ABSTRACT

This study investigated the effect of students' interactions with the virtual learning environment (VLE) and its effect on their performances using a mixture of SNA-based pictorial and mathematical analysis. To achieve this aim, a social network analysis was carried out on a VLE database gotten from the Open University Learning Analytics Dataset (OULAD). Python programming was used to clean and extract the needed data, Gephi software was used to produce a visualization of the interactions in the VLE, and SPSS software was used for the mathematical analysis. The results showed that most of the students that performed best interacted more with the system than those who failed to. The students that registered for the module late had below par grades. The result from the statistical analysis proved that student interaction was not a trustworthy factor to predict students' performance. This suggested that students had more chances of doing better if they had registered for the module early and had constant interaction with the system.

Keywords: Analyze; interaction; SNA; students' performance; VLE

ÖZET

Bu çalışmada öğrencilerin sanal öğrenme ortamı (VLE) ile etkileşimlerinin ve SNA tabanlı resimsel ve matematiksel analizlerin bir karışımı kullanılarak performansları üzerindeki etkisi araştırılmıştır. Bu amaca ulaşmak için Açık Üniversite Öğrenim Analitiği Veri Kümesi'nden (OULAD) alınan bir VLE veri tabanı üzerinde bir sosyal ağ analizi gerçekleştirilmiştir. Gerekli verileri temizlemek ve ayıklamak için Python programlama, VLE'deki etkileşimlerin görselleştirilmesi için Gephi yazılımı ve matematiksel analiz için SPSS yazılımı kullanıldı. Sonuçlar, en iyi performansı gösteren öğrencilerin çoğunun, başarısız olanlardan daha fazla sistemle etkileşime girdiğini göstermiştir. Modüle geç kayıt yaptıran öğrencilerin eşit notlarının altında olduğu görülmüştür. İstatistiksel analiz sonucu öğrenci etkileşiminin öğrencilerin performansını tahmin etmek için güvenilir bir faktör olmadığını kanıtladı. Bu, öğrencilerin modüle erken kayıt yaptırmış olmaları ve sistemle sürekli etkileşime girmeleri durumunda daha iyi olma şanslarının daha yüksek olduğunu göstermiştir.

Anahtar Kelimeler: çözümlemek; etkileşim; öğrencilerin performansı; SNA; VLE

INVESTIGATING THE EFFECTS OF INTERACTION ON STUDENT PERFORMANCE IN VIRTUAL LEARNING ENVIRONMENTS

A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCES OF NEAR EAST UNIVERSITY

By
PRECIOUS CHINONSO UGWU

In Partial Fulfillment of the Requirements for the Degree of Master of Science in Computer Information Systems

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I hereby declare that all the information in this document are retrieved and presented in accordance to the academic rule and ethical conduct. I also declare that, as required by the rules and conducts, I have fully cited and referenced all material and results that are not original to this work.

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Date: 17/07/20

To my Family…

ABSTRACT

This study investigated the effect of students' interactions with the virtual learning environment (VLE) and its effect on their performances using a mixture of SNA-based pictorial and mathematical analysis. To achieve this aim, a social network analysis was carried out on a VLE database gotten from the Open University Learning Analytics Dataset (OULAD). Python programming was used to clean and extract the needed data, Gephi software was used to produce a visualization of the interactions in the VLE, and SPSS software was used for the mathematical analysis. The results showed that most of the students that performed best interacted more with the system than those who failed to. The students that registered for the module late had below par grades. The result from the statistical analysis proved that student interaction was not a trustworthy factor to predict students' performance. This suggested that students had more chances of doing better if they had registered for the module early and had constant interaction with the system.

Keywords: Analyze; interaction; SNA; students' performance; VLE

ÖZET

Öğrenciler ve VLE sistemi arasındaki sanal etkileşimler, gerçekten araştırılmayan çok büyük ve öğrenmenin bir parçasıdır. Öğrenme ilişkilerinin VLE'de nasıl geliştiğini ve etkileşimlerin öğrenme sonuçları üzerindeki etkisini bilmek, öğrenim tasarımının hangi bölümlerinde gelişme sağlayacağını bilmek gibi birçok yolla yükseköğretim kurumlarına yardımcı olabilir. Sosyal ağ analizi (SNA), etkileşimli verilerden oluşan soruları araştırmak için gerekli araçları sağlar. Açık Üniversite Öğrenim Analitiği Veri Kümesinden elde edilen bir veri seti kullanılarak veri toplama, verilerin işlenmesi ve analizi için prosedürlerle birlikte SNA'da temel fikirler sunuyoruz. Veri seti üzerinde nicel analizler yapıyoruz. Ayrıca, veri kümesinden etkileşim ağlarının bir görselleştirmesini üretiyoruz ve etkileşim ile puan performansı arasında bir bağlantı bulmaya çalışıyoruz. Ayrıca elde edilen matematiksel sonuçlara dayanarak tahminler yapmaya çalışıyoruz. Amacımız, öğrencileri VLE sistemiyle daha fazla etkileşime girmenin onlara daha iyi olma şansı sağlayacağına ikna etmektir ve ayrıca öğrencilere elde edilen sonuçlara dayanarak sonuç verebilmek ve hangi araçları gösterebileceğini göstermek için veri setleri üzerinde nasıl analiz yapılabileceğini göstermektir. Böyle bir analiz yapmak için ihtiyaç duyulacak ve umarım bu, birçok öğrenciye SNA'ya daha fazla dâhil olmaları için ilham verecektir.

Anahtar Kelimeler: çözümlemek; etkileşim; öğrencilerin performansı; sanal öğrenme ortamlrı; sosyal ağ analizi

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LIST OF ABBREVIATIONS

CSEQ: College Student Experiences Questionnaire

DM: Data Mining

EDM: Educational Data Mining

ICT: Information and Communications Technology

LA: Learning Analytics

NSSE: National Survey of Student Engagement

OULAD: Open University Learning Analytics Dataset

SNA: Social Network Analysis

VLE: Virtual Learning Environment

CHAPTER 1

INTRODUCTION

Virtual Learning Environment (VLE) are combined in academic institutions, however, the choice of its acceptance remains a subject of discuss as it is difficult to convert it into a vital aspect of students' performance.

There are lots of factors which impacts students' performance, making it almost impossible to find out all of them and even harder to judge the impact of each one of those factors on students' performance and assessment results. This study concentrates solely on investigating the effect of students' interaction in VLE on students' performance, interpreted into barometers connected with: students' final scores which were entered into the system and what parts of the system they interacted with the most, among others.

Some of the methods used to investigate these interactions and its effect on performance are Social Network Analysis (SNA) and statistical analysis. SNA is a proper instrument for this analysis because it offers a method of analyzing connections quantitatively among a dataset. From the images that would be shown in this study, the usefulness of SNA and how it could be used to group and examine in contrast interaction shapes in a VLE were displayed.

Within the framework of this study, the amount of interaction with the VLE system will, in some circumstances, be looked at as the independent variable and the score variables will be looked at as dependent variables.

The hunt for improved education has been one of the main responsibility of lots of countries in the world currently. In this effort to come out with the best, lots of significance have been given to plans based on ICT, in which, over the previous years, the digital has become first in order over the analogue. Therefore, to advance and enhance educational practices, higher educational institutes have taken up learning management medium which is now known as Virtual Learning Environments (VLEs). These environments have been used by schools that are importantly aimed at onsite learning and also schools that are aimed at distance learning.

The powerful implementation of VLEs in schools, legitimize the worries with such environments so as to judge their impact on students' performance. Making firm the use of these environments suggests their putting in a specific context within the formal learning and teaching procedure as well as interrogating their potential for development according to their consolidated and popular features, which are the ones connected with the usual onsite class learning.

The connection between involvement and academic results has been researched in e-learning (Adeyinka and Abdulmumin, 2011) and traditional classroom settings (Carini et al, 2006). An excuse for a common absence of an understandable picture regarding this connection is that, the idea of learner involvement has been explained in another way and functionalized in various frameworks. “Student involvement” has reached a point of engagement learners seem to have in their traditional classrooms in the form of education. Learners’ involvement in schools has been functionalized in different means. Usually, applied procedures for deciding involvement consist of self-reporting by standard surveys, like the NSSE and the CSEQ, and digital evidences like VLE usage logs. In this study, we debate that student interaction with VLE is complicated and of huge magnitude requiring the sum of students’ interaction with the various activity types of the system connected with the personal learning experience. Therefore, in order to judge the connection between interaction and performance in the dataset, studies cannot only depend on visualization but also on the use of software.

In order to judge the effect of interaction with VLE on students’ performance, a dataset gotten from OULAD would be analyzed using SNA. Additionally, SNA would also be used to make predictions based on VLE usage for performances on scores.

It is hoped that this paper brings to awareness how to use SNA to analyze interaction and show the interaction in the dataset. From the results gotten form this SNA, It is believed schools would be able to identify what parts of the system learners are struggling to communicate with and come to their aid.

1.1 Background

The researcher started this paper by discussing the different nature of student interaction in different institutions. Our current dataset comes with different problems that requires answers. Therefore, the nature of interactions as it connects to VLE would be examined briefly.

1.1.1 Calculating the connection between interaction and performance

Interaction and participation in VLE have been discovered to have lots of correlation with different types of learning results (Asterhan and Hever, 2015; Zhu, 2006; Song and McNary, 2011). In a VLE, involvement is majorly explained in the framework of learners' communications with a system, usually a VLE. Learners are displayed to involve in a different way when getting education in a VLE as opposed to in a traditional classroom, leading to contrasting academic performance and a contrasting array of variables to forecast results (Harris and Nikitenko, 2014). The arrival of VLE has caused a shift towards the disintegration of the learning procedure, which has led to more attention on course content and structure, and improved amount of communications with the system, whilst allowing the traditional learning method transform into a further complicated and hard to methodically measure as a matter of course (Agudo-Peregrina et al., 2014). Researches utilizing tools that are confessing like surveys to calculate interaction in an online class reported a general good but rather feeble connections and restricted capability to forecast results across frameworks. Learners' virtual learning records have been used from time as substitute agent for interactions and involvements so as to beat the common belief of confessing, displaying once more to be restricted and forecasting lesser in a traditional environments than in online environments.

1.1.2 Interaction is context-dependent

Universities and colleges are extremely different in framework, containing the tangible settings, computerized machines and materials, the barometers that are used for judgement, and the instructional methods utilized (Harris and Nikitenko, 2014). A learning design, selected and used by the lecturers, symbolizes the group of academic events and items that are utilized in the period of carrying out these events (for example, publications, pictures, software packages and PDFs). It can also point to services (for example, discussion forums, blogs, and chats) utilized in the period of these events and may also contain the tools selected to analyze results. The variety of elements forms a large variety of probable learning designs.

Even though the significance of learning design for conceptualizing and improving the measurable analysis has been lately noticed, very little researches to this day have analyzed a large amount of learning designs with VLE agents and academic results. In terms of e-learning and flipped learning, learning designs, corrective difference and academic results, means were able to describe a substantial amount of the irregularities in VLE involvement. Learning design constituents like course length and assessment were displayed to impact interaction in VLE. Also, learning design was displayed to affect students' ways of learning and involvement. It was also discovered that the level of interaction is based on the school on the course and school, which may also be described by different learning designs and informational approaches.

1.2 The Problem

VLE has gotten lots of impetus over the previous years and this has drawn the interest of lots of researchers since this form of learning has become a very popular one. VLE permits students to get access to course materials from their home and to learn at a distance without any geographical or time limitation as far as internet is accessible to the student. Additionally, VLE encourages cooperative learning and boosts self-confidence. However, there is a huge question over if this learning method is better than the traditional learning method and what impacts it has on the grades students score at the end of the semester and this has been the main stimulating determinant for the researcher to carry out this research to find out if the more students interact with the system help them get better results. Most of the researches done on this subject are limited to the theoretical aspect of VLE and this has inspired the researcher to carry out a SNA on this subject that involves analyzing a dataset on students of VLE. Gephi software would be used to analyze that data, while MySQL would be used to combine the datasets into one, SPSS would be used for the correlation and prediction. These are the three main software that would be used for this SNA.

1.3 Aim of Study

This study is aimed at both providing information on VLE and also using SNA to analyze data gotten from VLE students to make conclusions on whether more interaction with the VLE system leads to students getting better scores. The results gotten will help to make some useful conclusion on VLE and also the theoretical aspect will provide more knowledge on VLE and how it works and how a SNA is carried out.

Adoption of VLE in academic institutions will have a big impact in the creation of learning and teaching procedures. Still, favorable implementation of this system is based on if it would help students perform better and how to inspire them to be more interactive with the system. Thus the goal of this study is on analyzing the success of learners that have used the system in other schools. In order to reach the goal of this study, the listed research questions were asked:

- RQ1: What social network analysis measures are related to student performance?

- RQ2: Can individual behavior like late registration be used as predictors of performance?
- RQ3: Can student interactions be used to predict performance?
    - In terms of the assessment score?
    - In terms of the final score?

1.4 Limitations of the Study

- The data was incomplete: There were lots of missing values in the tables and the rows containing these missing values were deleted to avoid interruption with our analysis (when treated or replaced).
- Possibility of Inaccurate Information: There is a chance that some of the students didn't give their best effort in the participation. If this is the case, then the data would be skewed.
- Vary in Quality and Format: Data collected from lots of people will have different features and design. Data from many people may not have much unity among data fields. Therefore, we would have to preprocess this data before we analyze it.
- The study focused on collecting data from just Open University students.
- The nature of data collection is by module-presentation – which are study groups of 20 people. Individualistic approach might have been better instead of grouping.
- The dataset is not very detailed; it only has student-system/content interaction.

1.5 Importance of the Study

Different researches have been carried out in different places to shed more light on VLE and user acceptance of this form of learning. Most researchers have mainly focused on user acceptance, adoption and usage of VLE. This study is the first of its kind as it talks about the user adoption, acceptance and usage of VLE and as well as a SNA of data gotten from students of VLE to come to a conclusion on the effect of interactivity with the VLE system.

Different educational stakeholders will also gain from this research. This information gotten from this study will be useful to researchers, educators and students. The advantages are explained below by the researcher:

- Educators: Students will know the advantages they stand to gain if they interact more with the system, how the system is currently used by other schools and also be more knowledgeable on how to properly use the system for their own good.
- Researchers: Researchers would be able to draw conclusions from this study and also get very useful information. It would also help them to recognize what aspect of this study needs to be improved and researched on.
- Students: This study could serve as a motivation for students. To motivate them to interact with the learning system more if they want to perform better academically.

1.6 Overview of Thesis

This paper is grouped into 6 different chapters which are explained below:

Chapter One: This chapter contains an introduction on the topic, background, problem, aim, importance and limitations of the study. It also contains the research questions

Chapter Two: This chapter contains a related research and literature review of the topic.

Chapter Three: Presents the hypothetical system whereby SNA, history of SNA, SNA theories and applications, areas of application, methods of aggregating data, level of analysis, graph theory concept and basics, types of graphs and networks, types of results gotten from SNA, DM, EDM and LA were analyzed.

Chapter Four: This chapter describes the software that was used by the researcher when analyzing data. It also explains research participants, method of data collection.

Chapter Five: This chapter explains the results gotten after the data was analyzed.

Chapter Six: This chapter gives a summary of the whole thesis and also form the conclusion and suggestions for future research.

CHAPTER 2

RELATED RESEARCH

In this part of the thesis, the researcher's aim is to discover related research that has been carried out by other researchers using SNA to analyze different forms of learning like VLE, online learning, moodle, flipped and blended learning, flipped learning data, what has been their research questions and what methodologies they applied and their results.

2.1 Related Research

Table 2.1: Related research

About Research	Source of Data	Number of Participants	Research Questions/Aim	Application of SNA	Results
A research by Saqr (Saqr et al., 2018) collected a dataset that included details of students for four courses that used BPL as a style of teaching.	Qassim University, Saudi Arabia.	215 students and 20 teachers were involved in this study.	1: How do indicators of SNA equate to performance in online PBL? 2: To what extent can indicators of SNA be applied as dependable performance predictors in online PBL?	SQL was used for extraction of interaction data and the analysis tool, gephi, was used to analyze the extracted data. Visualization was applied to get a social network in each group and course, while quantitative network analysis using SPSS software was done to measure the parameters of SNA for each group and course and for predictive modeling.	The results showed that students who communicated more with their fellows in groups tend to perform better. The findings also showed that using interaction data to predict performance is actually reliable, thereby proving a chance for support and intervention

Table 2.1: Related research continued…

Another study by Saqr (Saqr & Alamro, 2019) studied the role of SNA as a LA tools in online PBL.	PBL collection of individuals in the “growth and development” course at Qassim University.	The study involved 15 teachers and 135 students.	1: What can SNA pictorial and statistical analysis tell about PBL? 2: What measures of interaction as calculated by SNA correlated with improved performance?	Analysis was done with SNA pictorial and arithmetic methods on the group and personal learner level, roles of students were mapped and centrality measures were calculated. Spearman rank correlation test was used to find correlation among variables.	The results showed that SNA visualization can display patterns between each problem-based learning group and level of activity in the group, while pointing out interaction among members of the group, as well as outlining the active and inactive members of the group. Statistical analysis showed that students’ level of activity and communication with teachers positively correlated with educational performance. The interaction parameters were in degree, degree, betweenness and closeness centrality.

Table 2.1: Related research continued…

Another study by Saqr (Saqr et al., 2018) on SNA being used to supervise online CL and direct an informed intervention.	Qassim University, College of Medicine in Saudi Arabia.	82 students.	To ensure online collaborative learning meets the intended pedagogical goals.	Teachers post clinical case scenario via CSCL and learners are advised to engross in cooperative interactions in regards to the case. Graphfes web service and SQL were used to extract interaction data. Gephi was used for both network quantitative analysis and visualization. Force Atlas 2 was the gephi algorithm used for the visualization. For the analysis, Interaction Analysis (IA) and SNA were the two types of indicators considered on the group and individual level.	IA showed high level of interactivity while SNA showed the opposite. SNA proved the interactions was neither collaborative nor participatory. As a matter of fact, the interactions between students was few and students' network was limited and dominated by the tutor. The results led to an intervention – student-student communication and student-tutor communication improved.

Table 2.1: Related research continued…

A study by Saqr (Saqr et al., 2018) assessed the ability of SNA for analyzing online cooperative clinical situation interactions in a medical course and to discover which actions equate with improved accomplishment and aid to forecast final scores or describe difference in accomplishment.	LMS forum module of the Surgery course in Qassim University, College of Medicine.	35 students and 1 teacher.	1. What information can the analysis of the social network give about the rank of online CL on the communication, course, and personal levels? 2. Which parameters of network equate with learners' accomplishment best? 3. How can learner's rank, communications, and connections in a social structure be used to forecast final performance?	SQL was used for extraction, Gephi was used for visualization, PAST and SPSS were used for statistical analysis.	The results showed that the teacher received lots of interactions, there was a considerable amount of interaction between students as well. All centrality scores, eigen centrality, eigenvector centrality were all positively correlated with grades. Results showed that a learner's rank and part in spread of knowledge in discussions online, joined with the power of that learner's structure, can be used as accomplishment forecasters in appropriate environments.

Table 2.1: Related research continued…

A study by de Laat (de Laat et al., 2007) inspecting shapes of communication in CSCL and networked learning: a role for SNA.	The platform is the VLE program called WebCT and it gave a table that included the amount of messages sent by each student in each phase. WebCT was the source of raw data as it produces log-files that can be used for analysis for the activity of students of a learning environment.	8 students	RQ1. How compressed is activeness in the social structure and how does it evolve overtime? RQ2. To what length are students taking part in discussions and how does this evolve overtime?	UCINET was the SNA software used in visualizing the social patterns of the learning environment.	The results showed that rank of the learners in the social structure did not change, but the form or focal point of their contribution evolved over time. This means that students take on different roles and form different interest during their collaborative work. The structure of interactions showed transformation among students; some students got more active as it went on while some did the opposite. It was also discovered that most active participants do not always dominate discussion.

Table 2.1: Related research continued…

A study by Williams (Williams et al., 2019) on linking engagement and performance: The SNA perspective.	Physics course in FIU, Miami.	54,000 students.	RQ1. Does the in-class learner interaction forecast future educational accomplishment, even when ruling for previous performance? RQ2.Which centrality parameter gives the most information in the framework of in-class learner interaction? RQ3. How does the in-class learner society form over time? At what point in the semester do learner engagement become vital to future educational achievement?	For network analysis, igraph and tnet software programs were used to calculate the different parameters. Bootstrapping technique was used for the statistical analysis.	Three centrality measures correlated significantly with future educational achievement. Even when ruling for previous achievement. The results showed that closeness model has the best predictive power, the amount of ties tend to reduce over time, also it was discovered that predictive power was significant in a 16-week course between weeks 8-13 and the results are moderately constant. Amount of ties per person and sum amount of ties decreased a bit over time.

Table 2.1: Related research continued…

de-Marcos (de-Marcos et al., 2016) did a SNA of a gamified e-learning course.	The tool used was a friendly gamification instrument developed to offer features of social networking. Activities were uploaded weekly and they had to be completed and submitted to the system by students.	161 students.	RQ1.1 What is the shape of the system of connections of a gamified social course? RQ1.2 To what point does the shape looks like those of other social networks? RQ2.1 Can network parameters be used as forecasters of achievement? RQ2.2 Are forecasting designs understandable and illustrative?	Gephi visualization was made use of to analyze and depict the followers' social structure.	The results of the final network of students was depicted as a directed graph, it also showed that the produced system of connections can be grouped as a small-world. Also, correlation coefficients signified restricted but meaningful connections between students' performance and degree. The results also showed that the prediction models are incoherent.

Table 2.1: Related research continued…

A study by Munoz (Munoz et al., 2017) used a plugin through the use of SNA to analyze forums in a Moodle.	Moodle forums.	165 students.	To help tutors make decisions to improve and promote participatory education.	Bootstrap, Fixed-Header-Table, Jqplot, Jit, JQuery, and J3V3 were used to obtain graphs, while Pajek was used to obtain different indicators and measure parameters.	The analysis showed different behavior from undergraduate and postgraduate students. Postgraduate students were more participative and had a high level of interaction between the students. Mostly four to five students stood out as the most participative. The results helped tutors to analyze the attitude of their learners when using the forums in the Moodle.

Table 2.1: Related research continued…

A study by Rabbany (Rabbany et al., 2011) analyzed the activeness of students in e-learning environments employing SNA techniques.	Log files was used to extract information about student activity in the discussion forums. OpenNlp toolbox was used for drawing out noun group of words out of interactions discussions. The data was gotten from a course named "Electronic Health Record and Data Analysis" at University of Alberta in 2010.	21 students.	To elaborate on the significance of SNA for extracting architectural data and its use for monitoring and evaluating activeness of students in online learning environments.	Meerkat-ED was the tool used for analyzing the interaction of students in forums of discussion of e-learning environments. It also examines the content of the messages exchanged by bringing up a network of terms and identifying topics discussed.	The results was a visualization that formed a hierarchical summary of the topics discussed, which allows the tutor to know what is being discussed. Also, students activeness in these topics were illustrated by measuring their centrality in engagement of a specific topic, amount of replies and posts and the share of used terms by the students.

Table 2.1: Related research continued…

A study by Gobithaasan (Gobithaasan et al., 2019) aimed at boosting student's performance using the help of SNA.	Students of Computational Mathematics in Universiti Malaysia Terengganu were used as a case study.	100 students.	Teachers tried to create a peer support system which allows students share knowledge among each other, with the thought that students are likely to perform better if they are grouped properly (more intelligent students helping out the ones performing poorly).	UCINET was used to draw and analyze the sociology of the students and to describe the interaction that led to their performance. Also, they investigated the changes of grade patterns by perturbing the current friendship clusters. There was also a graph that depicted students and ties showed the interrelationshi p between them. UCINET was used to draw the network.	The study showed how measures like centrality and clustering can be used to form a social contagion effect, where students performing poorly were placed in the same group with students performing better. In the case where students performing poorly were placed in the same group with students performing averagely there was no improvement. Meanwhile the scenario where students performing poorly were places in the same group with students performing very well there seem to be improvement. However, some poor performing students failed to perform better when placed in the same group as students performing very well indicating they couldn't be influenced.

Table 2.1: Related research continued…

In a study by Divjak (Divjak & Peharda, 2010) investigated the connection between the educational achievement of learners and their rank in a system of connections.	The data was gotten from the University of Zagreb.	Two data models: the elementary model which had 27 students, and the lengthened model which contained 52 students.	To discover if students' educational performance have an effect on their position in various students' system of connections.	UCINET was used to visualize the system of connections of students.	The results showed that rank in the social structure cannot be influenced solely by educational performance. Still, students with very good academic performance tend to have good positions in social network.

Table 2.1: Related research continued…

A study by Gitinabard (Gitinabard et al., 2019) investigated how broadly can prediction versions be generalized? Performance forecasting in blended courses	Data of students for Discrete Math and Java Programming.	893 students.	RQ1. How do various forms of social diagram generation impact the achievement of forecasting models based upon them? RQ2. What characteristics of learners' learning manners and social relationships are most forecasting of learner achievement? RQ3. How early can we forecast learners' performance in these classes using the data from the same class? RQ4. Will forecasting models formed from one offering of a course transfer to another offering of the same course? RQ5. Will forecasting models generated on one course transfer to another? RQ6. How will these versions function in recognizing learners in danger?	5-fold stratified cross validation, predictive model; random forest, SVM, logistic regression were All used.	Most of the parameters have higher correlation with performance in the first group (GA) in all classes. Out-degree is the only parameter that has a higher correlation with performance in the second group (GB). Results show that study patterns like interacting more with the online tools, concentrating on one instrument at a time per session and providing answers to inquiry differentiate between high-performing and low-performing learners. Results show that using the early stage data, even though not as accurate as the entire semester data, students' performance could still be predicted with reasonable accuracy. Results show that the models can forecast the excellence category in the second course with an F1 score of 60% or above before the first exam. The models can make forecasting on the future outcomes of another course with an F1 score of 60%. The model can perform well at identifying at-risk students.

Table 2.1: Related research continued…

A study by Putnik (Putnik et al., 2016) analyzed the connection between measures of SNA and performance of learners.	An academic program that accompanied the SNEE procedure.	43 students.	RQ1: Are measures of SNA necessarily equated with the final grades of students? RQ2: Are measures of SNA necessarily equated with the value of work of students? RQ3: Are parameters of SNA necessarily equated with the amount of work of students? RQ4: Are parameters of SNA necessarily equated with the diversity of work of students?	UCINET software was used to perform SNA.	Learner had better grades for amount of work and final grades if they interacted, connected and were very close to other students. A student has a high probability to have a high grade if they did lots of duties for other students and were constantly interacting with other learners. A learner who had great median tie power, had a better grade for variety of work than those with lower median tie power.
A study by DeLay (Delay et al., 2016) examined the impact of peer influence on educational accomplishment.	Pre-test and Post-test data. Also included names of students' friends.	631 students.	Using SNA to analyze how a social-emotional learning interference may be connected with peer socialization on eduactional achievement.	A meta-network from the friendship nominations was created.	The results gave proof that social-emotional learning might impact social procedures in a structure of peers and improve educational performance while breaking down social segregation barriers.

2.2 Literature Summary

The main focus of the table above was to summarize research related to SNA in different forms of online learning. To be able to do this, information was provided about the researchers, how they got their data, the amount of participants used in the research, the aim/research questions of the research, and how SNA was applied to help carry out this research and the results they arrived at after the analysis was done.

Review of literature point out that a good number of researches and analysis have been conducted to find correlation between academic performance and interaction within and online learning or VLE using SNA (Saqr et al., 2018; Williams et al., 2019; de-Marcos et al., 2016; Divjak & Peharda, 2010; Putnik et al., 2016; Delay et al., 2016). Additionally, most of these studies have been carried out to understand students' attitude towards constant interaction. As proven by the studies, there seem to be evidence that student who interact more with peers and the learning system tend to perform better than those who do not (Saqr et al., 2018; Williams et al., 2019; Divjak & Peharda, 2010; Putnik et al., 2016; Delay et al., 2016).

With the presence of other factors that surround students of online learning or VLE, there arise a need to study and analyze using SNA to find out how SNA indicators correlate to performances. There is also a need to look into student behaviors (e.g. punctuality) that could probably lead to them having better academic performances.

The range of most of the current researches and analysis are limited to finding out how interaction is connected to performance or using SNA as reliable predictors. Additionally, there are no or few researches and analysis on SNA indicators that correlate to performance and how students' behavior can affect their performances and level of interaction with peers or the learning system. As VLE keeps growing and SNA keeps being useful, a comprehensive study that uses SNA to investigate VLE records to determine other external factors and students' behavior that could influence results and interaction becomes very important. This study can also help students of an online learning environment make better decisions.

The aim of this section was to summarize related research and identify gaps, with the view to come up with research questions that addressed the gaps identified; this chapter has helped to do just that.

CHAPTER 3

THEORETICAL FRAMEWORK

3.1 Social Network Analysis

SNA is a category of procedures and instruments that could be used to analyze communications connections. Thus, SNA is appropriate for the analysis and probably supervising of online communications as it can naturally examine data about communication, providing a comprehensive outlook of the category interaction structure, the social shapes, and also outlining of all interactions in the provided data. SNA can be put into action in two major methods, mathematical analysis and visualization.

SNA visualization uses graphs to show connections among social networks which can also be called sociograms; the sociogram shows actors (nodes in network analysis context) as points, and connections (edges in network analysis context) as arrows coming from the origin of the communication and directing to the target of communication. SNA can aid to make a picture of the interactions among members and also show the significant actors in the communications and show us the detached actors, also display the categories that display heavy communications or scanty communications that might require backing. It as well shows the very involved mediators who are communicating with the system, and the amount of their communications. VLE is an online setting where learners are expected to communicate with the system and thus examination of virtual interactions is vital.

The SNA arithmetic analysis measures network parametric quantities on personal actor position, and also the categorical position. Graph theory ideologies are used in the arithmetic analysis of SNA to measure metrics depicting the nodes and connections. Like the length to other actors within the network, the amount of communications with the system. These metrics are vital in measuring interactions, showing positions of nodes, or connections. Parametric quantity measured at the actor position are referred to as centrality scores, these scores are calculations of the node significance within the social network. Since there are various frameworks and possibly various methods to see the role as vital, there are various centrality figures. The calculations selected for this research are centrality calculations of aspects and rank in interaction. These parametric quantities would improve our amount of information about learners and may expand to LA. In the context of VLE, one would be curious about the interaction with the system, and what these metrics can tell us about VLE.

3.2 SNA Application to VLE

Learning is a social procedure which needs cooperation, communication and interaction of actors like tutors, students and course materials. These communications happen in a learning setting; these setting can be formulated to aid both informal and formal learning methods. Informal learning methods comprises of relations between students via social networks, distribution of course materials, groups discussion and projects. Contrarily, formal learning methods comprises of learning through lectures, assignments, tests and interaction with tutors.

Social network concept analyzes the shape of connections formulated from communicating with people, and how these shapes influence the people along with the capacity of their thinking (Zhang & Tu, 2006). SNA, as a method of analysis, was used a lot in behavioral and social sciences to study various kinds of social relations that happen among different groups of people.

Of recent, SNA measures and theory are used to analyze educational environments and problems. Measures of SNA are introduced to analyze the communications between students, between students and their tutors, between students and the learning system. SNA measures are not constrained to just social media networks, any connection depicted as networks can be analyzed by SNA. This study analyzes a virtual learning network and the interactions that occur between students and the VLE.

In addition, SNA is a measurable approach for analyzing social structures. This permits examining the traits of these shapes, like discovering which person is located at the center position within the network. Also, discovering which persons are very active in the network, and those isolated.

3.3 Social Network Analysis Approaches

3.3.1 Level of Analysis

The social structure can be analyzed on various analysis level. Three main levels: node, subgroups, and network. The level is selected on the basis of the concentration of the analysis. Here is a short explanation on the most vital calculations that are categorized on the basis of the analysis level (Gretzel, 2001):

- Node level calculations contains centrality calculations like closeness, degree and betweenness. They can identify the various nodes roles like bridges or isolates.
- Subgroups calculations contain calculations that discover components, factions, united subgroups.
- Network level calculations analyze the entire centralization and mass of the network being analyzed.

In addition, analyzing various stages of the structure gives an expansive and complete knowledge of the social structure. The entire structure calculations analyzes the amount of connections that create the structure. E.g. density calculates the amount of connections in a structure in comparison to the overall amount of connections that can truly be formed (Gretzel, 2001).

Subgroup level calculations discovers the amount of subgroups created from the entire structure interactions. The interactions among group members are more powerful than the other groups outside members. The subgroups members possess alike traits (Passmore, 2010).

Lastly, using calculations on personal level can discover the traits that differentiate the leading individuals with the best parts. E.g. degree centrality calculations discovers the well-known actors in the structure that is the one with highest amount of relationships. Betweenness centrality also discovers the usefulness of the actor's rank in the structure to spread the news among the other members of the structure. Lastly, closeness calculations is connected to the shortest interval of how one node is distant from all the others in the network.

3.3.2 Representing Social Relations

A relation describes a connection between two nodes which are either people or objects. This two way relation, can be either indirect or direct relation. In direct relation the node which begins the interaction is different from the one getting it. That is sending information. On the other hand, the indirect relation direction is not of importance. That is membership relations. However, a tried relation between three nodes group. A subgroup is a subdivision of nodes that have alike connections and detached from the remainder of the structure. Lastly, a social structure is an amount of affiliated people that are categorized via one definite affiliation (Passmore, 2010; Gretzel, 2001).

The result layout that depict the outcomes of social structure calculations are matrices or sociograms. A sociogram is a visual graph of the people and the relationships via edges and nodes. The indirect relation is depicted with an arrowless edge. While the directed relation is depicted with an edge that has arrows, that is differentiating the receiver from the sender (Passmore, 2010).

The second layout is a sociomatrix or adjacency matrix which is a mathematic interpretation of the structure via its links and nodes. Fundamentally, a sociomatrix is a collection of access organized in columns and rows. The passages in the collection are described via ranges of N2.

3.4 Social Network Analysis Results

3.4.1 Visualization

Visualization instruments have become a powerful constituent of systematic advancement in different sectors. In lots of instances, data represented as charts or graphs can aid to depict concepts. In other instances, ideas are now connected with a specific image that came out from study. A lot of knowledge can be gotten from non-complex visuals.

Benefits of visualization are:

- Helps to interpret data
- Clarity
- Aesthetic appeal
- Saves time

Network graphs, in exact, is a very helpful instrument that can aid model connections, data summary, and representation of abstract ideas in an understandable and instinctive manner. The importance of using network graphs to make a picture of data has been applied in various sectors, and has aided in developing our understanding of social networks (Moody & White, 2010), international telecommunications (Barnett, 2001), health studies (Valente, 2010), etc. SNA mostly utilizes a sociogram to explain various ideas. Sociograms are structure diagram in which nodes depict individuals and ties depict connections amongst nodes.

Sociogram is a very useful analysis instrument, aiding analysts to notice position of importance and architectural features that we would not notice in a mathematical data like adjacency matrix.

These days, there are societies online that converse, so it is no amazement that social network analysis is now well known for social structure study.

Other data visualization methods are:

- Alluvial diagrams
- Circle Packing
- Streamgraphs
- Slopegraphs
- Sunbursts
- Horizon charts
- Parallel Coordinates

Growing along with social network analysis is the production of various applications. Since little physically sketched samples, current automation can now develop structures with millions of individuals. The creation of SNA software packages has helped SNA study, as improved calculating strength has allowed quick complicated measurements and backed extensive network analysis like picturing thousand node networks. Analysts can carry out analysis on the basis of network structures, and lots of the arithmetic are in existence for use right away. Technical growths are often put along some software, like exploratory study with the help of Pajek software package.

Software packages for visualizing are:

- Commetrix
- Centrifuge
- Gephi
- Inflow
- Jung
- Keynetiq
- Meerkat
- Netlytic
- Netminer
- Network Workbench
- Networkit

- Networkx
- Nodexl
- Polinode
- Pajek
- R
- Socnetv
- Socioviz
- Ucinet
- Weka

Provided the strength of SNA, holes still exist that only of recent began to be paid attention to. E.g. Sociograms are, by character, motionless depictions. They are pictures of a network at a specific time, providing no ideas about how or why the network transformed into a specific shape, or what it might turn out to with time. Extra research into the progression of social structures would be advantageous for study, mostly in online societies, which could transform at a very fast pace.

Attributes of a Visualization Graph

- **Path**

A path between any two nodes is a vital terminology. It is described as the series of nodes that joins two major nodes. All the relationships and nodes that compose the course between the beginning and the end node should not be same. The extent of the path is measured as the nodes amount that make it up. If the course has very much alike nodes, then it is referred to as a *trail*. If the nodes or the relations are the same; no duplication then the course is referred to as a *walk*. More particularly, path calculates if two nodes are joint and discovers the interval. Path calculation is seen as an important element in calculations like geodesic distance, centrality and diameter calculation (Wasserman and Faust, 1994).

There are other calculations that are formed on the basis of path in its measurement, like shortest path and cycle. A cycle is a unique case of a course where the beginning and end nodes are alike. Meanwhile the abridged course has the lowest nodes amount that make it up. It is called a geodesic distance (Wasserman and Faust, 1994).

- **Geodesic Distance**

It is described as the shortest course that joins any two nodes in the diagram. This description changes based on if it is an undirected or directed graph. For directed graph, the shortest course between two nodes is the geodesic distance for the two nodes. The two nodes have dissimilar geodesic distance in respect to the direction of their connections (Wasserman and Faust, 1994).

- **Subgroup and Group**

A subgroup is any subset of nodes that are highly joint collectively seen as an element of the entire structure. Analyzing and noticing subgroups is important in network analysis and social network analysis calculations. The dissimilarity between group and subgroup is connected to the amount of nodes that form them. The members of either subgroup or group have one similar traits (Wasserman and Faust, 1994).

In any subgroup there is one particular node that is known as boundary node which is seen as the relation point between this subgroup and all the other nodes in the entire diagram. Additionally, it can be measured as a boundary size for every subgroup which is the addition of the boundary nodes. The nature of relation in a diagram is called the cut-edge. A connection is known as a cut-edge if its pair of edges is members of two dissimilar subgroups (Wasserman and Faust, 1994).

- **Density**

Density is described by the connection of addition of all connections that are actually occurring in the diagram to all probable connections that may appear in the diagram. The density numbers of the diagram is mainly connected to the capacity of the diagram. Bigger density numbers are affiliated with bigger graph sizes. So as to examine in contrast the densities of various diagrams, they have to have same capacity to be examined in contrast (Wasserman and Faust, 1994).

- **Graph's Connectivity**

Fundamentally, graph's connectivity show a calculation of graph if it stays joined even when nodes or relations are taken out from the entire diagram. Graph connectivity is connected to centrality calculations that are used to examine any social structure on the level of the node.

- **Components**

A component is a subgroup of the diagram that are closely joined with one another but detached from the rest of the diagram. The detached components have issues of getting news from the remainder graph or network. Fundamentally, for directed connections in a structure, there are two kinds of parts which are strong and weak parts. A strong part needs the presence of a directed path between pair of nodes so that they are a property of the same component. Meanwhile a weak part is a category of nodes that are joined as one aside from the entire diagram but their affiliation does not consider the direction of the network, more importantly its presence.

3.4.2 Interaction Analysis

On the measurable position, SNA interaction analysis provides non-complex, clear indicators for the level of activity among participants; these indicators help point out the active categories and actors. The indicators also help point out a possibly flawed or dormant categories/actors. The SNA calculations of parts and level in information exchange showed values that can be noticed without difficulty in a visualization. For example, betweenness centrality showed the parts of learners in controlling instruction, relating the unrelated learners and welcome them to the conversation. Closeness centrality highlighted learners who did not constantly interact with the system.

When combined with the visualization, it gave more understanding into the motion of the communications with the system, like those who are very involved, which learners interacted more and showed which students were inactive. The part analysis we have done in this research improved the range to the serviceableness of SNA. Pointing out every part and who performs, it helps lecturers to understand the motion in the category, aids in improving interaction and avoid flaws in interactions.

3.4.3 Network Quantitative Analysis

Is an arithmetic means to measure and calculate the relations and connectedness of nodes within a structure. *Centrality* is the build used to show how outstanding a specific actor is within a structure or how vital that node is to interaction with the system. Attraction to using centrality calculations as predictors of learners' accomplishment has grown with the arrival of LA as a study (Romero et al. 2013). Hommes et al. (2012) used in-degree (sum amount of arriving communications) and degree centrality (sum amount of arriving and leaving communications) calculations to forecast learners' achievement and discovered that most learners who performed well in the course have gotten high centrality scores. Gašević et al. (2015) discovered a good connection between degree centrality and learners education; that connection was more powerful than past scores, academic motivation, and social unification. Ángel et al. (2013) discovered closeness centrality (how accessible or familiar a learner is to his/her fellows) to definitely equate with better scores. Joksimovic et al. (2016) discovered an equation between centrality calculations and achievement in some courses and unfavorable in others. They decided that these combined outcomes do not imply that social network analysis forecasters are not useful, but instead these mixed results asked for more studies to find the framework in which social network analysis centrality calculations may function as trustworthy forecasters. In an attempt to evaluate the part of structure rank in forecasting accomplishment, Joksimović et al. discovered weighted degree (sum amount of communications, taking into consideration the value of communications) centrality to be the most important determinant. Very much alike to Ángel et al. (2013), Joksimović et al. (2016), associated the distinctness between their results and those of others to the framework in which the research was founded on.

Communications with the system are vital in in advancing involvement and improving the education method by permitting the students to create a working connection, build significance, and comprehend ideas via interaction. Improving interactivity between students and VLE has been stated to advance higher performance. Therefore, the research of interactions in VLE may be of help in predicting educational performance.

3.5 Social Network Analysis Measures

3.5.1 Degree

The amount of direct connections an entity has is its degree centrality. An active actor in the system of connections mostly has a high degree centrality.

3.5.2 Closeness Centrality

It calculates how fast an actor can access other actors in a system of connections. An actor with high closeness centrality has fast means of entry, short path and near other actors in a system of connections. It also possess high visibility so as to be able to see all what is happening in a network.

3.5.3 Eccentricity

Is the distance from a selected offset to the most distant node from it within the system of connections.

3.5.4 Eigenvector Centrality

The eigenvector centrality of a node is equivalent to the total of the eigenvector centralities of all nodes that connect to it directly.

3.5.5 Betweeness Centrality

The amount of shortest paths that pass through a node divided by all the shortest paths within the system of connections.

3.6 DM, EDM, and LA

3.6.1 Data Mining

As an outcome of lots of progress in technology and software which is highlighted by the presentation of Web 2.0, bigger data sizes can be collected from different web based. Additionally, broad usage of Web 2.0 in learning and teaching (Tim Berners-Lee and Lassila, May 2001). These days, there is a lot of data available online via points of supply like VLE in academic settings. All of that causes the need for analysis for mining big collection of data in order to obtain useful information.

DM is an analytical and computing procedure for examining big collection of data via uncovering and deriving underlying sequence of data. DM contains an array of popular approaches, like statistical algorithms, logic programming etc. More vital approaches and applications are text mining, visualization, statistics etc. (Romero and Ventura, 2007).

Fundamentally, DM is formed on the basis of analyzing underlying connections patterns from very big collection of data. DM is a wing from Knowledge Data Discovery (KDD). The goal of KDD is to derive vital and quality information from very big databases. The popular KDD procedures are collecting, transforming preparation, analysis, and explanation of the data (Romero et al., 2008).

Particularly, the examination procedure aspect of the DM is conducted via approaches like prediction, and social network analysis. Social network analysis is a vital study procedure for comprehending connections among cast study. The major concept of social network analysis is calculating and analyzing roles and connections between objects or people that are formed as structures. Social network analysis describe the investigated development by depicting it as a social structure network where the object or people are depicted as nodes and the connections between them as links among nodes. All of the communication in a social network are analyzed on the basis of social structure concept proposition. This thesis concentrates on using SNA to analyze student interaction with a VLE system.

3.6.2 Educational Data Mining

EDM is a technical procedure that is gotten from data mining and it is described as interested in creating procedures for analyzing the special types of data that originate from an academic environment, and using these procedures to improve understanding of learners, and the environments in which they learn.

EDM was presented in 1995 as an outcome for big number of online data that are at the mercy of examination (Romero and Ventura, 2007). On the other hand, EDM is created as a fresh study procedure and lots of workshops and conferences have been held to formulate this procedure. It is formulated for finding models and connections in a VLE, other kinds of online learning and learning framework. The purpose is to have an improved knowledge of connections between students and their interaction within themselves and the learning system (Romero and Ventura, 2010). The outcomes gotten from EDM can help in making VLE and other online learning environments better, improving students' interaction with the learning system, and discovering better learning methods. All of that helps to improve learning activities (Zaiane, 2001).

Particularly, EDM procedures are viewed as uses from different study environments like visualization, statistics. The fundamental application of EDM were formed on visualization and statistics. Deriving and finding examples of the examined data is seen as very vital procedure for knowing the context of the problem and connections of interactions (Baker and Yacef, 2009).

SNA as a function of EDM analyzes connection among people and with the system in a structure. SNA usage in a learning framework is seen as very vital progress in data analysis procedures. These progresses in data examination procedures is an enhancement for pedagogical and social ranges. This can improve knowledge of the learning framework in all ranges pedagogically, analytically, and socially (Granovetter, 1973).

3.6.3 Learning Analytics

LA is an idea that is described as an examining procedure for amassing networked learning data and examining their interaction and performance in a networked setting e.g. VLE. LA is interested in analyzing students' involvement in a learning environment indirectly by collecting the big collection of data of these practice. The aim of this examination is basically to discover any relation among students' accomplishment in the events and educational results, finding samples of students' communication and examining them in contrast with prior samples of former learners. The requirement is to discover fresh strategies for enhancing students' performance. LA concentrates on analyzing big databases from schools so as to get vital information, models and patterns to better student learning in the academic institution (Norris, 2010).

Additionally, LA is a new terminology that explains examining procedures in a scholarly framework. Another definition of LA is that it is a calculation, gathering, examination, and stating of data about students and their frameworks, for the aim of knowing and making schooling perfect and the settings in which they happen.

The aim of LA is to get samples that depict the communication of learners in a schooling environment. The schooling outcome permit giving guidance and suggestions for bettering learning procedure and also finding learners that are not performing well. The outcome of using LA procedure can be seen in different ranges, like visualization of interactions, students' communications model, and analytical information. These ranges can be very useful for schools for enhancing interaction between students and peers/lecturers and encouraging them to interact more with the system (Ferguson, 2012).

Fundamentally, LA various procedures are seen as very useful in analyzing courses with a very big amount of students. For the most part, in these enormous courses, it is hard to keep individualistic connections with learners. It will also be hard to notice learners who are failing or those who don’t interact much with the system (Ferguson, 2012)

There are a group of well-known adoption of LA procedures mainly in pointing out learners’ level of interaction and forecasting their performance. The result of this examination can be helpful for lecturers to notice problems in the learning system, quizzes, or assignments. Helping these lecturers to present new suggestions to change some of the learning methods in order to help students perform better (Norris, 2010).

CHAPTER 4

METHODOLOGY

The analysis was carried out on a dataset that contained data from courses at OU. The data contained information about students' interaction in a VLE. This allows students' interaction to be analyzed to draw conclusions. Included in the dataset is information about 7 courses, 32,593 students, their results and amount of times they interacted with the VLE which is depicted by the sum of clicks (10,655, 280 entries).

4.1 Procedure

Collection of data and analysis of the dataset followed the data mining procedure of Romero et al. (2008) which is grouped into three stages:

4.1.1 Data

Data was retrieved from OULAD. Link: https://analyse.kmi.open.ac.uk/open_dataset

4.1.2 Data preprocessing

173,740 cleaned observations were extracted from 1,048,576 observations of anonymized data, and data were saved in a format suitable with the Gephi software for import. Two new spreadsheets were saved: the first was the source which included the students' id and the second was the target which included information about the VLE site in connection with the students.

4.1.3 Data mining and analysis

Gephi 0.91 software was used to analyze and visualize the data. Gephi is an open source software that can be used to analyze and visualize network. It has different algorithms for producing a picture of network, the algorithm used for this study was *Force Atlas 2.* It makes use of a force directed physical arrangement that sketches each node based on its connection with other nodes. As a result, structurally connected nodes are located close to one another. This method gives a better explanation and visualization of the entire network shape. The main benefit of Gephi that other software do not have is its “dynamic mode” which allows analysts to have a picture of the network development and events time and shows evolvement in the rank of the node in the actual time of the action.

4.2 Statistical Analysis

SPSS software version 24 was used to perform a statistical analysis to calculate the correlation coefficients, to get statistics to help us make predictions. Gephi was also used it to get different kind of charts related to the data.

4.3 Network Quantitative Analysis

The parameters that correlate to the capacity of the structure, the length of the user’s interaction within the structure, cohesion and group relatedness were measured. The parameters measured for each network were:

- Network size: the amount of nodes.
- Average degree: the mean degree centrality of all the students. This is a measurement of the average position of interaction of students.
- Network density: the proportion of communication with the VLE; in comparison to the simple measurement given by the network size.
- Average clustering coefficient: shows the propensity of students to interact with VLE.

4.4 User Parameters

Centrality measures that show three categories that make them up were measured:

.4.1 The quantity of interactions

- In-degree centrality is the amount of interaction a part of the VLE system gets, and it is seen as a sign of fame. Parts of the system with a high in-degree centrality are very famous among the students.
- Out-degree centrality is a calculation of departing interactions from an individual. It is a measurement of the interaction an individual makes with the VLE and it shows how very involved in the activity the student is within the network.

4.4.2 Role in moderating and relay of information

- Betweeness centrality is a calculation of the individual activeness in controlling communications.
- Information centrality is a calculation of the value of a node in the flow of information and union of network.
- Closeness centrality is a calculation the closeness of a student to the other students within the structure.

4.4.3 Connectedness

- Eigenvector centrality calculates the value of an individual taking into account how well affiliated the individuals close to the actor are.
- Eccentricity calculates how far an individual is from other individuals within the structure network and can be seen viewed as a sign of seclusion.
- Clustering coefficient calculates the whole propensity of a student to interact with the VLE.

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1.1 RQ1: What social network analysis measures are related to student performance?

SNA visualization can be used to picture the connections among actors, nodes. Visualization was the analysis method used to investigate on students in a VLE and degree of their activity and interaction with the VLE system.

For this research question, the SNA method used was visualization. The variables that were considered were id_student and sum_click. The student identification variable is a one-of-a-kind description figure for each student, sum_click is the amount of times a student interacts with the system in a day. Gephi was the software used to carry out the visualization analysis. In order to upload the files to Gephi, the two variables had to be split into target/edges and source/nodes and uploaded differently. Sum_click was the target/edge and id_student was the source/nodes.

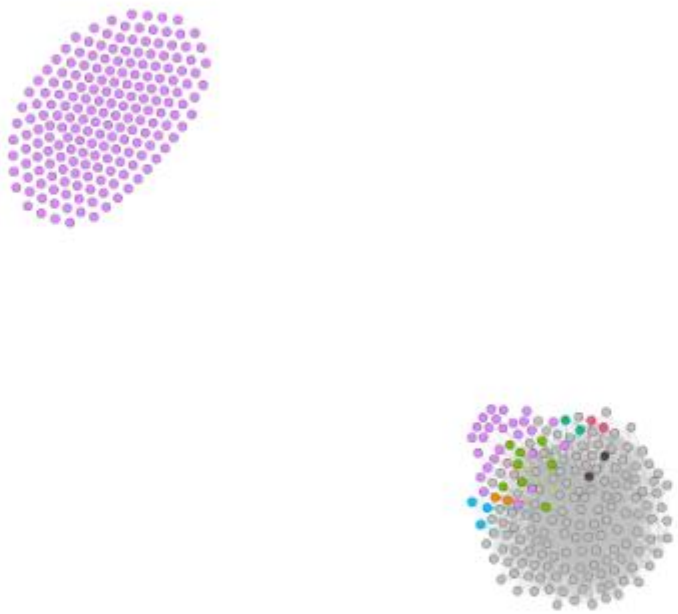

Figure 5.1: Betweenness centrality visualization

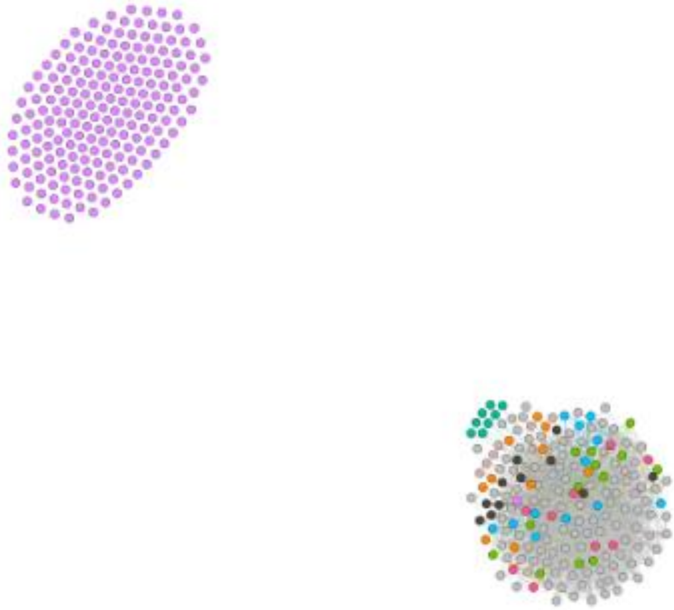

Figure 5.2: Closeness centrality visualization

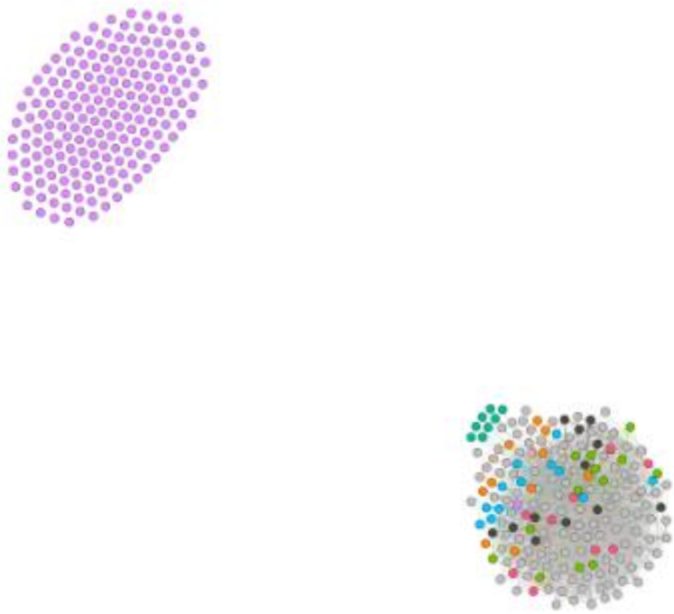

Figure 5.3: Degree visualization

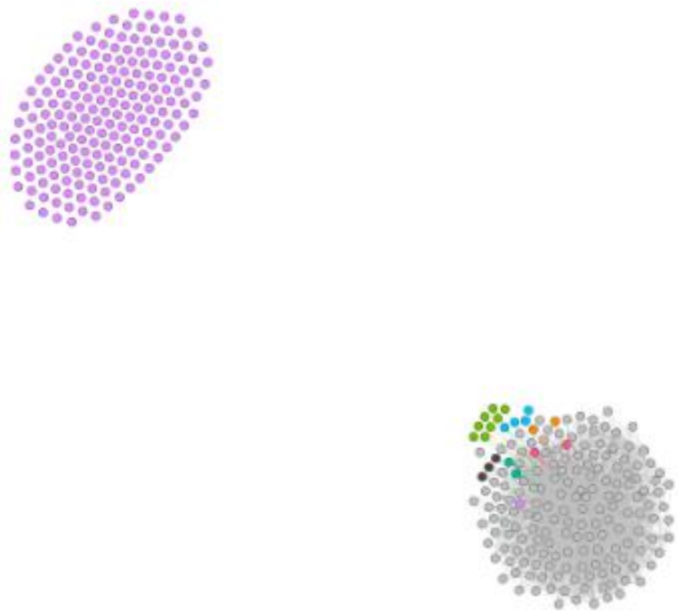

Figure 5.4: Eigenvector centrality visualization

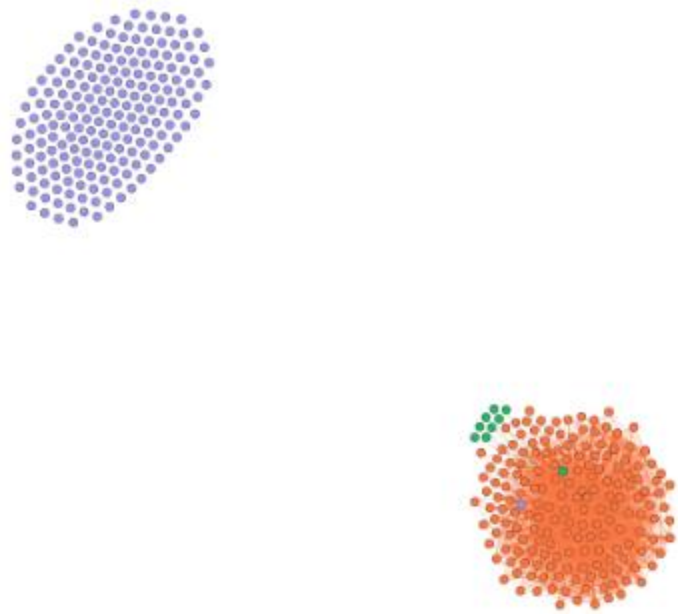

Figure 5.5: Eccentricity visualization

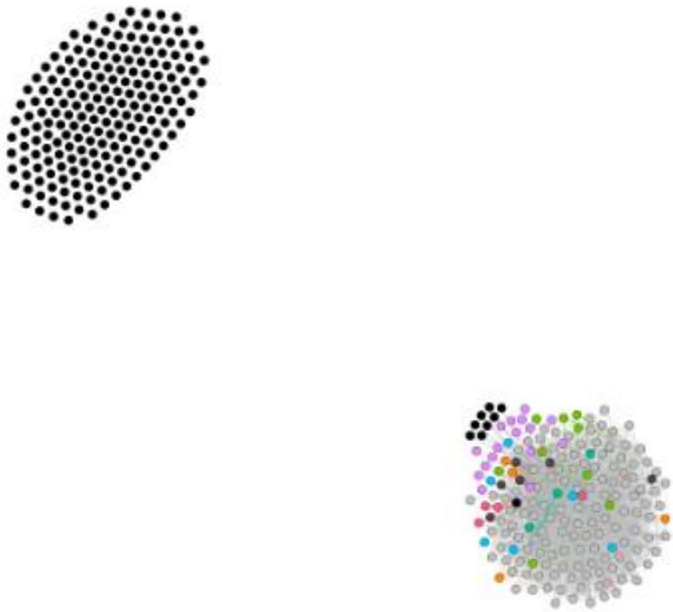

Figure 5.6: Clustering coefficient

The biggest benefit of SNA is its capability to visualize interactions, providing a pictorial evidence of the level of connection in social media. Fig 5.1, Shows the activeness of students in controlling interactions. This visualization is very helpful in locating the students who constantly interact with the VLE system and also those students who are not very active and need special attention. In this figure, the students represented by the grey color are the most active in this graph. Fig 5.2 shows us close the students are to the other students in the network. The closer the students, the easier it is to reach and interact with other students. The colors in the graph shows the students that are close to each other. Fig 5.3 represents the sum of outgoing and incoming interactions. Again, just like in Fig 5.1 with the most active students, the students in grey are the ones who interact and get lots of interaction from the system. Fig 5.4 measures the prominence of a student taking into account his/her neighbors, a student affiliated with prominent students in the network will have higher eigenvector centrality values. The students in color are the most connected students. Fig 5.5 calculates the length of a student from the remainder of the students in the system of connections and can be interpreted as isolation or hard to connect with. The graph also shows the cluster and separation between the students. The students in blue are the isolated ones in this graph. Fig 5.6 calculates the propensity of a student to form a collective with other students in the system of connections, the students with group cohesion have higher clustering coefficient. The students in colors are the ones who communicate the most and have group cohesion.

Students' interaction and participation was investigated and correlated with students' performance. It was discovered that parameters corresponding to how close a student is to the other students (Closeness Centrality), connection to neighbors (Eigenvector Centrality), which measures the distance of a student from other students (Eccentricity). These were the parameters that correlated best with student performance.

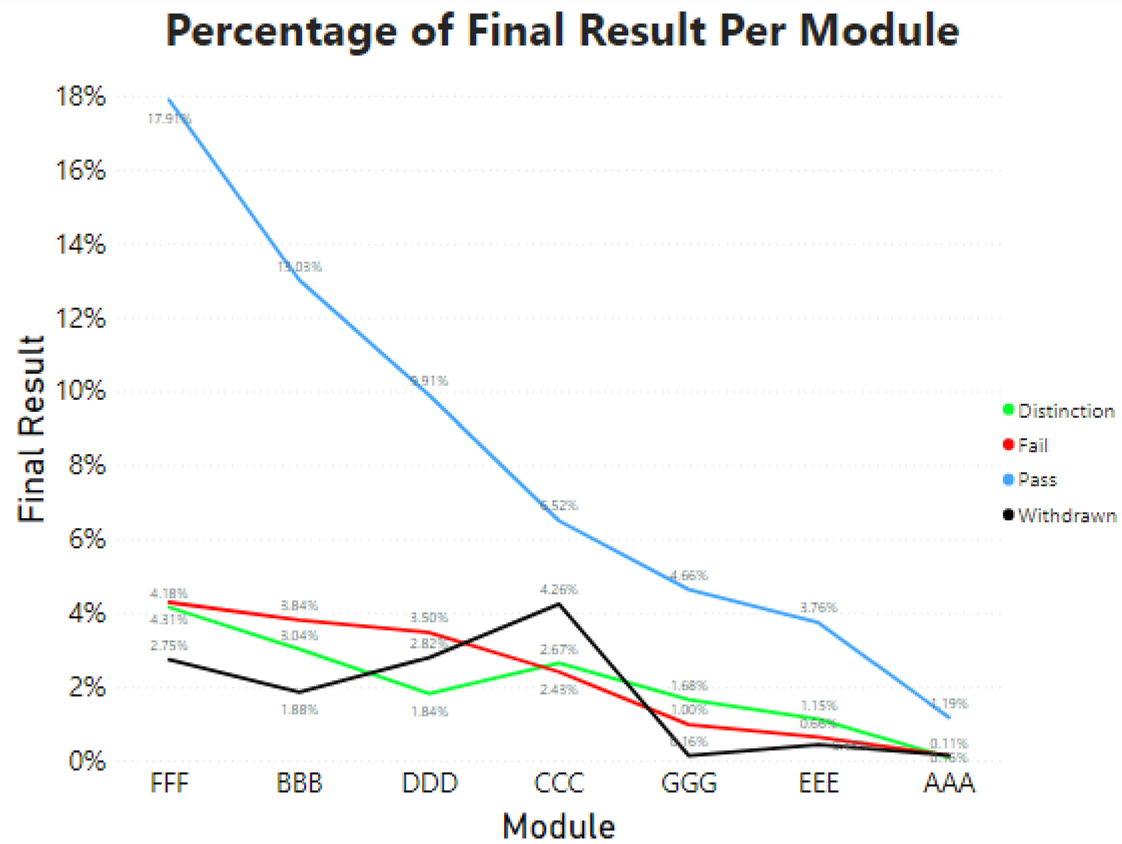

Figure 5.7: Module wise percentages of pass/fail/withdrawn

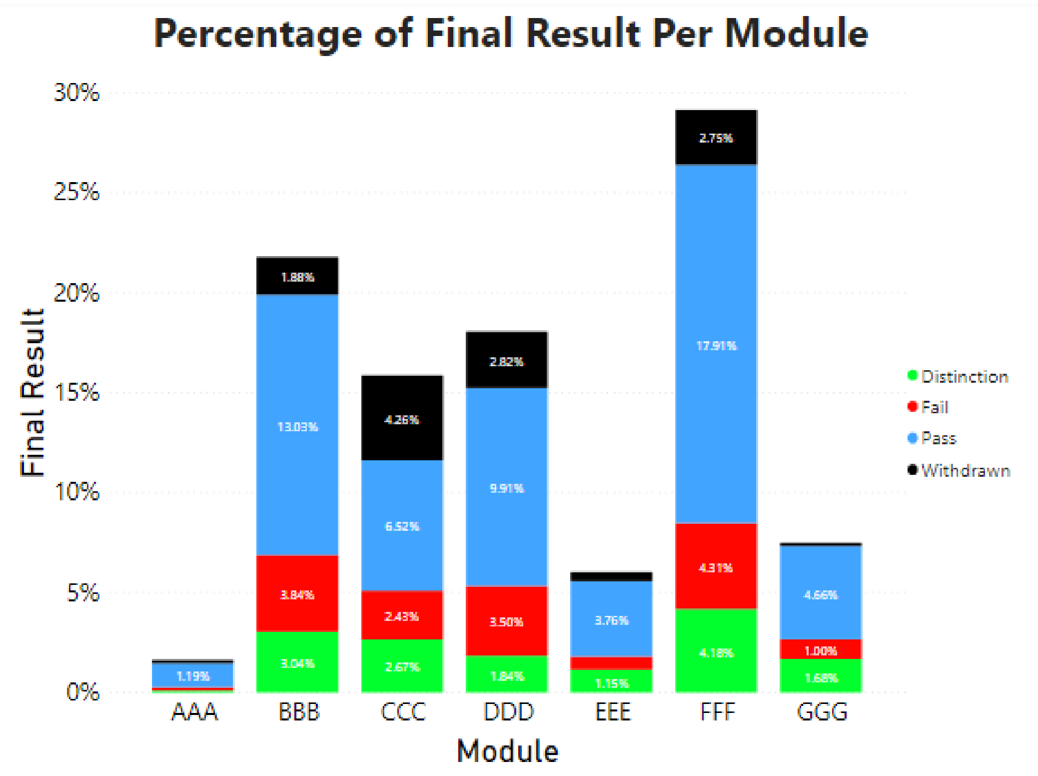

Figure 5.7: Graph of percentage of students' final result per module

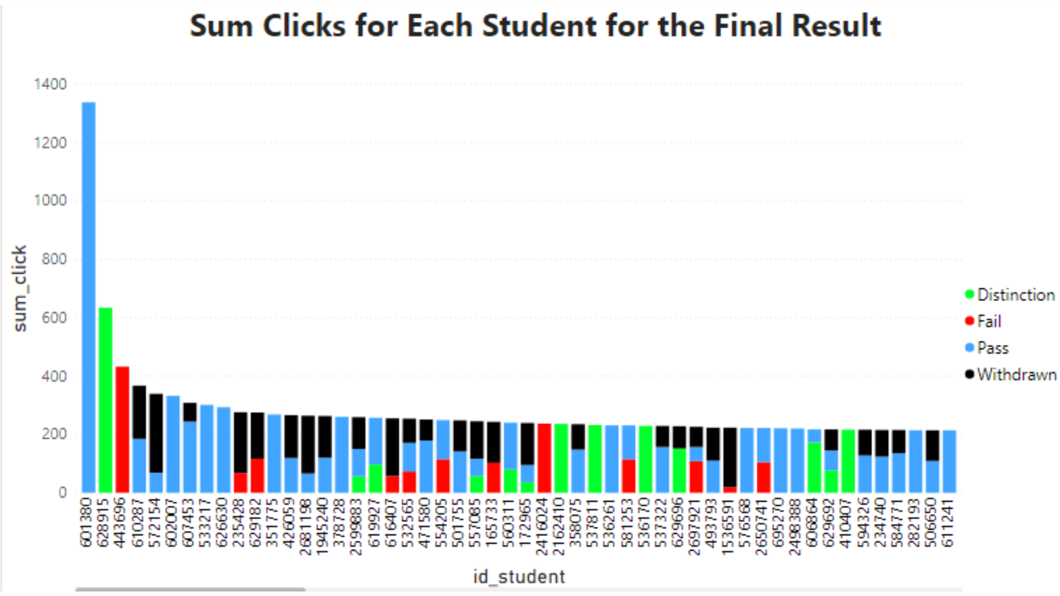

Figure 5.9: Sum clicks graph

The sum clicks (the amount of occasions a learner communicates with the system in a day) were calculated to get the total sum clicks for students who took the course module. Students also partake in various assessments and exam over time. Some students dropped out by withdrawing. From Fig 5.7 and 5.8, it can be observed that the learners in the course module AAA performed worse compared to any other module, while the students from the course module FFF performed better than others. The students from the course module FFF had the highest percentage of distinction, pass and fail, while the course module CCC had the highest percentage of students who withdrew. It could also be deduced that students who passed the modules had the highest amount of total sum clicks compared to those who withdrew or failed. The students from the course module AAA are in need of special attention, and there should be an investigation into course module CCC to discover why students from the module are withdrawing more compared to others.

5.1.2 RQ2: Can individual behavior like late registration be used as predictors of performance?

The statistical analysis used for this research question was Chi-Square Tests. The variables considered for this analysis were date_registration, score, final_result. The first variable is the date the learner enrolled to the module presentation, score is what the student got in the assessment, final_result is the student final score at the end of the module.

To be able to determine if the behavior of a student like the time of their registration could be used to predict if the student would pass or fail a course, a chi square test was done. So as to decide what a late registration is a threshold of 30 days was formed – any student who registered 30 days after the module started was considered someone who registered late. The full details of the chi square test is displayed in Table 5.1.

Table 5.1: Chi square test on late registration effect

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	3159.326[a]	3	.000
Likelihood Ratio	3398.006	3	.000
Linear-by-Linear Association	2610.555	1	.000
N of Valid Cases	207092		

0 cells (0.00) have predicted count < 5. The least predicted count is 8999.76. Since the (Pearson chi-square) **P-value (0.000) < 0.05,** the null hypothesis was rejected. From this, it has been observed that late registration significantly affect the grade of the student. Therefore it was accepted the statement that individual behavior like late registration can be used as a performance predictor.

5.1.3 RQ3: Can student interactions be used to predict performance?

- **In terms of assessment score?**
- **In terms of final score?**

The statistical analysis used for this research question was Multiple Regression. The variables considered for this analysis were date, sum_click, amount of previous attempts, code_module, score, final_result. The variable date is the day the learner communicated with the system, summation of clicks is the amount of occasions a learner interacts with the system in a day, amount of previous attempts is the amount of occasions a learner tried a course, code module is a description code for a module which a student is registered to, score is what the student got in the assessment, final result is the student overall score at the end of the module

Multiple regression was used to test if student interactions can be used to forecast the overall score and to what length can the score gotten be described by the activity of learners. SPSS software can be used to find out the importance of a predictor and that was the software used for this test. Values were provided for the standard error and p-value. The p-value of sum_click on relationship with Student's score is **0.203** with a coefficient of 0.010. Since the **p-value (0.203) > 0.05**, therefore the null hypothesis (H_{20}) is accepted which says sum_click has no significant relationship on Student's score. Hence, a unit increase in sum_click will cause an insignificant increase in Student's score. As a result the statement is rejected that student interactions can be used as a performance predictor for this database.

Coefficient of Regression			
Model	Unstandardized Coefficients		
	B	Std. Error	p-value
(Constant)	73.473	.101	0.000
Date	-0.15	0.001	0.000
Sum_click	.010	.008	0.203
num_of_prev_attempts	-2.891	.091	0.000
Code_module	0.963	0.26	0.000
a. Dependent Variable: Score			

Table 5.2: Multiple regression

The table above showed the coefficients of the variable in the equation with constant given as 73.473, date given as -0.15, sum_click as 0.010, num_of_prev_attempts as -2.891, type of module (code_module) as 0.963.

5.2 DISCUSSION

Most social network analysis carried out on LA concentrate on student performance prediction (final score). To be able to carry out such prediction, different variables are taken into account, but of recent the log in details of students in online learning classes is the factor that has been used the most. Different software are used for social network analysis, and also, different forms of online learning (e-learning, online problem based learning, blended learning, moodle, VLE etc.) have been used as a source of data for analysis. Different studies have different predictive variables that they use to carry out the analysis, despite this, most of the studies tend to accept that students who interact more with the system and their peers tend to perform better academically.

A research by Saqr (Saqr et al., 2018), showed that students who communicated more with their fellows in groups tend to perform better. The findings also showed that using interaction data to predict performance is actually reliable. Another study by Saqr (Saqr & Alamro, 2019) discovered that the metrics of interaction as calculated by SNA correlated with better achievement? were indegree, degree, betweenness and closeness centrality. A study by de-Marcos (de-Marcos et al., 2016) signified limited but meaningful connection between students' performance and degree. In a research by Divjak (Divjak & Peharda, 2010), the results showed that rank in the system of connections cannot be influenced solely by educational performance.

Although, students with very good academic performance tend to have good positions. A study by Putnik (Putnik et al., 2016) stated that student had higher grades for amount of work and final grades if they interacted, connected and were very close to other students.

This results from this study accepts with most of the related research that students with the best grades tend to be those students who are very active in discussion forums and interaction with the system. Also, this study disagrees with Saqr (Saqr et al., 2018), that interaction data is a very reliable predictor of academic performance, and this is due to the fact that in this study the p value of the interaction variable (Sum_click) is lesser than the standard 0.05 needed to accept that interaction has a significant relationship with student score. This study also agrees with Saqr (Saqr & Alamro, 2019) that the interaction parameters associated with better performance degree, betweenness and closeness centrality, while also adding eigenvector, eccentricity and clustering coefficient as parameters that associate with better performance. This study is unique in comparison to the related researches summarized as it seemed to be the only study that took into account individual behavior and analyze if it could be a predictor of performance.

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

To summarize all the finding from this research explained in the chapters before this, the researcher now gives his final points on the research findings and recommends how future studies should be carried out.

6.1 Conclusion

The outcomes of this research are:

- Closeness Centrality, Eigenvector Centrality, Eccentricity were the parameters that correlated best with student performance.
- Student interaction cannot be used to predict performance in this database.
- Most of the students that performed best seemed to have high amount of sum clicks.
- Some students have started accessing/interacting the material 10 days before the module-presentation, while some waited till after 238 days after the module-presentation. The average days before the interaction with the module is 99.79 days with a standard deviation of 76.596.
- Some of the students interacted with the material just once.
- The students interacted with different module materials. The materials were resource, url, outcontent, homepage, subpage, external quiz.
- Sometimes students do not use the module materials for the weeks they are planned to be used.
- Late registration significantly affect the grade of the students.

6.2 Recommendations

- The collection of information for the database was done over 8 months. The researcher strong recommends that the information be collected over an extended time period and also from different universities not just one specific university or college so as to be able to find out how widely accepted VLE is and too provide us with a more trusted amount of information.

- The researcher strongly recommends that the results from such social network analysis be taken serious – students that seem to be less active or isolated in graphs should be given special attention so as to help them become more active and more involved in interactions. Also those that seem to be failing should be reached out too.
- More VLE databases should be made available online. Also a more detailed database is highly recommended by the researcher. The database should contain information about teacher-student, student-teacher, student-student, student-VLE system interaction.
- Proper grouping of the database is highly recommended, so as to produce graphs that are less clustered and easier to interpret. The researcher would recommend a group of five with not more than 30 students per group.

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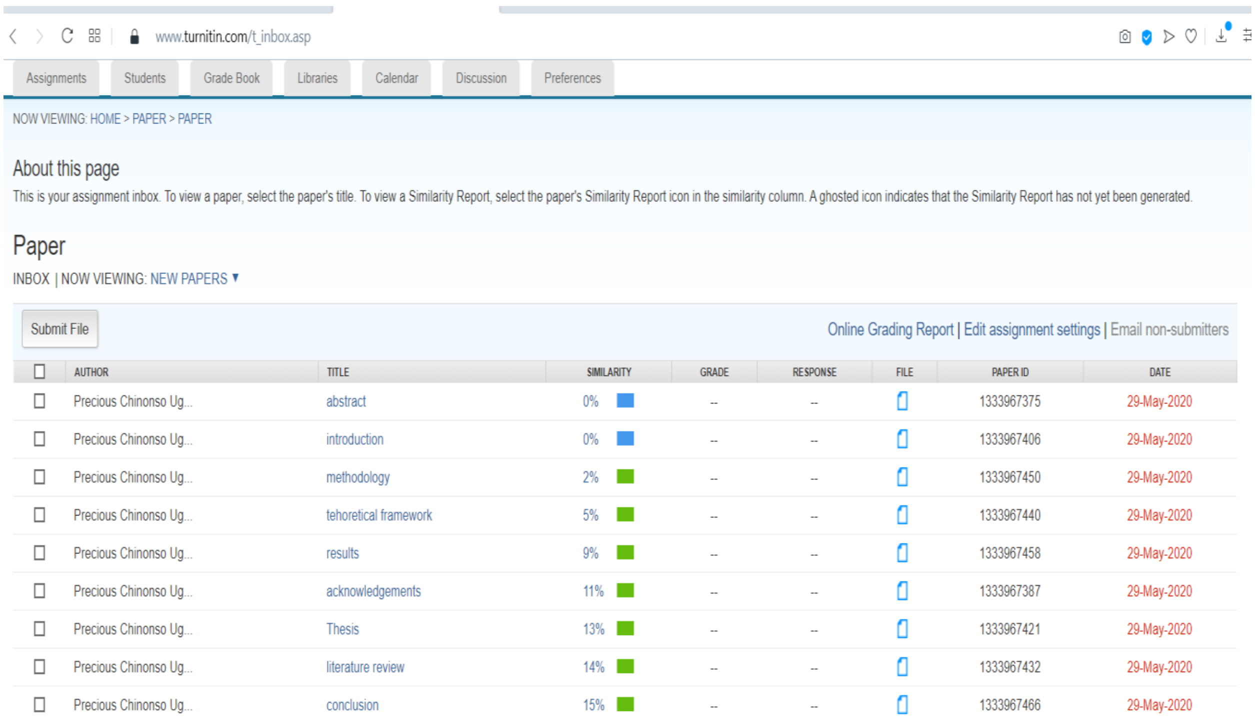
APPENDICES

APPENDIX 1

SIMILARITY REPORT



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APPENDIX 2

ETHICAL APPROVAL DOCUMENT

NEAR EAST UNIVERSITY

ETHICAL APPROVAL DOCUMENT

Date: __29_/_05__/_2020___

To the Graduate School of Applied Sciences

For the thesis project entitled as “INVESTIGATING THE EFFECTS OF INTERACTIONS ON STUDENT PERFORMANCE IN VIRTUAL LEARNING ENVIRONMENTS” the researchers declare that they did not collect any data from human/animal or any other subjects. Therefore, this project does not need to go through the ethics committee evaluation.

Title: Asst. Prof. Dr.

Name Surname: Seren Başaran

Signature:

Role in the Research Project: Supervisor