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Social Network and Sentiment Analysis: Investigation of Students' Perspectives on Lecture Recording

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ABSTRACT This article presents the results of a study aimed at understanding the value of lecture recordings to student learning. We analysed transcripts of discussions on social media (Facebook) that students generated on the value of lecture recordings. Students discussed whether recording lectures and making them available should be compulsory. While the efficacy of lecture recording has been studied using conventional methods (e.g. questionnaires and interviews) on highly structured data, we employed social network and sentiment analysis techniques to examine individual messages posted on the Student Union's Facebook page. We chose to employ social network and sentiment analysis because these methods are useful in examining semi-structured and unstructured social media data. Overall findings suggest students generally view lecture recordings as resources for supplementing live lectures rather than replacing them. Students stated that lecture recordings could facilitate the creation of an inclusive learning environment and inculcate a positive learning experience. Work presented in this article adds to the growing debate on the institutional deployment of lecture recordings and their impact on students' engagement and learning. It also demonstrated how educational researchers could utilise social network and sentiment analysis to examine critical issues in education.

INDEX TERMS Lecture attendance, lecture recordings, sentiment analysis, social network analysis.

I. INTRODUCTION

Students in higher education are increasingly demanding flexibility in accessing learning, because of the growing demands to balance work, life and family [1]–[3]. Lecture capture technologies enable lecturers to record lectures and make them available to students who might miss lectures for different reasons. The recorded lectures enable students to access lectures anywhere, anytime and multiple times. This would also provide those who miss lectures the opportunity to re-watch lectures and strategically plan their learning [3]. Multiple studies see [1], [4], [5] have indicated that students have continuously stressed the value of lecture recordings in enhancing their learning. Furthermore students mostly indicate lecture recordings help them to supplement their physical lectures [6]–[8]. However, lecturers have concerns on the provision of lecture recordings [9]. Some lecturers are apprehensive about losing their intellectual property rights as they fear digital learning materials can be easily distributed online [1], [10]–[14]. Furthermore, this can aggravate concerns from lecturers relating to the nature of sensitive discussions that might occur in class. Concerns about the intellectual property rights associated with the use of lecture recordings are similar to all forms of digital teaching materials, i.e. such rights are generally retained by the institution [7]. However, such concerns can be addressed by institutions establishing guidelines or policies around the appropriate use of lecture recordings. These policies generally suggest that the intellectual property rights relating to lecture recordings are reserved by the university and that the recordings are not to be used as tools for performance management, but as supplementary learning materials for students [7]. Regarding concerns about

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privacy, many of the lecture-recording systems are password-protected systems, with different ways in which recording is conducted and processed [13]. The most common argument against the provision of lecture recordings to students is that they can be used to replace live lectures, leading to a drop in class attendance [12], [15]. However, recently, research has revealed that the relationship between lecture recordings and attendance is still open to debate [3], [16].

Other studies reported that attending lectures does not necessarily translate to better learning outcomes [17], [18]. Nonetheless, it should be acknowledged that some students would substitute lectures with recorded lectures [19]–[21]. Lecturers have also raised concerns that providing lecture recordings to students before scheduled lectures is likely to alter teaching styles and increase workload see [1], [13], [14]. Most of these concerns, are centered on restricted structure of lecturing, adopting didactic styles of lecturing, as well as a change in general behavior see [1], [13], [14]. Moreover others indicated that the student lecturer interaction is likely to change when students are exposed to lecture recordings before scheduled lectures by adopting techniques such as flipped classroom [14].

Research has shown that the use of social media to facilitate learning and teaching has continued to increase over the years [22]. Students utilise social media to enhance engagement [23] as well as connect with peers [24]. Furthermore, Social Media applications can support sustainable education see [24], [25] and enhance student performance [26]. Social media can be used as a platform for debating critical issues in learning and teaching [27]. Data generated from these platforms can be harvested and analysed to reveal useful insights for improving the quality of learning and teaching. Our goal in this study was to use data obtained from discussions on Facebook to understand students views on the value of lecture recordings to their learning. We examined students' perspectives on whether or not lecture recordings should be made compulsory and the extent to which this would affect class attendance.

II. METHODS AND PROCEDURES

This study utilised data obtained through convenience sampling from a Student Union Facebook forum in a research-intensive university in New Zealand. The central question that guided the discussion was: "do you think lectures should be recorded?" The options available were to react with a like to indicate "OH YES!" or the angry emoji to indicate "NOOO!" Furthermore, participants were asked to elaborate on their reactions in the comments section. Through this, the study obtained a mixture of qualitative and quantitative data, with the qualitative data providing context for the quantitative data. The study addresses the following research question:

1. What are students' perceptions of the value of lecture recordings?

A. PARTICIPANTS AND SAMPLE

The question was posed on the university's student association's Facebook page, which had over 31000 current students and alumni. In total 1435 students reacted to the question via emojis (approximately 22% response rate). A further 220 likes and 65 comments were generated from 150 unique students. All names and the user identifiers were removed to preserve user privacy.

B. DATA ANALYSIS

To gain a better understanding of student's views towards lecture recordings, data presented as emoji were analysed for frequencies, while data from the comments section were analysed using social network and sentiment analysis techniques. The use of the two methods enriched insights gained from the data. More specifically, the social network analysis helped in identifying the influential students within the network using sociograms. Moreover, the sentiment analysis technique enabled us to garner further insights into students' feelings and identify the critical issues that resonate most with students. We used Networkx and Nxviz packages in Python to create the sociograms as well as obtain centrality measures for the sociograms. Sociograms graphically represent links between people [28], which can help in identifying the influential people in a community as well as the flow of information. Sentiment analysis uses natural language processing (NLP), such as text analysis to extract or classify sentiment [29]. We used Google natural language API for sentiment analysis to obtain the sentiments of the student's comments.

C. THE SENTIMENT ANALYSIS PROCESS

Natural language processing (NLP), a combination of machine learning and linguistics has become one of the most heavily researched subjects in Higher Education [30]. NLP technique, such as sentiment analysis provides insights on people's views towards an entity [31]. Furthermore, aspect-based sentiment analysis can identify opinions on different aspects of an entity as users tend to divulge multiple opinions on the specific issue [32], [33]. Recently [34], looked at predicting sentiment intensity using stacked ensemble. As emotions are an essential aspect of human experience [35], and emotion and sentiment are interrelated [34], sentiment analysis can be an essential technique for analysing user opinions. Sentiment analysis has been used in product and movie reviews as well as assessing political views see [36], [37], [38]. In higher education, sentiment analysis has been used to analyse lecture and peer assessment in Massive Open Online Courses (MOOCs), and, how students react to online educational videos see [39], [40]. Sentiment analysis has also been used in evaluating students' perceptions on learning strategies, learning experiences and learning outcomes; as well as the learning experience gained from using a chatbot to support learning a language in an informal learning space See [41], [42]–[44].

The Google Natural Language API used in this study provided access to robust NLP models, pre-trained by Google to perform various tasks. These models were trained on enormously large document corpora; and therefore, generally performed well on everyday language [45]. Furthermore, the use of pre-trained models via the API allows users to conduct predictions without the onus of providing a training dataset. Figure 1 provides a graphical illustration of the Google NLP Sentiment API.

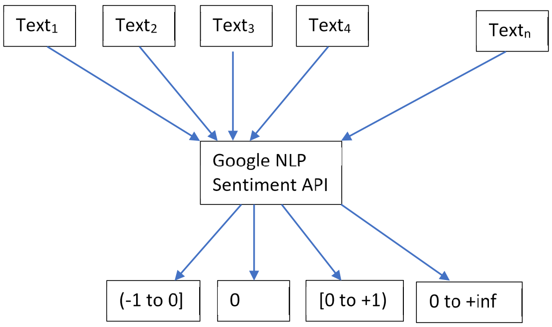

FIGURE 1. General Architecture of Google NLP Sentiment API.

The API returns sentiment scores that describe the emotional leaning of text ranging from -1 (negative) to $+1$ (positive), with 0 being neutral. Magnitude measures the strength and indicates the overall strength of the emotions (both positive and negative) within a given text. Magnitude ranges from 0 to positive infinity [46].

D. THE NETWORK ANALYSIS PROCESS

The employment of Social Network Analysis (SNA) in higher education previously focused on identifying students' interactions in online learning communities; the quality of academic writing as well as the development and measures of social capital see [47]–[49]. It is also used to analyse peer relationships and students learning experiences see [50], [51]. SNA helps understand the relationships and characteristics of individuals in a social context [52], [53]. In recent years, social networks have become more relevant in everyday life. These platforms provide users with an opportunity to freely express their views as well as obtain the views of others [34]. Social networks hold large amounts of data users generate during their engagement [54]. Research such as [54] provides an overview of the state of the art on SNA and the metrics for evaluating the structure of a network. Recent work has also looked at graph embedding see [55] as SNA uses graph theory, where nodes and engagement represent users as links or edges.

In a graph theory of social network, a node is referred to as the actor within a network, and edge specifies the relationship between nodes [28], [47], [56]. The sociograms used in the network analysis can be directed or undirected. In a directed sociogram, an edge only goes one way, and the source node is where the relationship begins while the target node is where the relationship ends [28], [47]. In an undirected sociogram, the edge is bi-directional [57], which means that the relationships between two nodes go both directions. In this study, a directed sociogram was utilised to represent the network. Discourses in social media are networked by nature, where the nodes are users and the edges relationships between users. Relationships can manifest as comments, replies and likes.

In this study, three sociograms were utilised to depict the comments, replies and likes. Each of these relationships can have a different social meaning as well as source and target users. The comments represented, as sociogram is a directed graph depicting a user that posted a comment as the source user and a target user, one that had initiated the post. For example, Table 1 indicates student (u2) posted a comment to the student (u1). The likes in the sociogram are also shown as a directed graph, with a source user that likes a comment or reply of a target user. For example, table 1 indicates student U51 liked the comment of a student (u3). The replies in sociogram are presented as a directed graph that represents the source user as the user that replies a comment or reply from the target user. For example, Table 1 shows the student (u6) replied to a student (u5's) comment.

TABLE 1. Sample of the Dataset Generated for the Network Analysis.

Index	Post	Source User	Relationship	Target User
1	Post2	u2	comment	u1
4	Post4	u51	like	u3
7	Post7	u6	reply	u5

Besides the graphical representation, the connectedness of individuals in a sociogram is determined by the degree of centrality. The degree of centrality is the measure of how many edges are connected to a node [58]. We used the degree of centrality to understand the density and connectedness of the sociogram. This is assuming the nodes are proportional to the in-degree, which means how many times a student replied or liked a comment. Equation 1 represents the metrics used to calculate the degree of centrality d^o, where n is the neighbours a network has, and N is the number of neighbours a network could have.

$$d^o = \frac{n}{N} \tag{1}$$

Equation 1: Degree of Centrality Calculation

III. RESULTS

The results of this study indicate that students maintained a shared view that lecture recordings should be available to them. This is evident from the number of students that indicated "Oh yes!" (97.6%) on the poll, compared to those that indicated the opposite (2.3%) (See Table 2). Insights obtained from sociograms centrality measures, as well as the results of the sentiment analysis, corroborated the view that lecture recordings are valuable resources to students' learning. More specifically, several of the comments and likes suggested the positive aspect of having lecture recordings, with only a few comments in opposition (see Table 6).

TABLE 2. Emoji Responses.

Response	Frequency (%)
Oh yes!	1400 (97.6)
Nooo!	33 (2.3)
Other	2 (0.1)

In this study, four sociograms are provided; the first depicts all the relationships in the network (comments, replies and likes) (see Figure 2). The second, third and fourth sociograms represent the comments, replies and likes sociograms respectively (Figures 3-5). The sociograms show that the students who were most influential in the sociogram gained attention from their peers in terms of posting and comments they made. A sample of the top five students based on degree centrality is provided in Table 3.

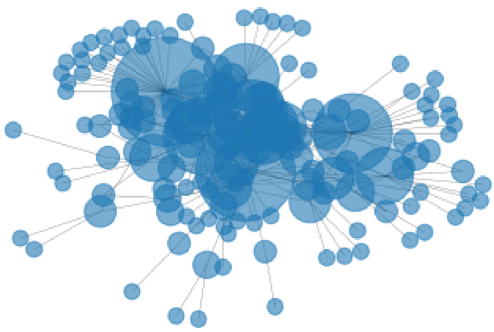

FIGURE 2. Edge list: list of all the edges within the nodes.

TABLE 3. Degree of Centrality for all Relationships.

User	Degree of Centrality
u25	0.327
u1	0.272
u11	0.170
u42	0.163
u10	0.150
u47	0.122
u5	0.088

Figure 2 represents the various forms of relationships (comments, replies, and likes) between the source and target users. In this sociogram, node sizes are proportional to the in-degree, which represents the degree of relationship amongst users. Further, the degree of centrality in table 3 shows the degree to which students were connected. The value also shows the overall density of the network. It shows students with the most clout in the sociogram. The Sentiment analysis conducted at sentence and comment level is shown in Tables 4 and 5.

TABLE 4. Sentiment Scores of the Individual Sentences.

Sentiment	Percentage (%)
Positive	42.0
Neutral	20.7
Negative	37.4

TABLE 5. Sentiment Scores of the Overall Comment.

Sentiment	Percentage (%)
Positive	39.4
Neutral	33.3
Negative	27.3

Table 5 shows the sentiments generated from the individual sentences in a comment, while Table 6 indicates the sentiments generated from all the comments. In both cases, sentiments were mostly positive. In comparing the two, however, there is a slight difference in the values with a higher percentage of positive sentiment depicted at the sentence level, though; the neutral sentiment for the general comments is higher. This indicates the value of breaking down text as more details can be generated when comments are broken down into chunks of sentences. Table 6 presents an example of the text and sentiment scores generated from the Google Sentiment API.

The 'IDX' column represents the index of the comment/reply made by each student that contributed to the conversation. The 'ID' column represents each sentence in a student's comment/reply. The 'Text' column represents the comment/reply from a student. The 'OS_SCORE' represents the overall sentiment score for each comment/reply. Finally, the 'OM_SCORE' represents the overall magnitude score for each comment/reply. For example, the comment with IDX 3 is split into two sentences: index 1 and 2, respectively. Sentence index 1 generates a sentiment score of 0.30, while sentence index 2 generates a sentiment score of 0.2. The overall sentiment score for this comment is 0.2 and the overall magnitude is 0.5. IDX 26 shows a comment made against the idea of having recorded lectures this comment, showing an overall negative sentiment of -0.2 and a magnitude of 2.4.

As earlier indicated, the study breaks down the sociogram (figure 2), to represent each of the relationships individually, as illustrated in Figures 3-5. The degree of centrality for the replies and likes sociograms are provided in table 7 and 9. Furthermore, an example of the text and sentiment scores of the student with the highest degree centrality in the replies and likes sociograms is provided in table 8 and 10.

Figure 3 represents the 'comments sociogram', In this network, node sizes are proportional to the in-degree,

TABLE 6. Sample of the Sentiments Generated from the Dataset.

IDX	ID	S_SCORE	TEXT	OS_SCORE	OM_SCORE
1	1	-0.5	Do they not record your lectures Ux, Uy?	-0.5	0.5
2	1	0	… yeah we have some that do not get recorded too	0	0
3	1	0.30	Could record a year's worth of lectures and recycle them.	0.2	0.5
	2	0.2	The lecture may be used for questions and research etc		
25	1	-0.2	Wouldn't that defeat the point of going to an institution to get a degree?	-0.2	2.4
	2	0	Because if you recorded all the lectures, pretty much all of the staff that teach would only be teaching to maybe five people if none at all.		
	3	0	Do you honestly reckon people would show up for "class"		
	4	-0.7	Hell no, they would not...		
	5	0.1	They are… Moreover, are mostly there for one thing.		
	6	-0.2	To get drunk, and scrape by Uni for three years, just so at the end they can say...		
	7	0	"Well... C's get degree's, I guess."		
	8	-0.9	So no, it is honestly a terrible idea, which is unless you want all the staff to retire early and want to promote research for oneself rather than having an "institutionalised" degree behind you.		
	9	0	#StopMakingItEasier#UniversityIsSupposedToBeAChallenge		

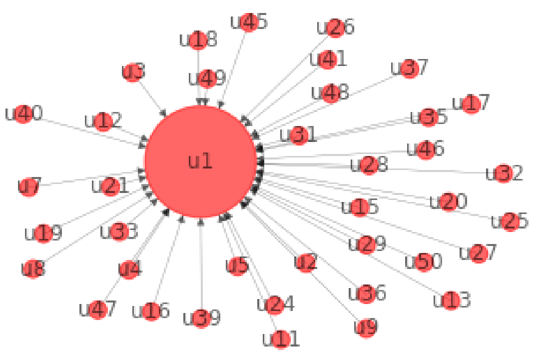

FIGURE 3. Comments Sociogram.

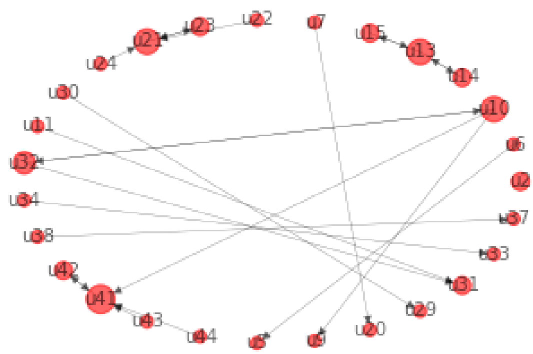

FIGURE 4. Replies Sociogram.

representing the number of comments students made on the initial post. Hence, the density of the node u1 indicates the originator of the post, and that other students contributed to the post. A total number of 38 students commented on this post, they include the following ('u2', 'u3', 'u4', 'u5', 'u7', 'u8', 'u9', 'u11', 'u12', 'u13', 'u15', 'u16', 'u17', 'u18', 'u19', 'u20', 'u21', 'u24', 'u25', 'u26', 'u27', 'u28', 'u29', 'u31', 'u32', 'u33', 'u35', 'u36', 'u37', 'u39', 'u40', 'u41', 'u45', 'u46', 'u47', 'u48', 'u49', 'u50').

The network illustrated in Figure 4 represents a 'replies sociogram' with source users replying comments posted by target users. Students ('u2', 'u5', 'u6', 'u7', 'u9', 'u10', 'u11', 'u14', 'u13', 'u15', 'u20', 'u21', 'u22', 'u23', 'u24', 'u29', 'u30', 'u31', 'u32', 'u33', 'u34', 'u37', 'u38', 'u41', 'u42', 'u43', 'u44') all contributed to this network, totalling 27 students. In this sociogram, the number of replies each comment attracted is provided. Nodes representing student u41, u10, u13, u21 and u32 have reasonably sized nodes compared to the rest suggesting they are the most influential in the network. This is further illustrated in Table 7. Furthermore, Table 8 provides sample text and sentiment scores for student u41 who had the most clout in the replies sociogram.

TABLE 7. Degree of Centrality of the Replies Sociogram.

User	Degree of Centrality
u41	0.192
u10	0.154
u13	0.154
u21	0.154
u32	0.115

TABLE 8. The Sentiments Generated by User 41.

Idx	Id	S_score	Text	Os_score	Om_score
48	1	-0.6	Should be recorded but only provided with a doctor's note.	-0.6	0.6

TABLE 9. The Degree Centrality of the Likes Sociogram.

User	Degree of Centrality
u25	0.353
u42	0.191
u11	0.169
u47	0.162
u10	0.125

As illustrated in Table 8; the overall attitude expressed within the text generated a negative score of -0.6 and a magnitude of 0.6. Hence, this comment may have attracted many replies due to its negative connotations which fellow students most likely rebuffed.

Figure 5 represents the 'likes Sociogram' illustrating the network of students that liked a comment or reply.

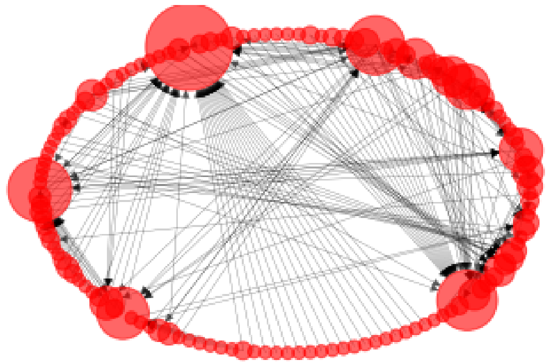

FIGURE 5. Likes Sociogram.

According to the network analysis, 220 likes were generated. The degree of centrality of the likes sociogram is provided in Table 9 to understand this network further. Furthermore, Table 10 provides sample text and sentiment scores for student u25 who had the most clout in the likes sociogram.

Table 10 illustrates the sentiment behind the comments posted by user u25 and the number of likes each comment generated. For IDX 57, the overall sentiment score of -0.3 indicated negative sentiment. The individual sentences also indicated a mixture of the negative and neutral sentiment of -0.8, 0, -0.3 for the three sentences with a magnitude score of 1.2. This comment obtained 42 likes the highest in the network. For IDX 30, the five individual sentences had a mixture of negative neutral and positive sentiment, -0.2, 0,

TABLE 10. The Sentiments Generated by User 25.

IDX	ID	S_SCORE	TEXT	OS_SCORE	OM_SCORE	Likes
57	1	-0.8	Considering all the different ways people learn, keeping it "old school" is just discrimination against people who struggle to take in information in that way.	-0.3	1.2	42
	2	0	What a weird poll.			
	3	-0.3	Not everyone with a learning disability or quirk or a physical constraint (hearing/vision) is diagnosed.			
	4	0	I legit cannot even believe this is being asked			
30	1	-0.2	Why punish those who could benefit from it cos some will use it instead of turning up to class?	0.1	1.2	5
	2	0	Who cares if they do not turn up to class anyway?			
	3	0.8	The future is moving towards flexible learning and e-classrooms etc.			
	4	0	… is right; there does not need to be an ethical debate over this.			
	5	0	If it is possible, get it done son.			

0.8, 0, and 0 for the five comments, respectively. Overall, the sentiment was positive (0.1) with a magnitude score of 1.2. This comment obtained five likes.

IV. DISCUSSION AND CONCLUSION

Contemporary students expect that institutions of higher education offer flexibility to access learning. Research suggests that students believe flexibility can be achieved through the provision of lecture recordings see [1], [4], [5]. However, lecturers continue to resist the provision of these materials because such provision would have detrimental consequences in lecture attendance see [12], [15]. Although, research has indicated students prefer to access recorded lectures after scheduled live lectures see [59], underscoring the supplementary usage of lecture recordings. Although there is an ongoing debate against providing students with lecture recordings see [16], students have maintained that lecture recordings are valuable learning resource and should be provided as an option for learning see [1], [4], [5].

Our findings suggest that students use lecture recordings as supplementary learning materials and not a replacement for scheduled lectures. Students emphasised that lecture recordings helped them to compensate for missed lectures. However, others used lecture recordings to replace live lectures due to circumstances such as illness or work commitments.

These findings suggest that the value in the lecture recordings, whether as supplementary or replacing live lectures is dependent on individuals' circumstances.

Although lecturers also contest the provision of lecture recordings as there is a concern, they can be easily distributed online see [1], [13], [14]. Students in our study indicated the system does not allow them to download videos on their devices, and cannot, therefore, share and distribute. We also noted a variation in the provision of lecture recordings across departments, suggesting a need for the development institutional policy to promote an equitable provision of lecture recordings to all students. Some students indicated that with the current shift to flexible learning, it is a matter of time until this would be the standard norm in institutions.

While the social network analysis provided an overall structural view of the students' value of lecture recordings, the sentiment analysis gave further insights into what students thought about the recording of lectures. The positive sentiments support the value of using lecture recordings. The Negative sentiments suggest concerns about not having access to recorded lectures. Overall, the findings of the study suggest that students generally view lecture recordings as resources for supplementing live lectures. Lecture recordings provide students with flexible and equitable learning they can facilitate the creation of an inclusive learning environment, especially for students with special needs.

Some of the concerns academics raise against the provision of lecture recordings can be mitigated through the development and implementation of an institutional policy outlining best practice in the use of these resources. This article contributes to the growing debate on whether or not instructors need to record their lectures and make them available to students at any time. We also showed that rather than relying on structured data obtained through questionnaires, educational researchers could employ social network and sentiment analysis to leverage the potentials afforded by social media data that are often semi-structured or unstructured to answer important educational research questions.

The combination of social network and sentiment analysis used in this research provided an alternative way of understanding different forms of data students generate on social media.

A. LIMITATIONS

- The use of automated sentiment analysis does not necessarily replace the need to manually read qualitative data.
- The use of pre-trained classifiers in sentiment analysis can be disadvantageous as the context of the text is not considered
- The Student Union Facebook page might include alumni so some comments may have come from non-students
- Anyone can join the page, so there is a possibility of students not from the university making comments on the issue.
- Ethical and privacy concerns is also another risk associated with network analysis, and this issue must be considered carefully in the design and analysis stage.
- Network analysis may not capture the influence of those beyond the network or all the relevant actors.
- Our data did not indicate student's preference on accessing recordings before or after lectures; however, this will be explored in a future study.

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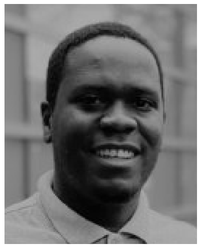

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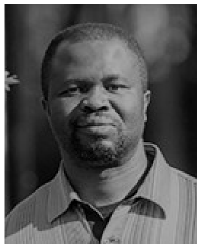

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