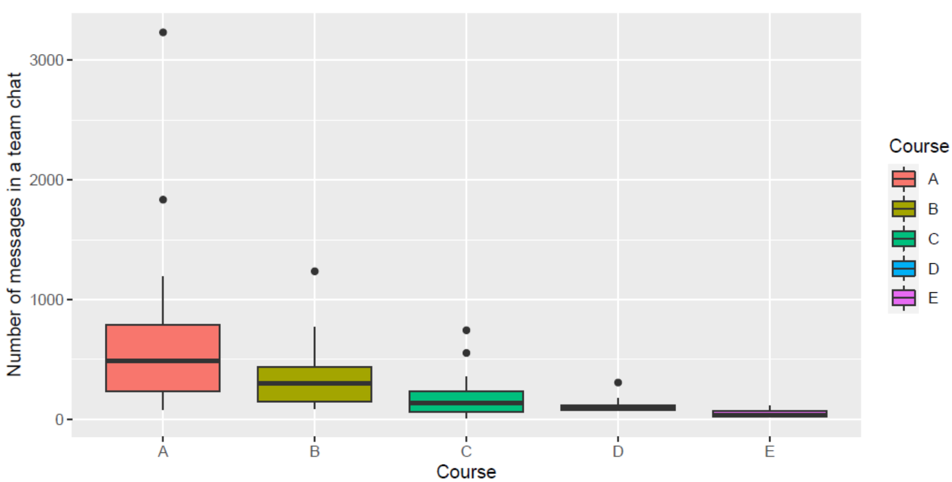
The chart of the number of messages from each team is shown in Figure 2 and of the word count in Figure 3. Note that students in course D wrote much longer messages on average than students in the other four courses.

In each course, a part of assessment was a team project and the instructor asked the students to add him to their WhatsApp chat. The primary purpose of adding the course instructor to the chat was to give him access to information that later could be used to grade individual contribution of team members to the project. Thus monitoring WhatsApp chats was a part of ordinary teaching and learning process, i.e., our data do not come from an educational experiment.

We processed the raw data in R and converted text files to data frames containing message texts with extra annotation – time stamp, the name of the message’s author, the team, the course, word count, date, weekday, project score. Below is a sample of one of the 79 datasets that we have obtained.

Figure 2 Box plot of the number of messages per team coloured according to the course (see online version for colours)

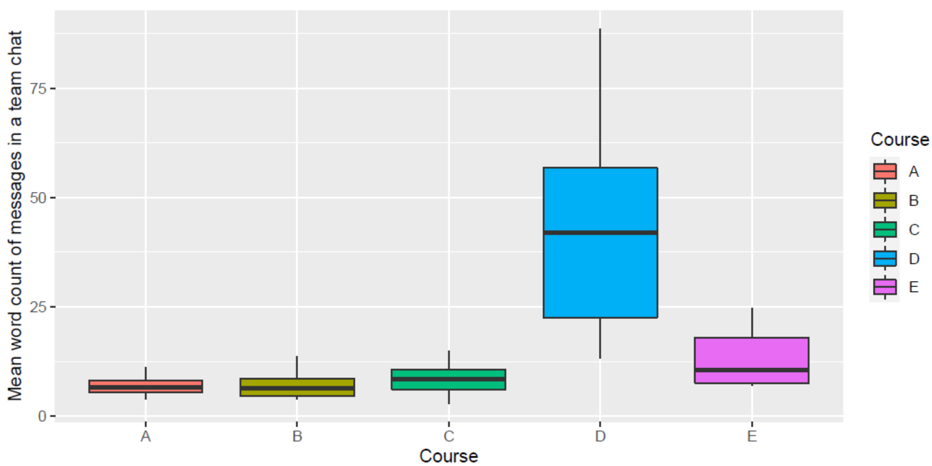
```
# A tibble: 306 x 5
   time_stamp       message                              name  word_count project
   <chr>            <chr>                                <chr>      <int>   <dbl>
 1 "06/09/2018, 2~ " What are the major forces, trends ~ 18201         20      84
 2 "06/09/2018, 2~ " guys i think lets start on this qu~ 18201          8      84
```



Note: We see that students in courses A and B (math) wrote more messages than students in courses C, D, and E (business).

Figure 3 Box plot of the mean word count in messages by team (see online version for colours)

```
 3 "06/09/2018, 2~ " lets start the ball rollin"         18201          5      84
 4 "06/09/2018, 2~ " hmmm"                               18201          1      84
 5 "06/09/2018, 2~ " i think big data and AI is one poi~ 18201         11      84
 6 "06/09/2018, 2~ " what are your thoughts?"            18201          4      84
 7 "06/09/2018, 2~ " Oh ... it increases the amount of ~ 18204         16      84
 8 "06/09/2018, 2~ " According to research, more than 8~ 18206         38      84
 9 "06/09/2018, 2~ " wow nice lea!"                      18201          3      84
10 "06/09/2018, 2~ " and kirk too"                       18201          3      84
# ... with 296 more rows
```



Note: We see that students in course D wrote much longer messages than students in courses A, B, C, and E.

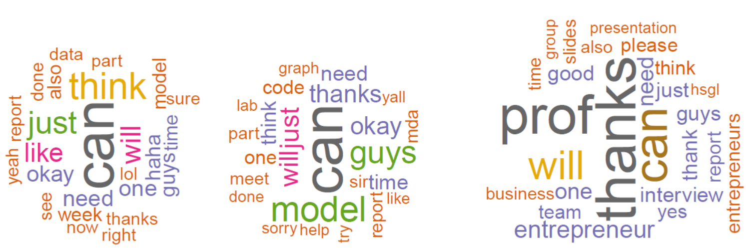
4 Results and discussion

4.1 Content analysis

4.1.1 Vocabularies

We have examined vocabularies used by different teams. To do it, we looked at word clouds. The size of a word in such a word cloud is proportional to the word frequency. Only most frequent words have been included, but stopwords have been removed.

Figure 4 Word clouds for each of the five courses (see online version for colours)



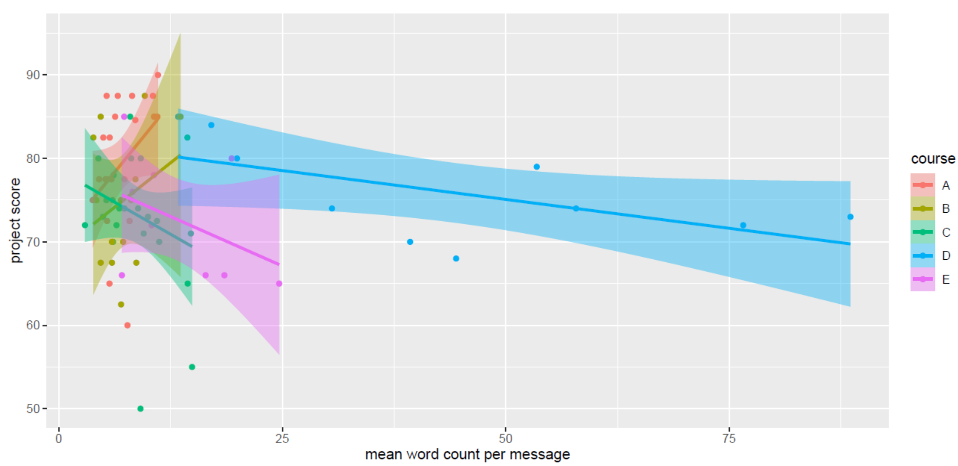
(a) (b) (c)

Figure 4 Word clouds for each of the five courses (continued) (see online version for colours)

(d) (e)

While it is clear that vocabularies would be different across different courses as shown in Figure 4 we did not find any noticeable differences across teams within one course that help to provide useful insights as to what was being discussed – Figures 12, 13, 14, 15, 16.

Figure 5 Scatterplot of project scores vs. mean word count per message (see online version for colours)



4.1.2 *Word count*

As shown in Figure 3, the average number of words in a message is drastically different across teams. A few teams in course D have written extremely long messages – sometimes, above 200 words. A part of such a message is below:

> "I particularly agree with you on how AI will improve planning processes by allowing the leaders to develop training and recruitment strategies, and that there will always be some skills that AI cannot replace. To elaborate, I believe that AI can help in more than just that. AI can allow leaders to focus more on interpersonal skills, by leaving the calculating and algorithms to AI. According to a research paper done by The Economist Intelligence Unit and sponsored by

> Salesforce, and based on a survey of 800 business executives, based in France, Germany, the Netherlands, 65% of respondents say that it is likely that internal networking will be more important in the future. This implies that due to the impact of AI, leaders should push employees to focus on their soft skills, since AI and the digital economy can deal with most of the rest. However, I do not agree that there is a need for atanew KPIs to drive the adoption of AI."

Such long messages are usually not suited for WhatsApp chat which is a medium for quick exchanges. WhatsApp chat is not the medium for deliberate, thoughtful, and detailed elucidation. By contrast, short messages are probably typed on a smartphone and often do not follow grammar rules. An example of a short message is below:

> "Kinda true also haha seems like a shift towards more incorporating people with tech."

We have explored a relation between the mean word count per message and the final project score. As shown in Figure 5, teams that write longer messages in two math courses (where messages are generally short) tend to get higher project scores. At the same time, teams that write longer messages in business courses (where messages are generally long) tend to get lower project scores.

We have fitted seven linear regressions with the project score as a dependent variable and mean word count per message as an independent variable. The first regression includes all the courses and courses dummies are used as extra independent variables (a course dummy takes value 1 for all teams from that course and 0 for all teams from other courses), the second regression includes all the courses, but no course dummies are used; each of the rest of the regressions includes one course. Results are shown in Table 2.

Table 2 Regressions for the project score

	Dependent variable:						
	Project score						
	All	*All*	*A*	*B*	*C*	*D*	*E*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Word Count, Mean	−0.14	−0.06	1.32*	0.85	–0.61	–0.14*	–0.47
	(0.09)	(0.06)	(0.71)	(0.92)	(0.49)	(0.06)	(0.36)
CourseB	–4.66*						
	(2.70)						
CourseC	–5.99***						
	(2.21)						
CourseD	1.65						
	(4.49)						
CourseE	–5.81*						
	(2.92)						
Observations	79	79	23	12	24	10	10
R^2	0.14	0.01	0.14	0.08	0.07	0.37	0.18
Adjusted R^2	0.08	–0.0002	0.10	–0.01	0.02	0.29	0.08

Note: *p<0.1; **p<0.05; ***p<0.01

Note that none of the regression coefficients are statistically significant at the usual level $p \leq 0.05$ and hence we cannot reject the null hypothesis that the project score is not correlated to the mean word count per message. A limitation in this study is that we did not have enough teams. Still, it is an interesting finding that higher project scores are associated with longer messages only in math courses and only up to a certain extend while extremely long messages are associated with lower project scores in business courses. A simple explanation is that short messages facilitate quick exchange of ideas, but if they are too short, there won't be any room for deeper discussion.

4.1.3 Number of messages

Our conjecture is that intensive WhatsApp discussions are associated with higher project scores. To verify it, we plotted project scores vs. mean number of messages per student (Figure 6) and fitted seven linear regression models (Table 3).

Figure 6 Scatterplot of project scores vs. mean number of messages per student (see online version for colours)

Notes: Each point here is a team coloured according to the course. Regression lines show general trends.

Table 3 Regression of the project score vs the mean number of messages per student

	Dependent variable:						
	Project score						
	All	*All*	*A*	*B*	*C*	*D*	*E*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
No. of messages per student	0.02 (0.01)	0.03** (0.01)	0.01 (0.01)	0.04 (0.04)	0.06 (0.04)	0.36** (0.11)	0.21 (0.44)
CourseB	3.86 (2.76)						
CourseC	–4.91** (2.40)						

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3 Regression of the project score vs the mean number of messages per student (continued)

	Dependent variable:						
	Project score						
	All	*All*	*A*	*B*	*C*	*D*	*E*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
CourseD	–1.92						
	(3.09)						
CourseE	–4.82						
	(3.15)						
Observations	79	79	23	12	24	10	10
R^2	0.14	0.08	0.01	0.11	0.10	0.57	0.03
Adjusted R^2	0.08	0.07	–0.04	0.02	0.06	0.52	–0.09

Note: *p<0.1; **p<0.05; ***p<0.01

Results are inconclusive. Out of the five courses, only in course D we observed a statistically significant positive relation between the mean number of messages per student and the project score. Recall that in this course, students on average wrote very long messages and longer messages are associated with lower project scores. WhatsApp chats are more effective for quick focused exchange of ideas or views, rather than for detailed discussion that takes up too much time.

4.1.4 Bivariate regression

We have also fitted seven bivariate regressions to predict the project score with both the word count and the number of messages in a WhatsApp chat. Results are shown in Table 4. They confirm our (rather weak) findings, i.e., a positive relation between the total number messages and the final project score and a positive in math courses but negative in business courses relation between the mean word count in a message and a project score.

4.2 Process analysis

4.2.1 Day of the week

The the number of messages by the day of the week is shown in Table 5. The uneven distribution of weekdays is explained by time tables – WhatsApp discussions become active near deadlines that fall on a particular day of the week.

4.2.2 Time of the day

Distribution of the time of the day by course is shown in Figure 7. All the courses display similar patterns with peaks around midday and midnight. A distinctive feature of course A is particularly high activity during night hours.

4.2.3 Timelines

We have calculated the daily number of WhatsApp messages written by each team – intensity of communication over WhatsApp. Figure 8, as represented by course B, shows that all teams have a peak of communication intensity at the end of the term near the deadline. The different visible duration of communication is due to differences in when team started work on their projects: some started early while others started late.

Table 4 Bivariate regressions for the project score

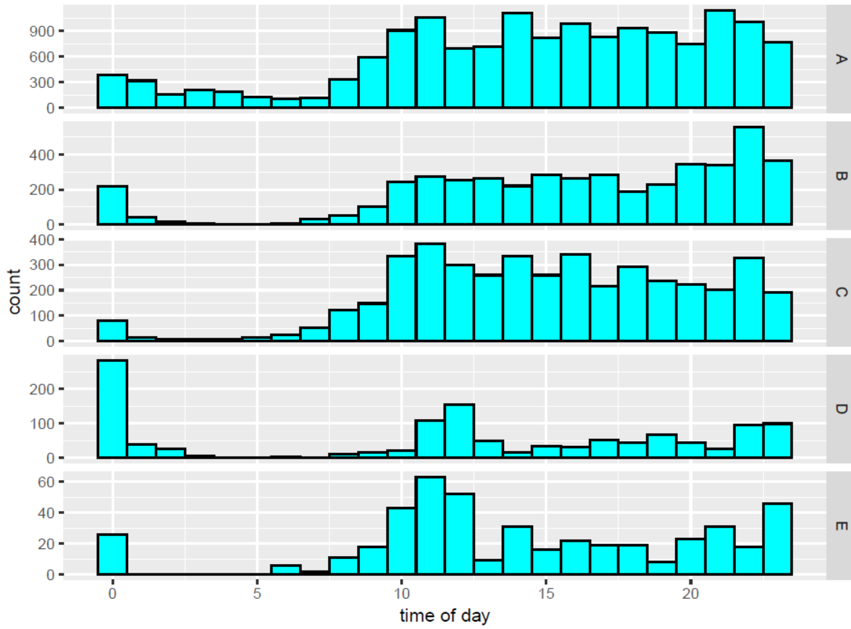
	Dependent variable:						
	'Project score'						
	All	*All*	*A*	*B*	*C*	*D*	*E*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
'Word Count, Mean'	–0.13	–0.03	1.59**	1.63	–0.38	–0.05	–0.67
	(0.09)	(0.06)	(0.74)	(0.90)	(0.49)	(0.08)	(0.49)
'No. of messages'	0.003	0.005**	0.003	0.02*	0.02	0.05	–0.06
	(0.002)	(0.002)	(0.002)	(0.01)	(0.01)	(0.03)	(0.11)
CourseB	–3.90						
	(2.74)						
CourseC	–4.71*						
	(2.41)						
CourseD	2.65						
	(4.53)						
CourseE	–4.20						
	(3.15)						
Observations	79	79	23	12	24	10	10
R^2	0.16	0.09	0.20	0.36	0.17	0.55	0.22
Adjusted R^2	0.09	0.06	0.12	0.22	0.09	0.42	–0.0003

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5 Number of messages by the day of the week

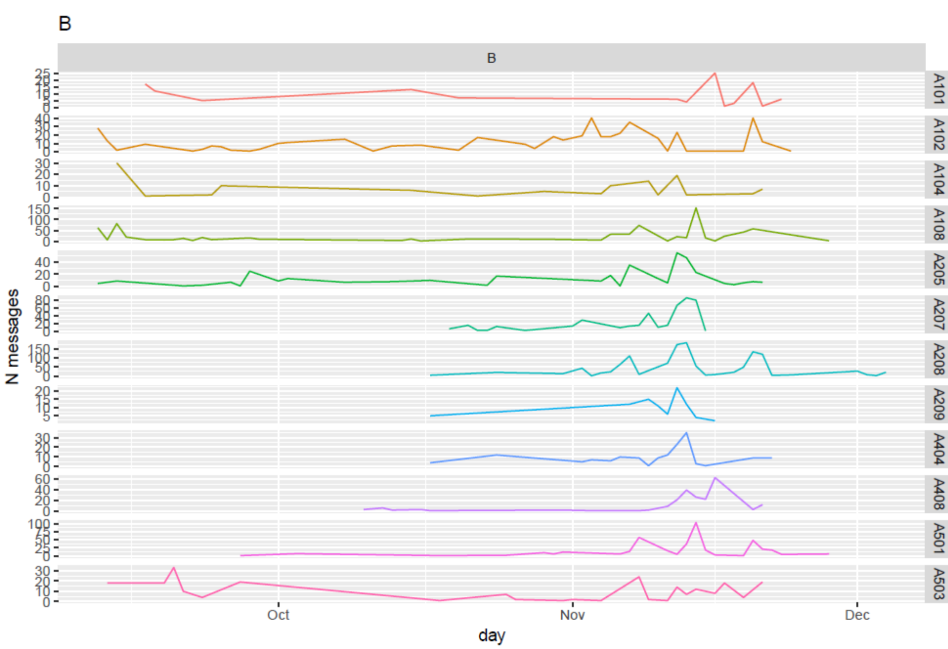
	A	*B*	*C*	*D*	*E*
Monday	2,075	856	685	101	19
Tuesday	3,091	1,018	700	57	47
Wednesday	2,863	1,187	606	42	47
Thursday	2,540	408	529	289	201
Friday	1,834	528	751	609	59
Saturday	1,005	284	752	56	58
Sunday	1,711	302	350	72	32

Figure 7 Distribution of time WhatsApp messages are written for each course (see online version for colours)



Note: A distinctive feature of course A is its unusually high activity all night. Course D has particularly high activity around midnight.

Figure 8 Daily number of messages written by each team in course B (see online version for colours)



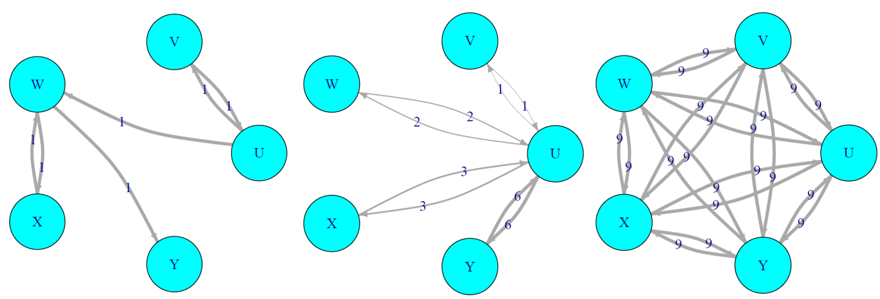
4.3 Network analysis

4.3.1 Basics of network science

While it is relatively straightforward to track and quantify behaviour of individual students and whole teams, it is challenging to capture student interaction within a team. Here, we propose an approach to this problem based on network science.

A *network* or a *graph* is a collection of objects called *nodes* or *vertices*. Some vertices are connected to each other. Connections are called *edges* or *links*. Depending on whether we distinguish between edges from *U* to *V* and from *V* to *U*, a graph may be *directed* or *undirected*. In this study, we will work with directed graphs. An example is shown in Figure 9(a).

Figure 9 Examples of directed networks with 5 vertices, (a) simple network (b) highly centralised network (c) highly decentralised network (see online version for colours)



(a) (b) (c)

Given a WhatsApp chat, i.e., a sequence of messages, we will construct a directed graph whose vertices represent chat participants and links the intensity of communication. To understand how this is done, let us look at a simple example first. Whenever chat participant B replies to chat participant A, i.e., B's message directly follows A's message, we connect *A* to *B* by an edge. For example, Figure 9 shows the graph corresponding to the sequence of messages U, V, U, W, X, W, Y.

Further, our networks are *weighted*, i.e., every edge has a weight. The weight of an edge from A to B is the number of B's messages directly following A's messages. Note that we don't know whether B actually replied A's message since WhatsApp logs do not include information on who replies to whom. Unfortunately, this is just what our data are like. The absence of a more detailed structure in WhatsApp logs is a limitation of our study. Still, we believe that the weight of an edge from A to B can be seen as a proxy for communication intensity from A to B.

Applying this method, we have obtained a graphical representation of interaction within each of 79 teams. Four of these plots are shown in Figure 10. Arrow thickness represents intensity of communication between students in the team. Note that communication in team 20P1 was quite uniform with approximately equal number of messages between every two students while communication in team F129 was mostly channelled through two out of six students.

All communication networks are shown in Figures 17, 18, 19, 20, and 21.

4.3.2 Centralisation coefficient

Centrality of a node is an important concept in network science. A lot of different methods to define centrality are known, among them degree, closeness, betweenness, eigenvector centralities (Freeman 1978), to name a few. Perhaps, one of most famous is the PageRank centrality that the Google search engine is based on.

Usually, given a network, one calculates the centrality of every node in it and compares centralities of different nodes. Centrality is a measure of node importance within the network. However, for the present study, we are interested in how an entire network is centralised rather than how central each node is.

We will calculate the *centralisation coefficient* of an entire network. According to (Freeman 1978), the centralisation coefficient of a network N is calculated as follows. First, letting $c(v_i)$ be centrality of a vertex v_i and $c_{\max}(N)$ the maximal centrality of any vertex in N, we denote

$$C(N) = \sum_{i=1}^{n} \left(c_{\max}(N) - c(v_i) \right),$$

where the sum is taken over all vertices of N. Note that D(N) is zero when all vertices have the same centrality and maximised when one vertex has the maximal centrality and all other vertices have minimal centralities. Further, the centralisation coefficient of N is

$$C(N) = \frac{D(N)}{\max_N D(N)}.$$

By construction, $0 \le C(N) \le 1$ and $C(N) = 0$ if and only if all vertices in N have the same centrality.

We need to choose the method to calculate centrality of a vertex in a way that makes sense for weighted directed networks and which allows us to compare centralisation coefficients of networks with different numbers of nodes in a meaningful way. These two conditions rule out some of the popular centrality measures. In the end we used the simplest of all, the degree centrality. We define c(v) to be the total number of incoming and outcoming edges. With degree centrality, a most centralised network possible is one where all communication channels through one node, as in Figure 9(b). The most decentralised network possible is the one with all edges of the same weight, as in Figure 9(c).

We conjectured that highly centralised networks are less effective than decentralised networks. However, it does not seem to be the case, as shown in Figure 11. To carefully verify our conjecture, we ran multiple linear regressions with the project score as the dependent variable and centralisation coefficient and the mean number of messages per student as independent variables. Results are shown in Table 6. The absence of statistically significant negative trends shows that our conjecture is not confirmed.

Figure 11 Scatterplot of project scores vs. centralisation coefficient (see online version for colours)

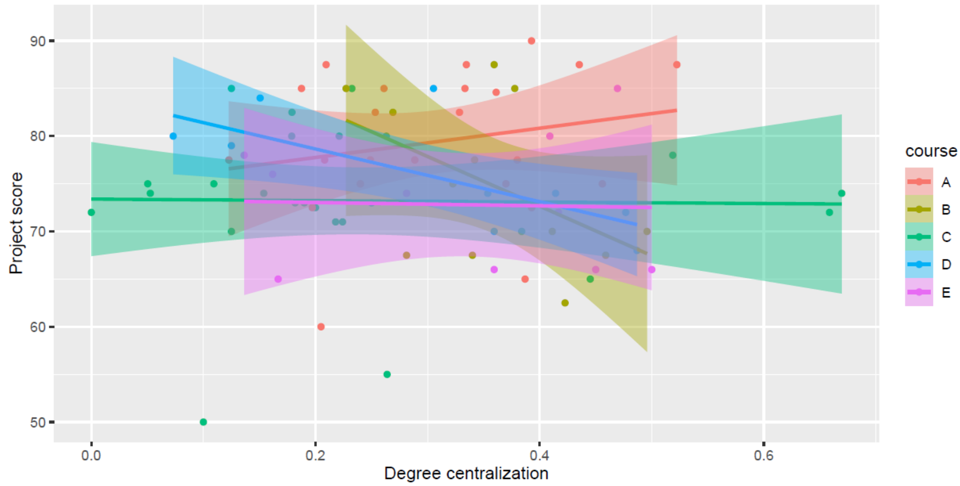


Table 6 Regressions of the project score vs. just centralisation coefficient and centralisation coefficient together with mean number of messages per student

	Centralisation	*p-value*	*Centralisation and mean no. of messages*	*p-value*
All courses	−4.629	0.481	−4.547	0.486
A	15.349	0.352	14.673	0.388
B	−52.05	0.109	52.721	0.1
C	−0.776	0.937	2.862	0.771
D	−27.65*	0.025	−18.567	0.057
E	−1.75	0.924	−3.727	0.651

Notes: Coefficients at the centralisation coefficient are shown; * denotes statistical significance at level $p \leq 0.05$

4.4 Discussion and future research

The study shows that WhatsApp can be used as a productive pedagogical resource in tracking and visualising how students communicate and interact on group chats in team projects (Escobar-Mamani and Gómez-Arteta, 2020). The study also indicates that both our research questions have been addressed. Our three-pronged approach in visualising collaboration in students' group chats in their team projects (content-oriented analysis, process-oriented analysis, and network analysis), our first research question, yielded important results that shed light on the 'black box of collaboration in learning' (Kent and Cukurova, 2020). Some findings were inconclusive or not significant (word frequency and number of messages) whereas other findings were significant (length of messages, activity threads of postings and responses, and network centrality). Inconclusive findings will need further investigation. Our three-pronged approach was able to track and visualise how students interacted and collaborated on WhatsApp group chat in their team projects. This approach in visualising collaboration in students' group chats potentially provides an integrated approach that can be considered a methodological contribution.

Our second research question was addressed as the results demonstrate novel correlations between students' collaboration on WhatsApp group chat with team project performance that raises new questions and potentially spark new insights. The relative length of messages (short or long) is associated with lower or higher project scores in different disciplines (mathematics vs. business). This raises an interesting question: is there an optimal or ideal length for a WhatsApp message? This brings to mind the Goldilocks and the Three Bears story ('not too hot and not too cold, just right'): is there an optimal length or 'just right' of a WhatsApp message, not too long and not too short? Is there a disciplinary difference that is associated with the length of WhatsApp message?

Although Whatsapp does not have character limit which means that we can type as long a message we want unlike in a tweet, for example, there is the related issue of attention span and processes in the nascent but growing literature studying the impact of internet use on attention and memory processes (Firth et al., 2020). The questions raised in our study and their implications will need to be investigated in future research.

The results also provide an insight into network centrality arising from our visualisation of how students collaborated on WhatsApp group chats (Freeman, 1978). Based on our approach in calculating the centralisation coefficient of an entire network, we found that highly centralised networks are less effective than decentralised networks. A decentralised networks open communication lines between team members and avoids any one position being more central than another (Forsyth, 2018). How students communicate and collaborate with each other on group chats has significant implications on team formation, team development cycle, and team process. We believe that teams who are not dominated by one student (decentralised networks) will tend to perform better. Our finding provides further confirmatory support on the importance of decentralised networks in collaborative learning in the extant literature.

Future research can involve further theorising on networks in online collaboration as well as measures of network centrality. More empirical research is needed to study the relationship between network centrality and team performance in diverse educational settings as the research so far has produced mixed results.

Another potential area for future research is to consider using natural language processing (NLP) to process and analyse large amounts of natural language data in WhatsApp chats, capable of 'understanding' the contents of documents, including the contextual nuances of the language use in WhatsApp chats. Data-driven insights on the personality, learning style, and collaboration style of learners can be generated.

As a start, it is important to develop practical tools for WhatsApp chat mining, at least as an R package similar to Hadavand et al., 2019). We are going to work on it and we hope that our work will be useful for other researchers and educators.

5 Conclusions

Through learning analytics, collaboration visualisation and network science, the findings show that WhatsApp data can be a rich resource that offers educators valuable insights on how students collaborate in learning teams.

Our study demonstrates that an integrated approach in tracking and visualising how students collaborate on WhatsApp group chats in their team projects can reveal important insights for educators.

As more and more courses involve projects and online collaboration, and as classes move to online and hybrid learning mode amid the COVID-19 crisis, it will be in the educator's best interest to have a deeper and better understanding of how students collaborate in teams in an online environment, from task assignment to team setup to assessment.

All tables have been created with the R package 'stargazer' (Hlavac, 2018).

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Appendix

Table 7 Summary of statistics by team

Team	*No. of students*	*Course*	*Project score*	*No. of messages*	*Mean word count*	*No. of messages per student*
18T1	5	D	85	172	13.3	34.4
18T10	6	D	68	78	44.4	13.0
18T2	6	D	84	306	17.1	51.0
18T3	6	D	80	118	19.9	19.7
18T4	5	D	79	102	53.5	20.4
18T5	5	D	74	118	30.6	23.6
18T6	5	D	74	76	57.9	15.2
18T7	6	D	73	70	88.6	11.7
18T8	6	D	72	74	76.6	12.3
18T9	5	D	70	112	39.3	22.4
19AB1	5	E	85	68	7.3	13.6
19AB10	4	E	78	22	10.6	5.5
19AB2	5	E	66	31	16.4	6.2
19AB3	5	E	66	108	7.1	21.6
19AB4	5	E	74	61	7.3	12.2
19AB5	4	E	80	39	19.3	9.8
19AB6	4	E	65	20	24.7	5.0
19AB7	5	E	76	68	8.3	13.6
19AB8	4	E	72	21	10.4	5.3
19AB9	5	E	66	25	18.5	5.0
19F1	5	C	78	355	6.1	71.0
19F2	5	C	72	75	6.5	15.0
19F3	5	C	85	258	10.7	51.6
19F4	6	C	70	107	6.1	17.8
19F5	6	C	74	124	8.9	20.7
19F6	3	C	70	13	11.2	4.3
19F7	6	C	71	55	9.5	9.2
19F8	2	C	72	26	2.9	13.0
19P1	5	C	73	64	10	12.8
19P2	5	C	75	279	6	55.8
19P3	5	C	80	209	4.4	41.8
19P4	5	C	80	553	9.2	110.6
20F1	5	C	82.5	142	14.4	28.4
20F2	5	C	85	134	8	26.8
20F3	5	C	55	53	14.9	10.6
20F4	5	C	80	143	8.1	28.6

Table 7 Summary of statistics by team (continued)

Team	*No. of students*	*Course*	*Project score*	*No. of messages*	*Mean word count*	*No. of messages per student*
20F5	5	C	72.5	50	11	10.0
20F6	5	C	65	112	14.4	22.4
20F7	3	C	50	36	9.1	12.0
20P1	4	C	75	743	5.3	185.8
20P2	4	C	71	133	14.8	33.3
20P3	3	C	73	165	4.9	55.0
20P4	4	C	74	322	7.4	80.5
20P5	4	C	74	222	6.8	55.5
A101	5	B	85	118	13.6	23.6
A102	5	B	87.5	449	9.6	89.8
A104	5	B	67.5	115	5.9	23.0
A108	5	B	70	770	5.9	154.0
A205	5	B	67.5	361	8.7	72.2
A207	6	B	85	433	4.7	72.2
A208	5	B	82.5	1236	3.9	247.2
A209	5	B	62.5	89	7	17.8
A404	6	B	70	155	7.2	25.8
A408	5	B	67.5	219	4.7	43.8
A501	6	B	75	402	4.2	67.0
A503	6	B	77.5	236	8.6	39.3
D104	4	A	77.5	1188	4.5	297.0
D105	5	A	82.5	1099	5.7	219.8
D107	6	A	77.5	254	5.9	42.3
D108	5	A	75	148	3.8	29.6
D308	6	A	72.5	496	7.9	82.7
D601	6	A	85	486	6.3	81.0
E105	5	A	87.5	261	8.2	52.2
E106	6	A	90	464	11.1	77.3
E108	5	A	85	171	11	34.2
E109	5	A	75	212	6.9	42.4
E201	5	A	77.5	503	7.3	100.6
E205	6	A	77.5	488	5.4	81.3
E206	6	A	60	888	7.7	148.0
E505	5	A	72.5	137	5.4	27.4
E506	5	A	77.5	337	5.2	67.4
F101	5	A	85	82	10.7	16.4
F104	6	A	87.5	255	6.6	42.5
F105	6	A	87.5	687	10.5	114.5

Table 7 Summary of statistics by team (continued)

Team	*No. of students*	*Course*	*Project score*	*No. of messages*	*Mean word count*	*No. of messages per student*
F108	6	A	82.5	3234	5	539.0
F111	5	A	84.6	1059	8.6	211.8
F116	5	A	75	166	8.1	33.2
F124	5	A	65	669	5.7	133.8
F129	6	A	87.5	1835	5.3	305.8

Figure 12 Word clouds in course A (see online version for colours)

Figure 12 Word clouds in course A (continued) (see online version for colours)

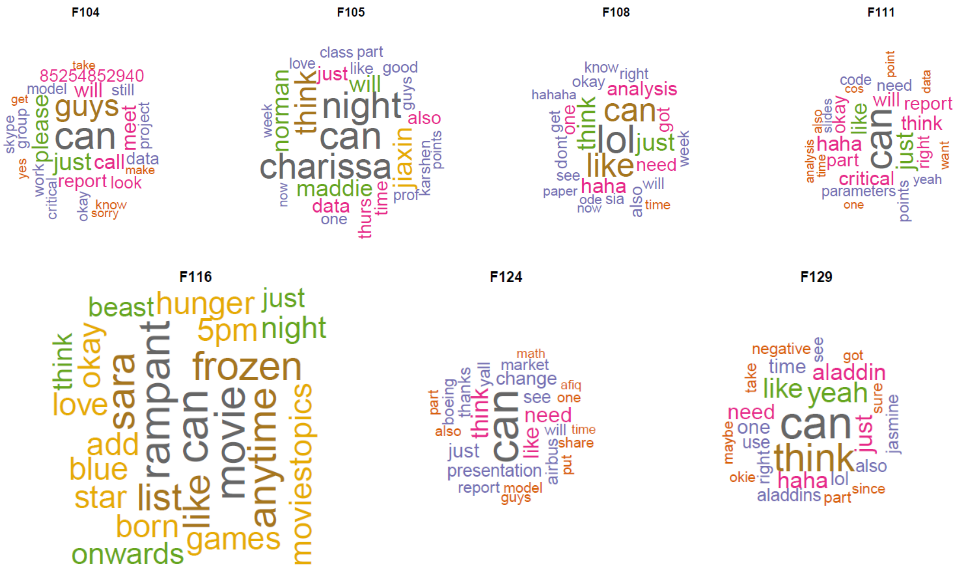

Figure 13 Word clouds in course B (see online version for colours)

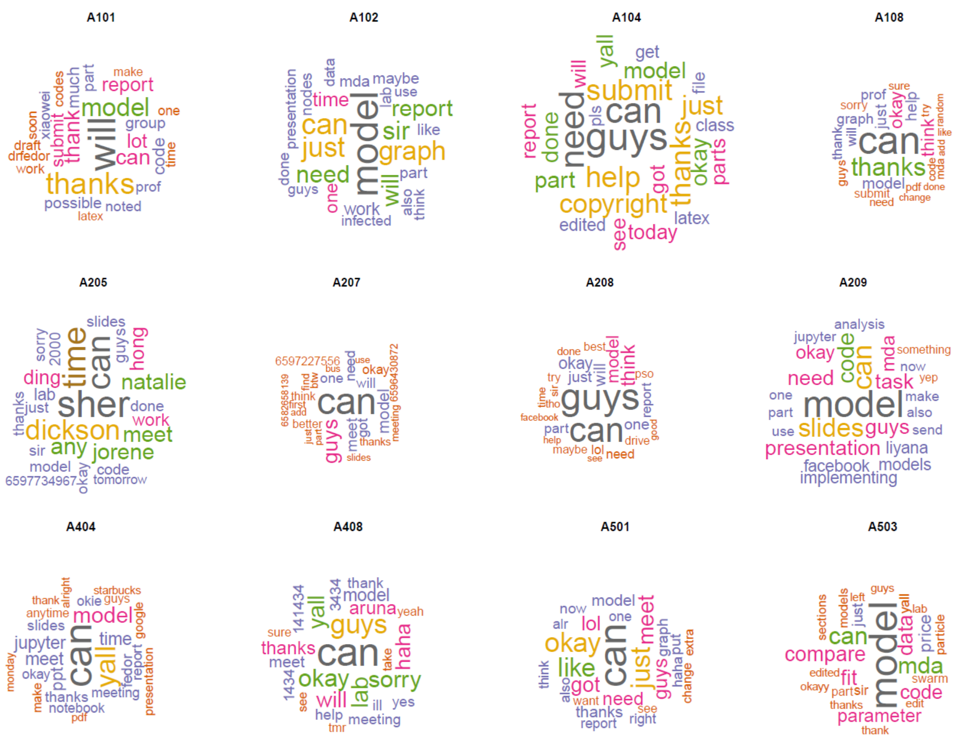

Figure 14 Word clouds in course C (see online version for colours)

Figure 14 Word clouds in course C (continued) (see online version for colours)

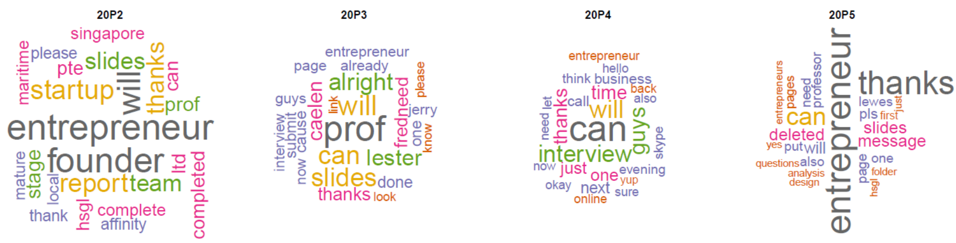

Figure 15 Word clouds in course D (see online version for colours)

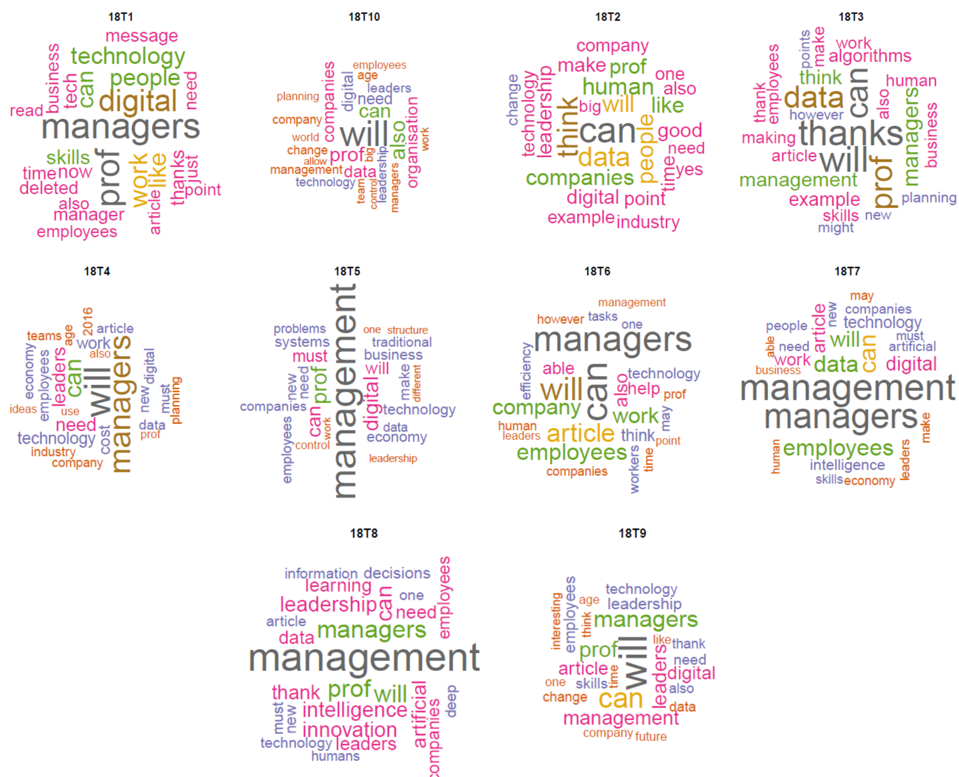

Figure 16 Word clouds in course E (see online version for colours)

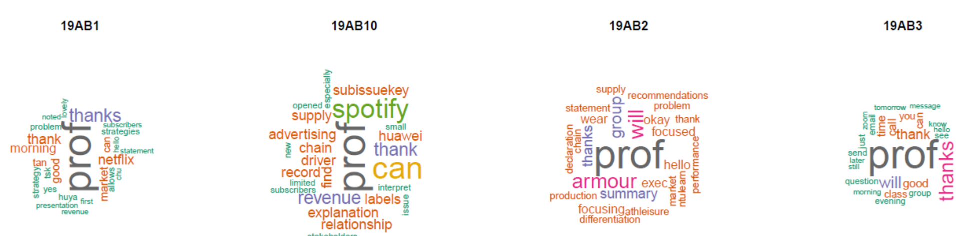

Figure 16 Word clouds in course E (continued) (see online version for colours)

Figure 17 Communication networks in course A (see online version for colours)

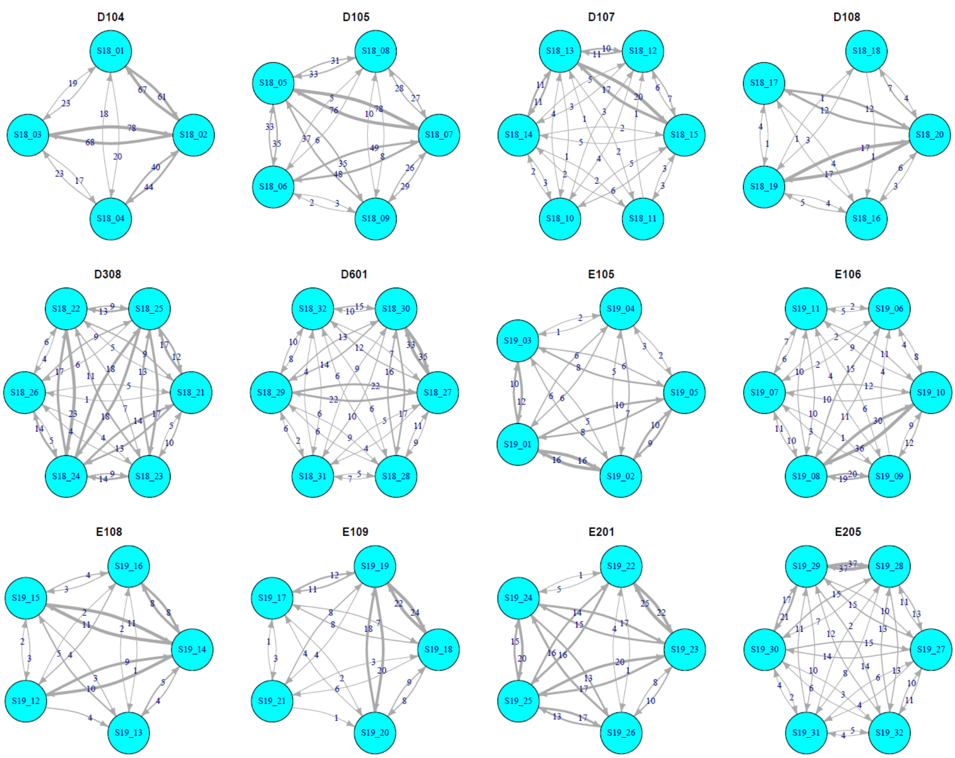

Figure 17 Communication networks in course A (continued) (see online version for colours)

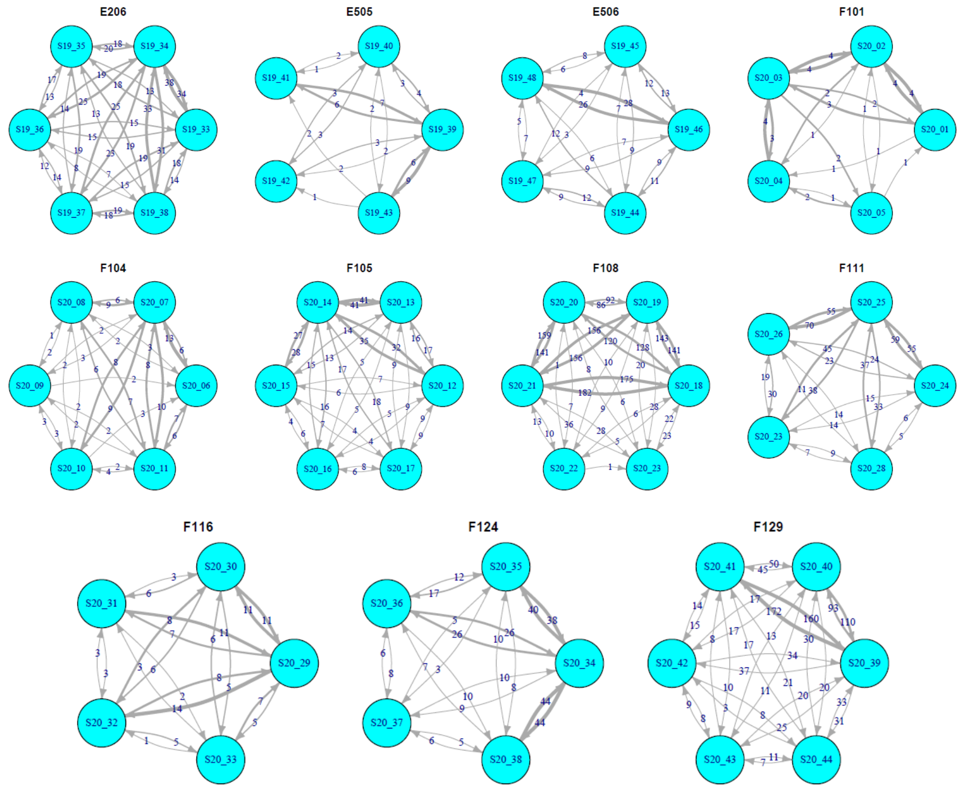

Figure 18 Communication networks in course B (see online version for colours)

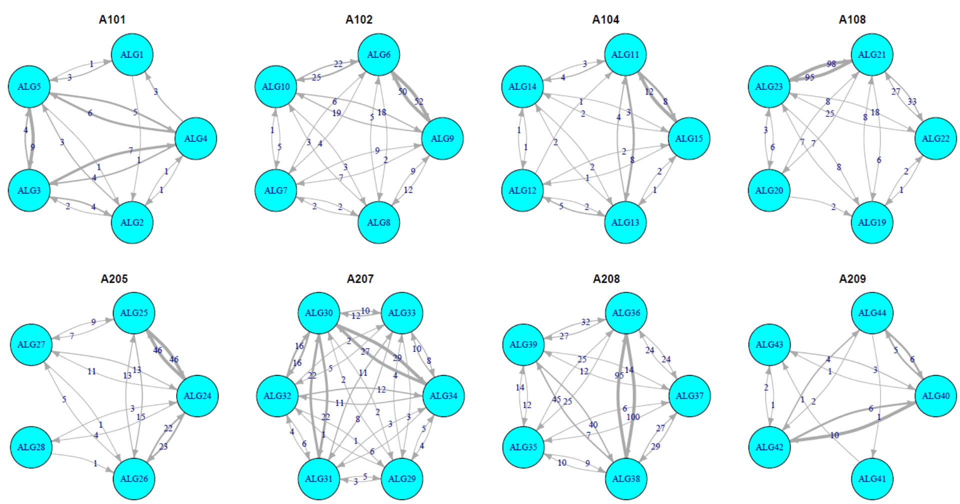

Figure 18 Communication networks in course B (continued) (see online version for colours)

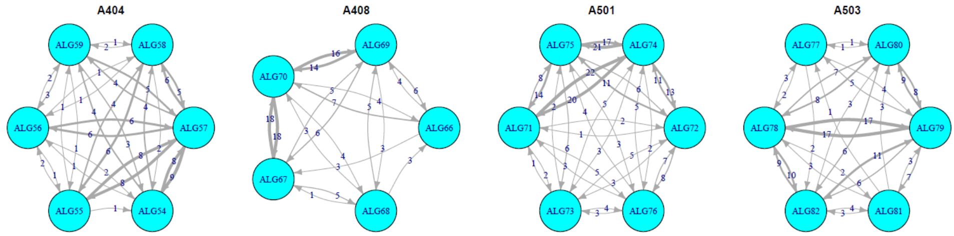

Figure 19 Communication networks in course C (see online version for colours)

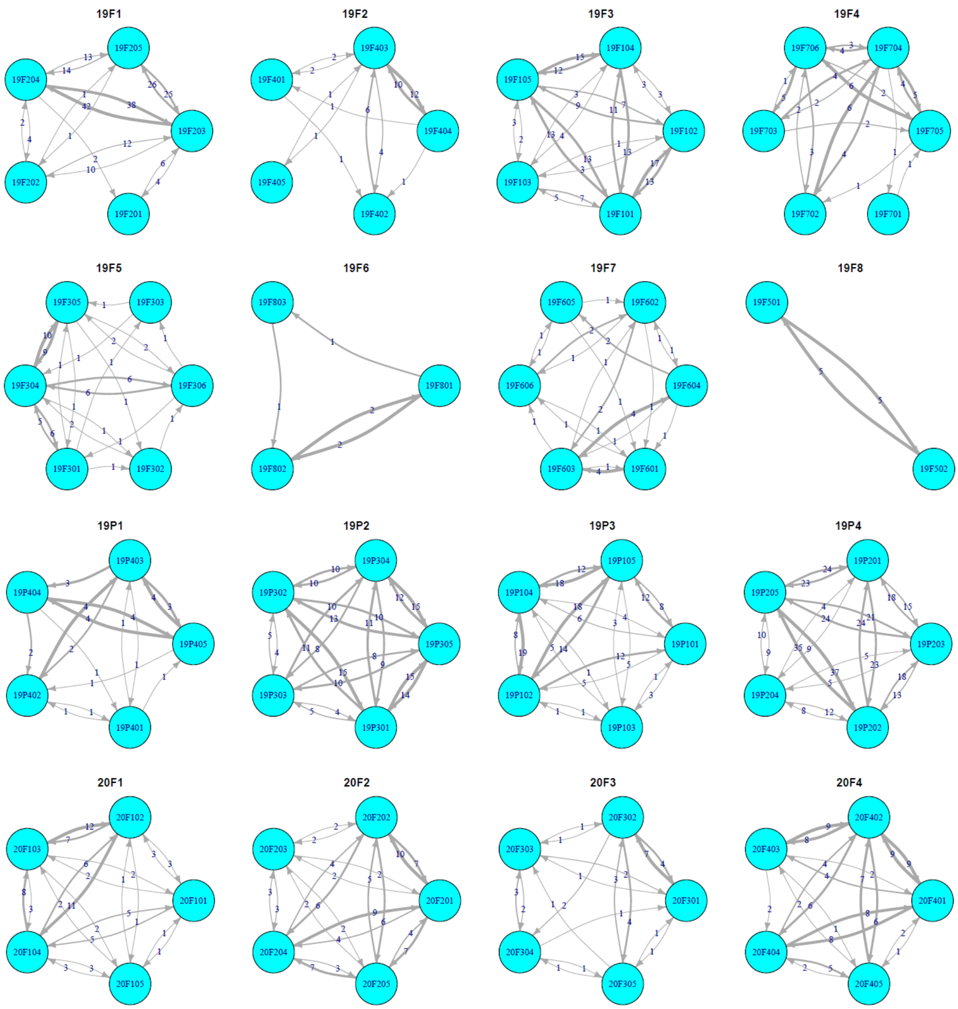

Figure 19 Communication networks in course C (continued) (see online version for colours)

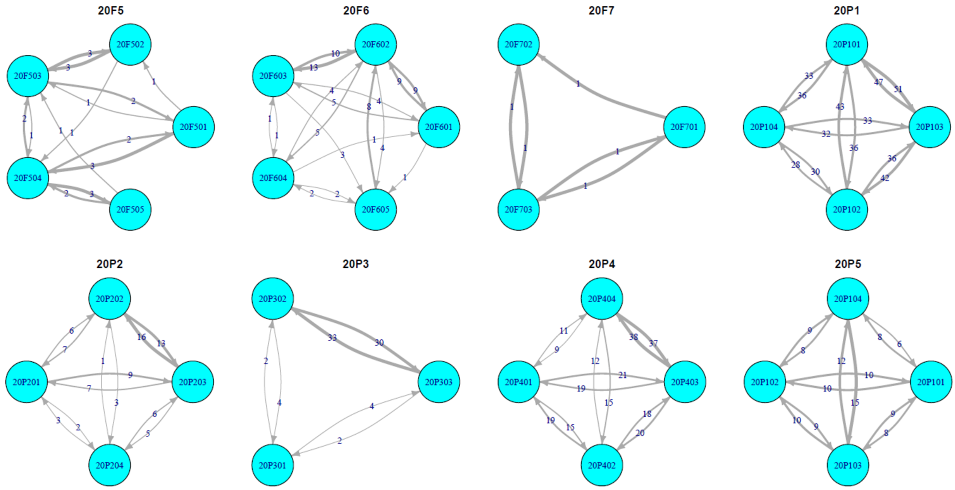

Figure 20 Communication networks in course D (see online version for colours)

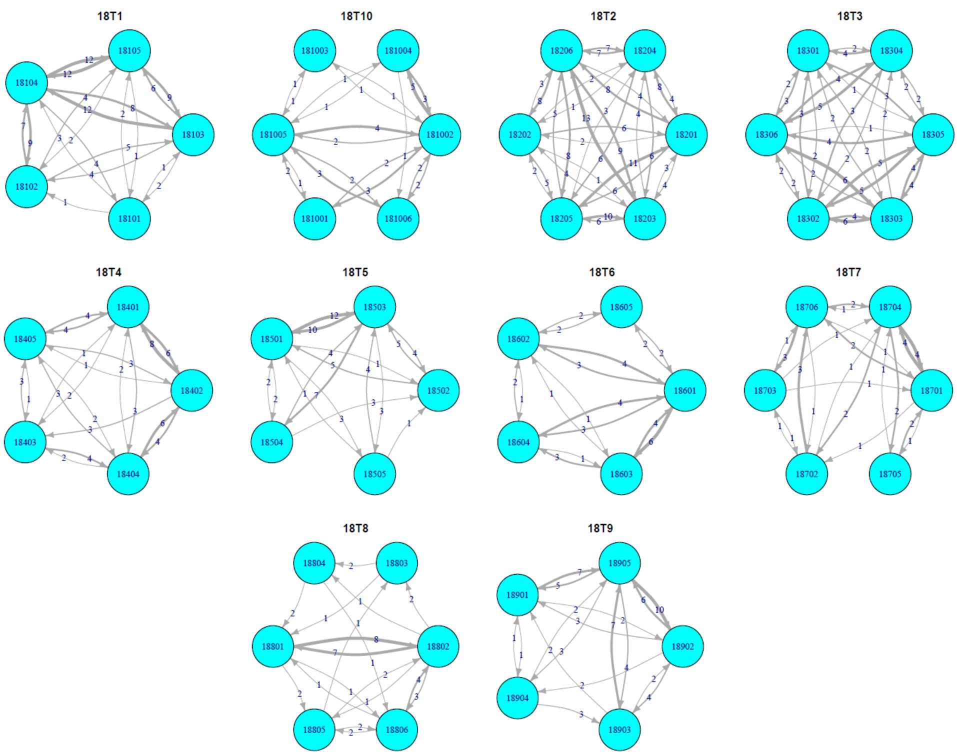

Figure 21 Communication networks in course E (see online version for colours)