# DETEMINANTS OF LEARNING ANALYTICS TOOL ADOPTION BY UNIVERSITY STUDENTS

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

**By**
**AHMAD MOHAMED IBRAHIM DAGANNI**

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

**NICOSIA, 2018**

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last Name: AHMAD DAGANNI

Signature:

Date:

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It is with great joy that this study was a success. Without the help of key people who sacrificed their resources and time, this study would not have been a success. Firstly, I would like to take this time to acknowledge my supervisor, Prof. Dr. Seren Başaran who was there guiding me throughout my thesis. Without her immense knowledge, expertise in SPSS and constant help and encouragement I would not have pulled through. In addition, I would also like to thank Prof. Nadire Cavus for her administrative guidance for the degree programme courses.

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**To my family…**

# ABSTRACT

Learning analytics refers to a systematic process involving measuring, collecting, analyzing and reporting data about learners with the aim of fully understanding how best learning environments can be optimized to increase efficiency. The aim of this study is to understand the determinants of learning analytics adoption by university students in North Cyprus. Participants comprised of students from 3 universities in North Cyprus. The obtained results have shown that there was a weak negative correlation between Performance Expectancy and Technology Use Intention implying that when students are aware of how a technology operates and if it satisfies their requirements, then they will be ready to adopt learning analytics. There was also a negative weak correlation between Effort Expectancy and Technology Use Intention.

A positive weak correlation between Social Influence and Technology Use Intention was observed while there was a negative weak correlation between Technology Use Intention and Technology Use Behavior implying that when a student has intentions of using learning analytics, they show a positive behavior towards the technology. The study also shows that there was also moderate positive correlation between Technology Anxiety and Technology User Behavior.

This study is considered to be of great benefit and practical implementation to researchers, instructors, students, universities and the ministry of education.

***Keywords:*** Higher education; learning analytics; learning tools; North Cyprus; students; technology

# ÖZET

Öğrenme analitiği sistemik bir süreç olup ölçme, toplama, analiz ve öğrenenlerin verilerinin raporlanarak en iyi öğrenme ortamlarını anlamak ve verim oranını artırmayı hedeflemektir. Bu çalışmanın amacı Kuzey Kıbrıs'daki üniversitelerdeki öğrencilerin öğrenme analitiğininin belirleyici etkenlerinin araştırmasıdır.

Çalışmada kullanılan katılımcılar Kuzey Kıbrıs'daki 3 ünüversiteden oluşturulmuştur. Yapılan araştırma sonucunda Performans Beklentisi ve Teknoloji Kullanma Niyeti arasında negatif bir ilişki olduğu görülmektedir. Öğrenciler teknolojinin nasıl kullanılacağının farkında iseler öğrenme analitiğini kullanmaya hazır görünmektedirler. Efor Beklentisi ve Teknoloji Kullanımı arasında da negatif bir ilişki olduğu görünmektedir.

Sosyal Etki ve Teknoloji Kullanma Niyeti arasında ise zayıf pozitif bir ilişki görünmüş Teknoloji Kullanım Niyeti ve Teknoloji Kullanma Davranışı arasında ise zayıf negatif bir ilişki bulunmuştur. Bu sonuçlarda öğrencinin öğrenme analitiği kullanma niyeti olduğunda teknolojiye karşı pozitif bir davranış içerisinde olduğudur.

Çalışma ayrıca Teknoloji Endişesi ve Teknoloji Kullanım Davranışı arasında orta derecede pozitif bir ilişkinin olduğunu gösteriyor.

Bu çalışmanın araştırmacılar, eğitmenler ve eğitim bakanlıkları kullanımı açısından yararlı olacağı düşünülmektedir.

***Anahtar Kelimeler:*** Yüksek Öğretim; öğrenme analitiği; öğrenme araçları; Kuzey Kıbrıs; Öğrenciler; teknoloji

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## ABBREVIATIONS

| | |
|---|---|
| **EE** | Effort Expectancy |
| **FC** | Facilitating Conditions |
| **LA** | Learning Analytics |
| **LAAM** | Learning Analytics Acceptance Model |
| **PE** | Performance Expectancy |
| **PE** | Performance Expectancy |
| **PEU** | Perceived Ease of Use |
| **SI** | Social Influence |
| **SI** | Social Influence |
| **STEM** | Science, Technology, Engineering, Mathematics |
| **TA** | Technology Anxiety |
| **TEF** | Teaching Excellence Framework |
| **TUB** | Technology Use Behavior |
| **TUI** | Technology Use Intention |
| **UTAUT** | Unified Technology of Acceptance and Use of Technology |
| **VLE** | Virtual Learning Environment |

# CHAPTER1

# INTRODUCTION

This introductory chapter provides a detailed introduction about the topic under study to guide the reader and furthermore it goes on to explain the research problem, limitations of the current study, aim of the study and a summary of the chapters to follow to provide an overall understanding of the subject under study.

## 1.1 Overview

Learning analytics refers to a systematic process involving measuring, collecting, analyzing and reporting data about learners with the aim of fully understanding how best learning environments can be optimized to increase efficiency. Various learning analytical tools have been discovered through research and development in a bid to improve the overall learning experience. Educators play an important role in determining which analytical tool best suites them considering how the tool supports both their pedagogical as well as organizational goals (Ali et al., 2014).

A digital footprint is left behind each time a student uses the university learning system through various activities such as library login, logging in to the virtual learning system or submitting online assignments. Learning analytics is the process of thoroughly analyzing the digital footprint to get more information about the users of the system which can help enhance the overall learning process (Sclater et al., 2017).

In an educational setting, data analytics has four forms namely descriptive analytics, diagnostic, prescriptive and predictive analytics as explained by Boyer and Bonnin (2017). Figure 1.1 below describes the relationship between the different analytics as explained by the researcher and the section below explains the meaning behind each:

- ***Descriptive Analytics:*** As the name denotes this type of analysis is mainly focused on explained what transpired and results are often depicted in virtual formats such as pie charts, graphs etc. Students may find results obtained from this analysis important in determining their performance and instructors may find it important in determining his/her level of impact by checking assessment results.

- ***Diagnostic Analytics:*** This analysis seeks to find the cause behind projected results in order to understand events that may have contributed to such an outcome. Techniques often used during diagnostic analytics include statistical correlations, pattern mining and data discovery. Results obtained can be used to determine the reasons that led students to pass or fail.

- ***Predictive Analytics:*** This type of analytics aims at being pro-active by analyzing results based on future predictions. Information obtained in this analysis is vital for decision making and can assist both student and instructor in making the best decisions. Students will be able to know if they are working in the right direction based on what they want to accomplish and on the other hand, the instructors will be able to identify students at risk and come up with solutions before the worst happens which is failure.

- ***Prescriptive Analytics:*** This type of analysis involves thoroughly examining available data and coming up with strategies which can be used to achieve the long term goals of the institution. Tools that fall in this category include data mining tools, simulation and recommendation tools. Institutions may use this type of analytics to help them identify the trend for dropouts and take necessary measures before it's too late.


**Figure 1.1:** Types of learning analytics (Boyer & Bonnin, 2017)

## 1.2 Problem Statement

Due to the recent "smart" advancement in the technology sector, there is a need to shift to an electronic form of learning moving away from the traditional paper-based usage in an attempt to keep up with the standard of education in North Cyprus given the increasing number of students with each session in North Cyprus. Adopting learning analytics in the educational sector has led to higher retention levels and prediction of drop-outs allowing institutions and instructors to be proactive hence improving the entire learning process in some countries such as Australia, UK, America and Italy (Boyer & Bonnin, 2017). Learning analytics have been used by instructors in improving their overall teaching experience as well as by institutions in fostering good learning practices and improving the entire learning system. In addition, learning analytics can be used to effectively monitor engagements among students and boost participation and to improve attainment levels by offering support to struggling students. For these reasons, the researcher seeks to understand acceptance of this technology in North Cyprus.

## 1.3 Aim of Study

The student directly aims to evaluate the correlation between the Performance Expectancy and Technology Use in different dimensions as stated in the following stipulated hypothesis;

- **H1:** Performance Expectancy (PE) will have a positive effect on Technology Use Intention on the adoption of learning analytic tools in higher education.
- **H2:** Effort Expectancy (EE) will have a positive effect on Technology Use Intention on the adoption of learning analytic tools in higher education
- **H3:** Social Influences (SI) will have a positive effect on Technology Use Intention on the adoption of learning analytic tools in higher education
- **H4:** Technology use intention will have a positive effect on Technology Use Behavior on the adoption of learning analytic tools in higher education.
- **H5:** Facilitating Conditions (FC) will have a positive effect on Technology Use Behavior of learning analytics tool adoption.
- **H6:** Technology Anxiety will have a positive effect on Technology Use Behavior when it comes to learning analytics tool adoption.

## 1.4 Importance of Study

This study is important to various educational stakeholders. Learning analytics play a crucial role in improving the overall educational sector and enhancing the learning environment. Below are reasons why learning analytics are important to various educational stakeholders:

- ***Student:*** Learning analytics enable students to monitor their performance based on their set goals and check how others are performing and this can be motivating. Learning analytics gives more insight to the student on the areas they need to improve in order for them to score better grades.

- ***Instructors:*** The instructors or teachers will be able to monitor their students' progress in real time and get more insight on their performance. Students lagging behind can be easily identified and the instructor will be able to be proactive and assist the student before they fail hence improving retention levels.

- ***Training managers:*** Training managers will be able to identify educational stakeholders be it students or teachers who are lagging behind or are having difficulties in using the system and training managers will be able to focus on problem groups only.

- ***Educational institutions:*** By making use of learning analytics, institutions will be able to retain more students as proactive measures are taken once signals are seen on students underperforming and dropout levels are also minimized once proactive measures are taken.

- ***Researchers:*** Researchers who are interested in knowing how best learning analytics can be adopted in educational settings will be interested in this study.

## 1.5 Limitations of the study

This study has limitations which should be made aware to the readers and fellow researchers who may be interested in using the same study as a reference or a starting point for future research. The limitations are explained in detail below:

- ***Geographical limitation:*** The study is limited to three universities located in North Cyprus.
- ***Research Duration:*** This study has a limiting factor of time, the study will be conducted during the fall semester of 2018. Research targeting a longer period of time is strongly recommended.
- ***Research participants:*** Participants of this study are limited to students currently enrolled at 3 universities in North Cyprus.
- ***Research tool:*** A paper based questionnaire will be used to collect data from research participants. The limiting factor comes as a result of the nature of the instrument used, questionnaires are subjective and responses are only based on the honest opinion of the participant which is difficult to determine.

### 1.6 Overview of the Thesis

This research is divided into six distinct chapters which are summarized in detail below to give the readers a better understanding of the overall study:

**Chapter one:** This introductory chapter provides a detailed introduction about the topic under study to guide the reader and furthermore it goes on to explain the research problem, limitations of the current study, aim of the study and a summary of the chapters to follow to provide an overall understanding of the subject under study.

**Chapter Two:** This chapter explores the literature in order to find out more about learning analytic tool adoption in higher education. This section will focus on the views of students on learning analytics adoption as well as exploring the advantages and disadvantages behind using this technology.

**Chapter Three:** This chapter provides a detailed description of the learning analytics model and how the system functions, more insight is given on the dimensions of learning analytics, Jisc's learning analytics architecture is described and the UTAUT model that serves as the model for the study.

**Chapter Four:** This chapter gives a detailed description of the research model that was adopted by the researcher, the relationship that exists between the various dimensions, a narrative of research participants, data collection tools, reliability test of questionnaire dimensions as well as an overview of the research procedure that was followed by the researcher in conducting the study.

**Chapter Five:** This chapter provides results of the study. Data collected is analyzed and results discussed in this chapter. Findings are compared with previous research findings to gain a better understanding of the subject under study.

**Chapter Six:** This chapter concludes the study by giving a closing summary of the entire study and the researcher suggests recommendations for future research that act as guidelines to future researchers who may be interested in the same area under study.

# CHAPTER 2

# RELATED RESEARCH

This chapter explores the literature in order to find out more about learning analytic tool adoption in higher education. This section will focus on the views of students on learning analytics adoption as well as exploring the advantages and disadvantages behind using this technology.

## 2.1 Learning Analytics in Education

Learning analytics have been described as a systematic process involving measuring, collecting, analyzing and reporting data about learners with the aim of fully understanding how best learning environments can be optimized to increase efficiency. In this section, we shall attempt to answer the first two research questions in order to fully understand both instructor and student perceptions on the adoption of learning analytic tools.

### 2.1.1 Views of university students on learning analytic tool adoption

**RQ1:** What are the views of university students on adoption of learning analytics tool in higher education?

Sclater et al. (2017), adopting learning analytics in higher education has the power to make students make well informed decisions on their own by monitoring their overall performance in real time and have control over their progress and what they wish to study based on results projected. A study conducted at Nottingham Trent University in the UK showed that 89% of the students considered signals a positive experience whilst on the other hand 74% stated that their motivation level was increased by using analytic tools. In addition students reported that by being able to see their own engagement online, it had a positive spur for them to stay engaged.

Boyer and Bonnin (2017) conducted a study at many universities across USA to fully understand the adoption of learning analytics and his findings are depicted in Figure 2.1 below. In the second week of the term, instructors identified problems as far as learning analytics deployment was concerned. Students were in need of help more frequently, however this led to 12%more B grades and c grades and failure rates for grade D and F dropped by 14%. At Maryland University in the United States, learning analytics through the use of VLE made it possible for instructors to identify effective teaching strategies that could be deployed on other courses and the analysis which was found made it clear that students who obtain low grades use the system 40% less than those who get C grades or even higher grades (Boyer & Bonnin, 2017). In addition, the researchers conducted a study at California State University found out that students were motivated by the use of the virtual learning system and this increased their pass mark by 25%.

A study conducted at Marist College in New York showed that predictive models were a key to students in giving them early feedback and therefore allowed them to be pro-active and this resulted in a 6% increase in student's final grades. Furthermore, study conducted at New York Institute of Technology showed that 74% of dropouts were already predicted by the system and this information is vital to instructors as they can support students who are at risk of dropping out and dropout rates can fall (Boyer & Bonnin, 2017).

A study conducted at Nottingham Trent University in the UK showed that there was a strong link with retention levels, a quarter of the students who had low average engagement were able to progress to the second year. In addition there was a strong link with achievement levels as well with 81% of the students graduating with a first class and 2:1 degree contrary to the 42% who had low engagement and this is depicted in Figure 2.2 (Boyer & Bonnin, 2017). In addition, the researchers also conducted another study at the Open University, UK and learning analytics were used in enhancing student experience and retention rates as well as driving interventions at student module and qualification levels.

In Australia at the University of New England, social media is the main platform that is used in engaging students and promoting learning analytics and this has fostered a sense of community among the students both those studying full time at the university and those studying part time (Friessen, 2017). Furthermore, the researchers found out that at Edith Cowan University in Australia, learning analytics helped instructors identify which students needed support and helped them in creating probabilities of retention scores. At Wollogong University in Australia, learning analytics were used using a system known as SNAPP and it has the ability of visualizing relationships that exist between participants in real time in the form of a network diagram. This enabled instructors to encourage engagements among students especially those students who were less connected with their peers (Friesen, 2017).

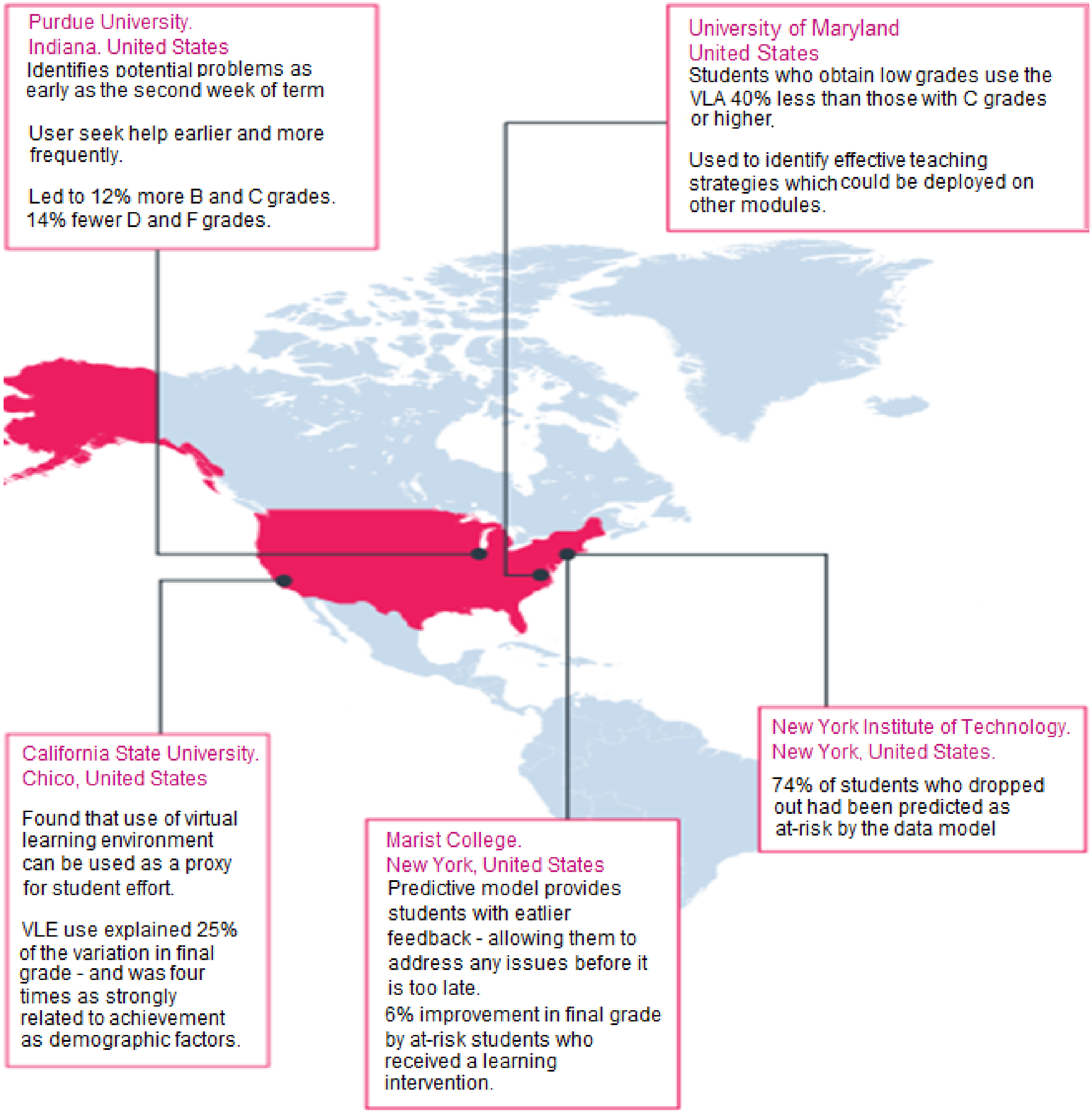


**Figure 2.1:** Showing outcomes for learning analytics deployment at USA universities (Boyer & Bonnin, 2017)

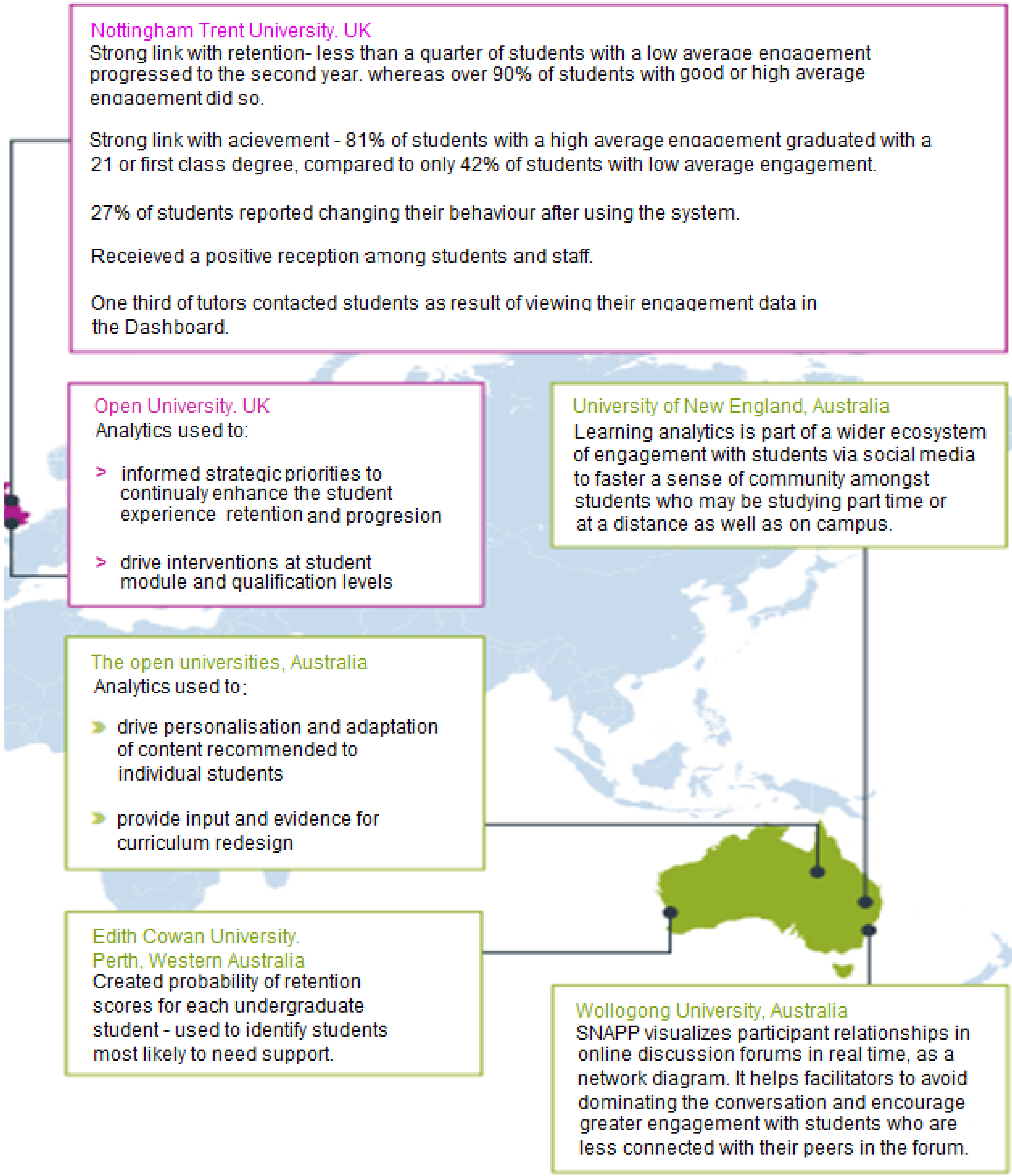


**Figure 2.2:** Showing outcomes for learning analytics deployment at UK and Australian universities (Boyer & Bonnin, 2017)

### 2.1.2 The difference among views on learning analytic tool adoption between instructors and students

The world is undergoing what is known as a data revolution were by there is massive data that is being generated from various sources in great speed and according to Khan et al. (2014) it is projected that data will be double the current rate every month as of 2010. The emergence and adoption of new technology in the educational sector has resulted in a massive influx of data however the problem emerging has been inefficient use of available data to improve the entire educational sector (Olugbenga (2017).

In a recent study conducted by Nicolae et al. (2015) in India, students indicated that although the use of learning analytics has had a significant impact in their personal studies they are not keen on sharing their digital footprints with the university and instructors as they feel it is invasion of privacy. Students' feel uncomfortable in the learning environment knowing that all their browsing history will be analysed by their instructors. However, on the contrary, instructors feel that by gaining access to such valuable data that is the only way they will be able to identify the needs of students and see how best they can help each student at an individual level.

It has also been noted that tools available on the student dashboard to show student progress relative to their own set goals are motivating although in a number of cases it has also been reported that successful students are the ones who tend to use these tools more compared to struggling students (Olugbenga (2017). This shows the need for educating all students on the effective use of such tools so that a clear picture and clear results can be derived based on all students despite their intellectual level and ability. It was also noted that an increase in student performance as a result of the use of learning analytics had a positive impact on other courses which the same student is studying. It is also vital to note that, Friesen (2017) reported that objections by students on the use of learning analytics has not been reported in the literature by many researchers.

## 2.2 Advantages of Using Learning Analytics in Higher Education

As technology keeps on advancing each day in different sectors, neither is the educational sector being left behind. Many researchers in the literature have explained the importance of this technology and how it is revolutionizing the educational sector. Explained below are some of the advantages for adopting this technology in the educational sector:

- ***As a tool for quality assurance and quality improvement***: Learning analytics have been used by instructors in improving their overall teaching experience as well as by institutions in fostering good learning practices and improving the entire learning system. Learning analytics data could be used as a submission for institutions as evidence of support for Teaching Excellence Framework (TEF) applications. At the University of Maryland, it was found out that use of learning analytics resulted in quality teaching and improved student and instructor relationships (Sclater et al., 2017).

- ***As a tool for boosting retention levels***: Using learning analytics helps instructors and the institution to identify students that are at risk and by being pro-active intervention can be done quickly hence retention levels are boosted. At Purdue University in the United States, problems related to retention and the identification of students at risk can now be done within the second week and measures are quickly taken which is something that could not be done before (Sclater et al., 2017). Student data analytics can be used to predict the students who will not make it to the next semester, at New York Institute of Technology (NYIT), 75% of the students who do not progress to the next semester would have been predicted at risk by the learning analytics model way back (Daniel, 2014).

- ***As a tool used for analyzing differential outcomes among students***: Learning analytics can be used to effectively monitor engagements among students and boost participation and to improve attainment levels by offering support to struggling students (Nicolae et al., 2015).

- ***For the development of adaptive learning***: This refers to personalized learning that is delivered at an individual basis based on ones capability to retain information and also based on one's schedule (Sclater et al., 2017).

## 2.3 Challenges of Learning Analytics

It is crucial to know that adapting any new technology has challenges that come with it and this is also the same with the adoption of learning analytics in higher education. The following key points are challenges that have been recorded by researchers in the literature:

- The adoption of learning analytics in an educational sector implies creating a new culture among all stakeholders in order to adapt to the new processes in place and that calls for change management (Daniel, 2014).

- Like every new technology, adopting learning analytics comes with additional costs that must be incurred and this normally affects budgets (Jordaon & Merwe, 2016).

- Data plays an important role in the implementation of learning analytic systems as successful implementation relies on both effective data integration and the quality of the data and the main restriction often comes in play when data systems are not interoperable (Daniel, 2014).

- Lack of dedicated data management systems for the production of datasets within a short space of time (Jordaon & Merwe, 2016).

# CHAPTER 3

# CONCEPTUAL FRAMEWORK

This chapter provides a detailed description of the learning analytics model and how the system functions, more insight is given on the dimensions of learning analytics, Jisc's learning analytics architecture is described and the UTAUT model that serves as the model for the study.

## 3.1 Learning Analytics Acceptance Model

An educator should be able to quickly get an insight of the entire learning process by using learning analytics through the use of effective virtualization techniques to monitor users' movements. Current learning management systems provide little insight as far as data analytics is concerned, mainly the number of users logged in and the time log is reflected. Little or no information is given on the movements of users' online. Given the above limitations with most of the current systems, Ali et al. (2017) proposed a model to help in the adoption of learning analytics known as the Learning Analytics Acceptance Model (LAAM).

A learning analytics tool called LOCO-Analyst was used in the study to create the LAAM model and investigate the impact of the aforementioned factors. Learning analytics are provided at varying levels of interest using LOCO-Analyst. The model is centered upon the study by Davis (1989) who described perceived usefulness as the extent by which an individual believes that their task performance will be improved as a result of using the system. Furthermore, Ease of use is the extent by which an educator believes that a system will be free of effort. Figure 3.1 below shows the high level view of the model.

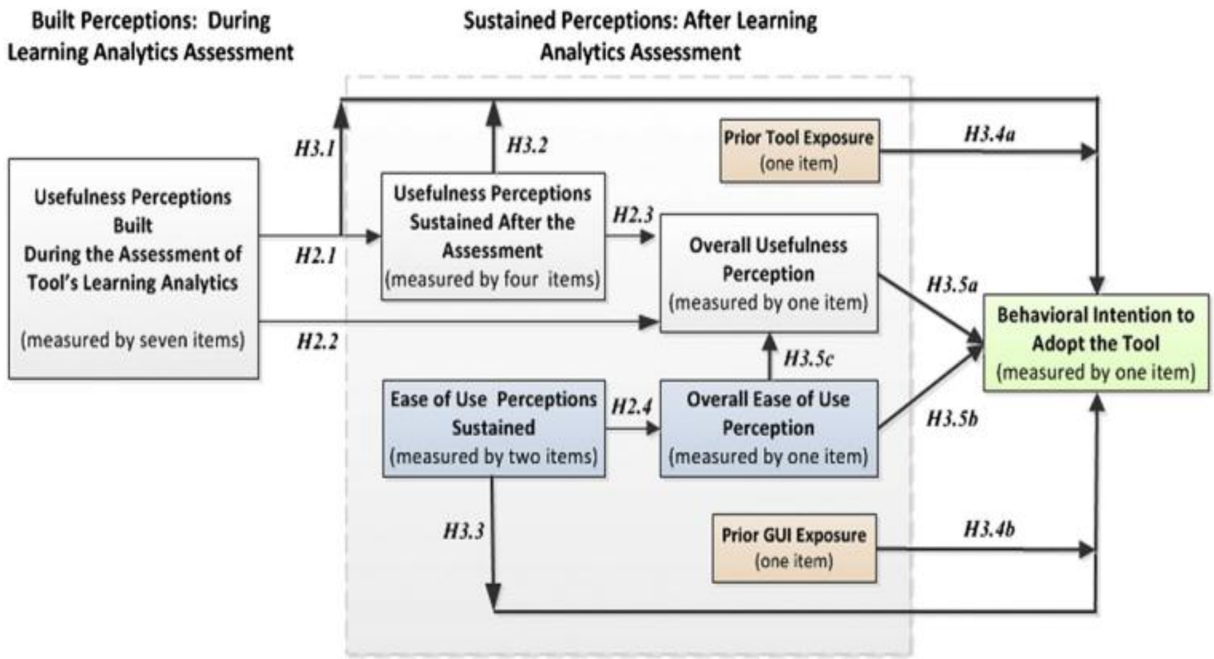


**Figure 3.1:** Showing a high level view of the LAAM model (Ali et al., 2014)

### 3.2 Dimensions of Learning Analytics

According to a study done by Buckingham (2016) it was found out that learning analytics varies depending on one's interest whether they are interested in a university, department, specific course or a region. The researcher categorizes the interests into three distinct groups, micro, meso and macro analytics. Chatti et al. (2014) describes a model for learning analytics that is based on four dimensions which are depicted in Figure 3.2 below.

- ***What:*** This dimension seeks to know the type of information that has been collected, managed and used.
- ***Who:*** This seeks to find the actors involved who will ultimately receive results.
- ***Why:*** Which objectives will be used in order to analyze the collected data.
- ***How:*** Which methods will be used in analyzing available data.

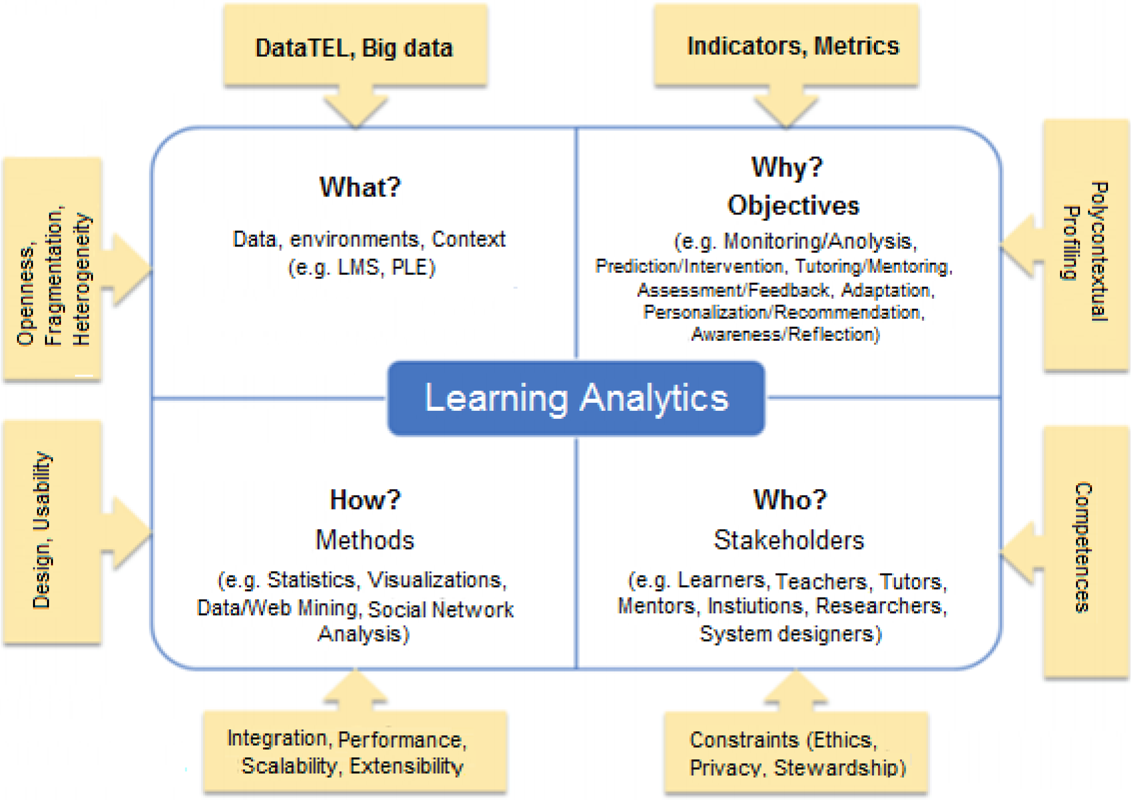


**Figure 3.2:** Dimensions of learning analytics (Chatti et al., 2015)

### 3.3 Jisc's Learning Analytics Architecture

The architecture developed by Sclater et al. (2017) shows how data from various learning environments is fed into the learning analytics warehouse. Predictive analytics takes place at the center of the architecture resulting in actions being coordinated by the system. Analytics can be visualized in a series of dashboards allowing both students and instructors to engage and compare their progress with others. Using such information allows both instructors and students to plan and set targets. Furthermore, the student consent service available allows students to share their information to certain people therefore maintaining privacy of data captured, Jisc's learning analytics software is available for free to institutions for the first 2 years and the system is cloud based allowing institutions to share the scalable structure yet maintaining their data and the system can be customized easily. Figure 3.3 below shows the architecture.

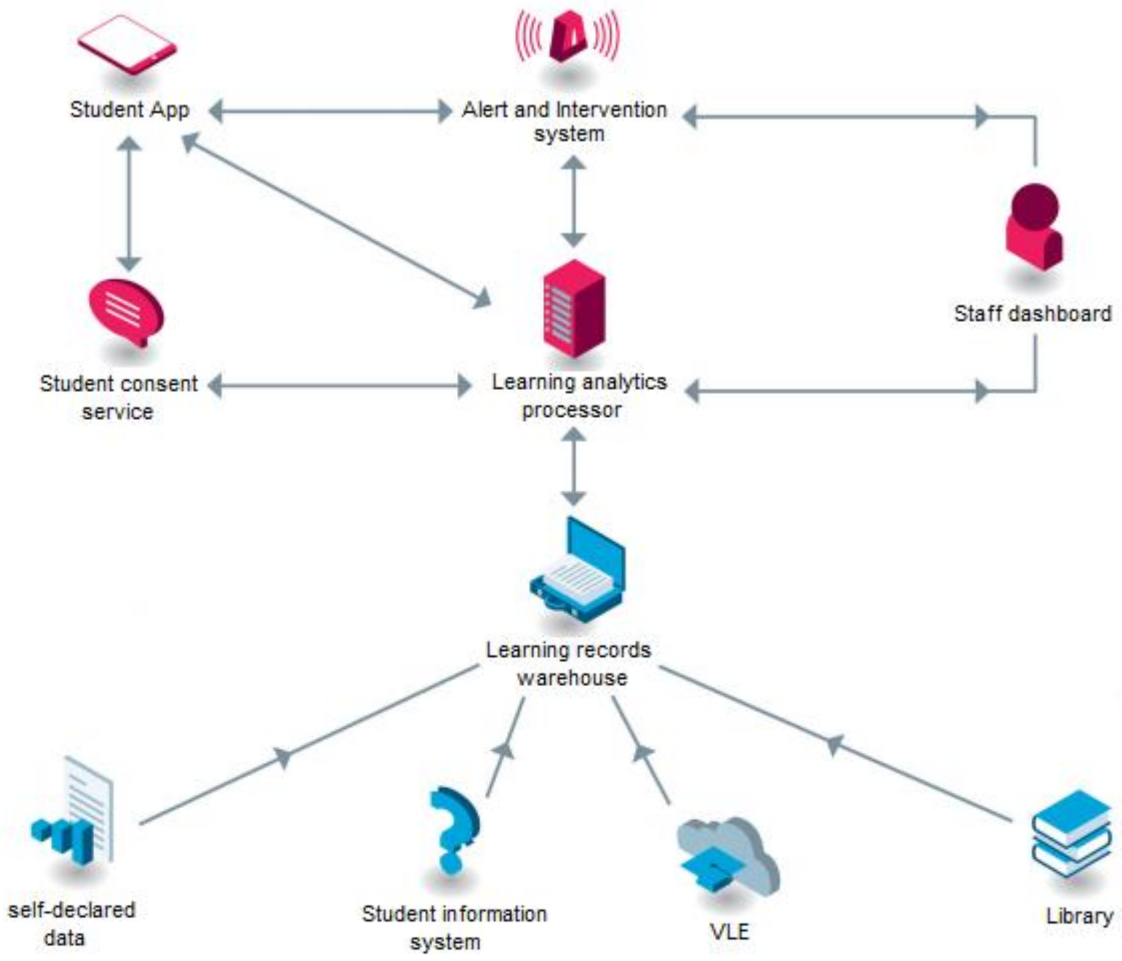


**Figure 3.3:** Jisc's learning analytics architecture (Sclater et al., 2017)

### 3.4 Unified Theory of Acceptance and Use of Technology (UTAUT)

This research model forms the basis of this study and according to the developer Venkatesh et al. (2003), the researchers explained that acceptance of technology is influenced by various factors that include social influence, performance expectancy, effort expectancy and facilitating conditions. The model also includes moderating factors of age, gender, experience and voluntariness of use, however it is important to note that in this study moderating factors will not be considered. The terms used to describe the model are explained in detail below and the model is depicted in Figure 3.4 below:

- ***Performance Expectancy:*** The degree by which an individual believes that by using a certain system their overall performance will be enhanced.

- ***Effort Expectancy:*** The degree to which a person believes that by using learning analytics the system will require minimal effort.
- ***Social Influence:*** The degree to which an individual believes that their choice to use a particular technology is greatly influenced by their associates.
- ***Facilitating Conditions:*** The degree to which an individual believes that other factors such as the institution play an important role in their decision to use learning analytics.

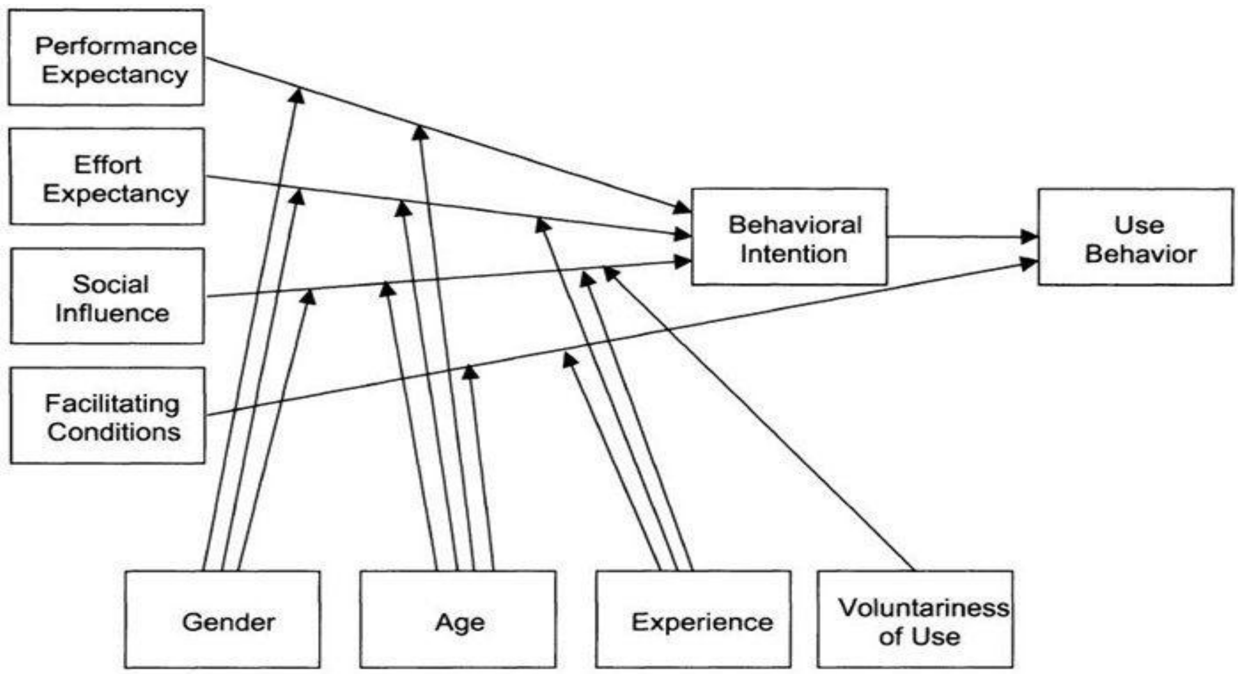


**Figure 3.4:** Unified theory of acceptance and use of technology (Venkatesh et al., 2003)

### 3.5 Summary of Thesis Research Model

The Unified Technology of Acceptance and Use of Technology (UTAUT) forms the basis of this study. The study is based on all dimensions in the model. Technology Anxiety is another dimension that is not part of UTAUT that was adopted from a study by Nistor et al. (2014) however the researchers call this computer anxiety in their study. In total the model used in this study has a total of 7 dimensions as illustrated in section 4.1 of this study. These dimensions will be used to find out the determinants of learning analytics adoption by students in North Cyprus. Figure 3.5 below shows the model by Nistor et al. (2014).

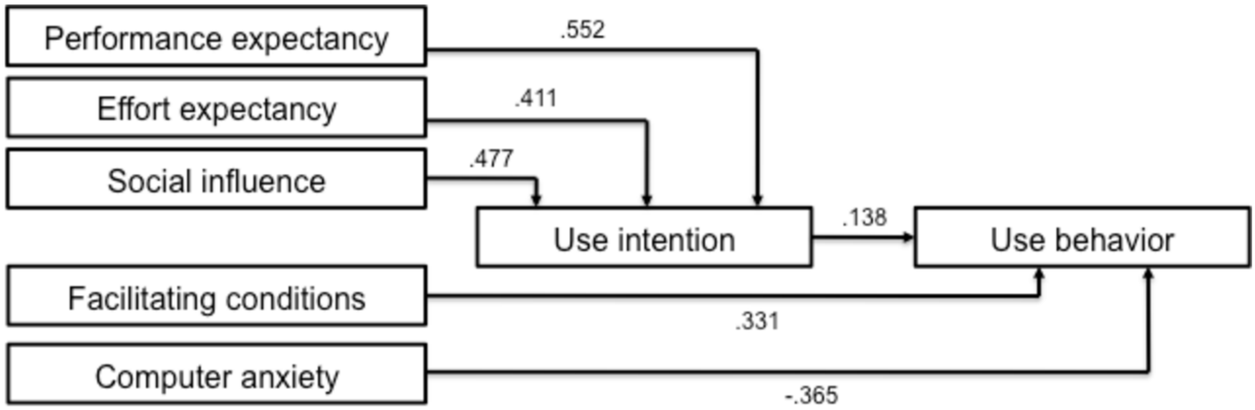


**Figure 3.5:** The extension of the UTAUT model (Nistor et al., 2014)

# CHAPTER 4

# RESEARCH METHODOLOGY

This chapter gives a detailed description of the research model that was adopted by the researcher, the relationship that exists between the various dimensions, a narrative of research participants, data collection tools, reliability test of questionnaire dimensions as well as an overview of the research procedure that was followed by the researcher in conducting the study.

## 4.1 Research Model

The research model that will be used in this study is depicted in Figure 4.1 below and it comprises of the Unified Technology of Acceptance and Use of Technology (UTAUT) model by Venkatesh et al. (2003) which was modified and another dimension Technology anxiety was added. The model used in this study was adopted from a study by Nistor et al. (2014). The model comprises of 7 dimensions namely performance expectancy, effort expectancy, social influence, technology use intention, technology use behavior, facilitating conditions and technology anxiety. The researcher aims to explore these dimensions and find out to what extent does each dimension affects determinants of learning analytics tools used by students.

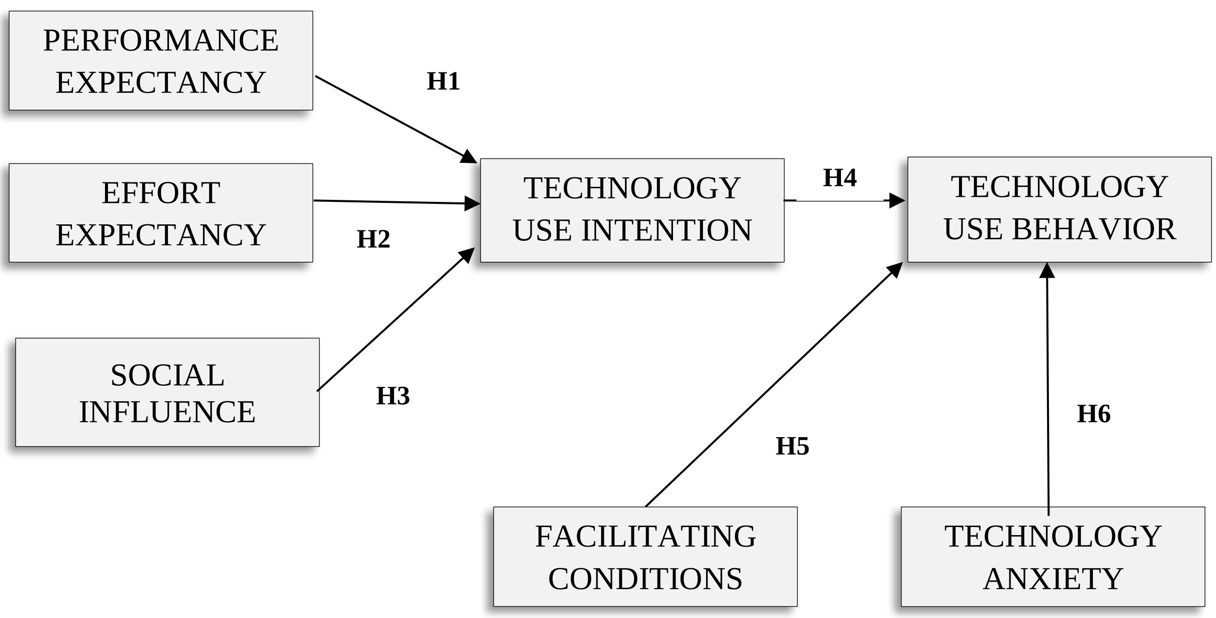


**Figure 4.1:** Research model for the study

### 4.2 Research Participants

Participants who took part in this study were students who are currently studying at three universities in North Cyprus. A study conducted in 2018 showed a total population of 102 944 students studying in North Cyprus. Given that the margin of error is 5%, a normal distribution expected and 95% confidence interval it then means that the recommended sample size will be 383. This makes the sample size of 718 valid for analysis in this study.

The study was voluntary meaning any one was free to take part in the study, furthermore it was anonymous no personal information was collected that could be used to trace back the participant. Due to several departments at the universities with students specializing in various fields, in this study for the purpose of data analysis department was split into two distinct groups namely STEM (Sciences, Technology, Engineering and Mathematics) specifically for students with a technical background and Other for non-technical students. The aim being to find out if there is any differences in results as far as technical background is concerned. Students from all three university levels were encouraged to participate, undergraduates, masters and PhD students.

The total number of questionnaires that were distributed were 800, however of the 800, 36 went missing when the researcher was collecting the questionnaires from the participants. Furthermore 46 questionnaires were discovered on data capturing that they were not fully completed and for that reason they had to be disposed and results excluded from the study. The result was a total of 718 questionnaires which were considered valid and were further entered into SPSS for analysis.

#### 4.2.1 Demographic data of research participants

Table 4.1 below depicts the demographic data of research participants. It is clear that the majority of the participants were male students 403 comprising 56.1% of the total population group, female students were 315 which constituted 43.9% of the total participants. Furthermore, the majority of the students were in the age group 17-26 which totaled 334 (46.5%), followed by age group 27-36 years which were 231 students which constituted 32.2% of the total participants and the last age group 37 years and above had 153 students (21.3%) and this group was mainly dominated by PhD students and a few masters students.

In addition, among the three distinct levels of study, a lot of the participants were undergraduate students who comprised of 391 students (54.5%) of the total participants. Masters students who took part in the study were 244 (34%) and PhD students were 83 (11.5%). The numbers narrow down as the levels go higher in any educational setting. The STEM department which comprised of students in technical fields and science subjects totaled 424 (59.1%) whereas those from other departments were 294 (40.9%).

**Table 4.1:** Demographic data of research participants

| Demographic Variable | | Number | Percentage (%) |
|---|---|---|---|
| Gender | Male | 403 | 56.1 |
| | Female | 315 | 43.9 |
| | Total | 718 | 100.0 |
| Age group | 17-26 | 334 | 46.5 |
| | 27-36 | 231 | 32.2 |
| | 37+ | 153 | 21.3 |
| | Total | 718 | 100.0 |
| Level of Study | Undergraduate | 391 | 54.5 |
| | Masters | 244 | 34.0 |
| | PhD | 83 | 11.5 |
| | Total | 718 | 100.0 |
| Department | STEM | 424 | 59.1 |
| | Other | 294 | 40.9 |
| | Total | 718 | 100.0 |

### 4.3 Data Collection Tool

A paper based questionnaire was the main tool that was used by the researcher to obtain information from participants. The questionnaire had a total of 28 questions with the first part asking general demographic data. The other 7 dimensions, Performance Expectancy, Effort Expectancy, Social Influence, Technology Use Intention, Technology Use Behavior, Facilitating Conditions and Technology Anxiety were based on a 5 Likert scale. Apart from the 4 questions that were based on the demographic data of the participant, Figure 4.2 below shows the dimensions which were in the questionnaire.

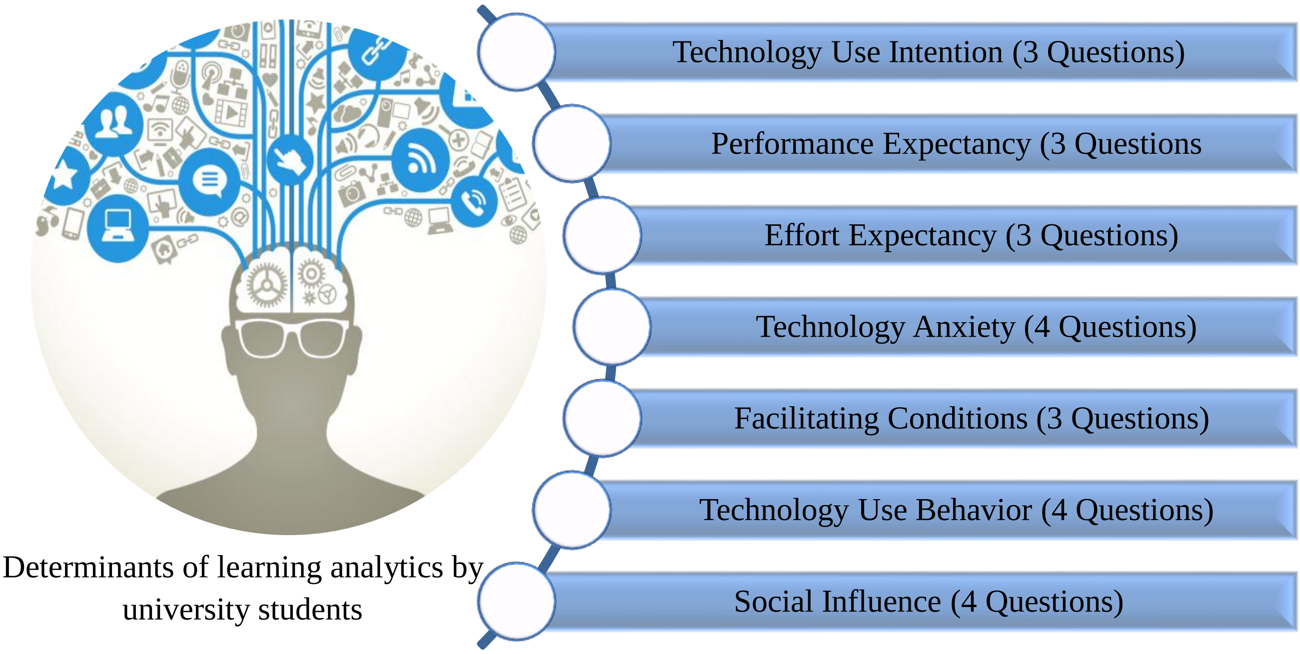


**Figure 4.2:** Questionnaire dimensions for the study

### 4.3.1 Reliability tests of questionnaire dimensions

As a way of assessing the feasibility aspect of the study, a reliability test was done to check if the questions were well structured to avoid biased information. The Cronbach Alpha was used as an instrument to check reliability in SPSS. Acceptable reliability should range from 0.6 coefficient going upwards, anything less than that is considered unacceptable and amendments must be done until a satisfactory result is obtained (Sekaran, 2000). As shown on table 4.2 below all the dimensions had a reliability of more than 0.6 coefficient which meant all dimensions had satisfactory questions.

The highest reliability was found in Facilitating Conditions which had a total reliability coefficient of .794 followed by Technology Use Intention .774, Technology Anxiety .756, Technology Use Behavior .706, Performance Expectancy .688, Social Influence .684 an Effort Expectancy .675. These results were pleasing and meant the study could proceed as evidenced by a total reliability of .851 for the entire questionnaire.

**Table 4.2:** Questionnaire constructs and reliability tests

| Constructs: | Number of Items | Cronbach Alpha |
|---|---|---|
| Performance Expectancy | 3 | .688 |
| Effort Expectancy | 3 | .675 |
| Social Influence | 4 | .684 |
| Technology Use Intention | 7 | .774 |
| Technology Use Behavior | 4 | .706 |
| Facilitating Conditions | 3 | .794 |
| Technology Anxiety | 4 | .756 |
| TOTAL | 28 | .851 |

## 4.4 Data Analysis

The total number of questionnaires that were distributed were 800, however of the 800, 36 went missing when the researcher was collecting the questionnaires from the participants. Furthermore 46 questionnaires were discovered on data capturing that they were not fully completed and for that reason they had to be disposed and results excluded from the study. The result was a total of 718 questionnaires which were considered valid and were further entered into SPSS for analysis. The following methods were used by the researcher to analyze the data:

- Descriptive analysis
- Pearson Correlation

## 4.5 Research Procedure

Figure 4.3 below shows a flow of the steps that were taken by the researcher in conducting the study. A literature review was conducted throughout the study. The researcher analyzed related questionaries' in order to derive relevant questions for the study. Next a panel of experts were consulted on the suggested questions and their input was taken into consideration. A questionnaire was then drafted and the experts reviewed it and this also included the ethical research board. A pilot study was then conducted among a few randomly selected students to check the feasibility of the questionnaire. Results obtained were analyzed and feedback taken into consideration and a final draft was made. The reliability test of the final version of the questionnaire was done and a good reliability was obtained which meant the study could proceed. Data was collected over a period of 2 months using the systematic analytical methods and analyzed using SPSS descriptive statistics and Pearson Correlation.  Finally data was interpreted and reported. A thesis review was done by the supervisor and feedback was taken into consideration.

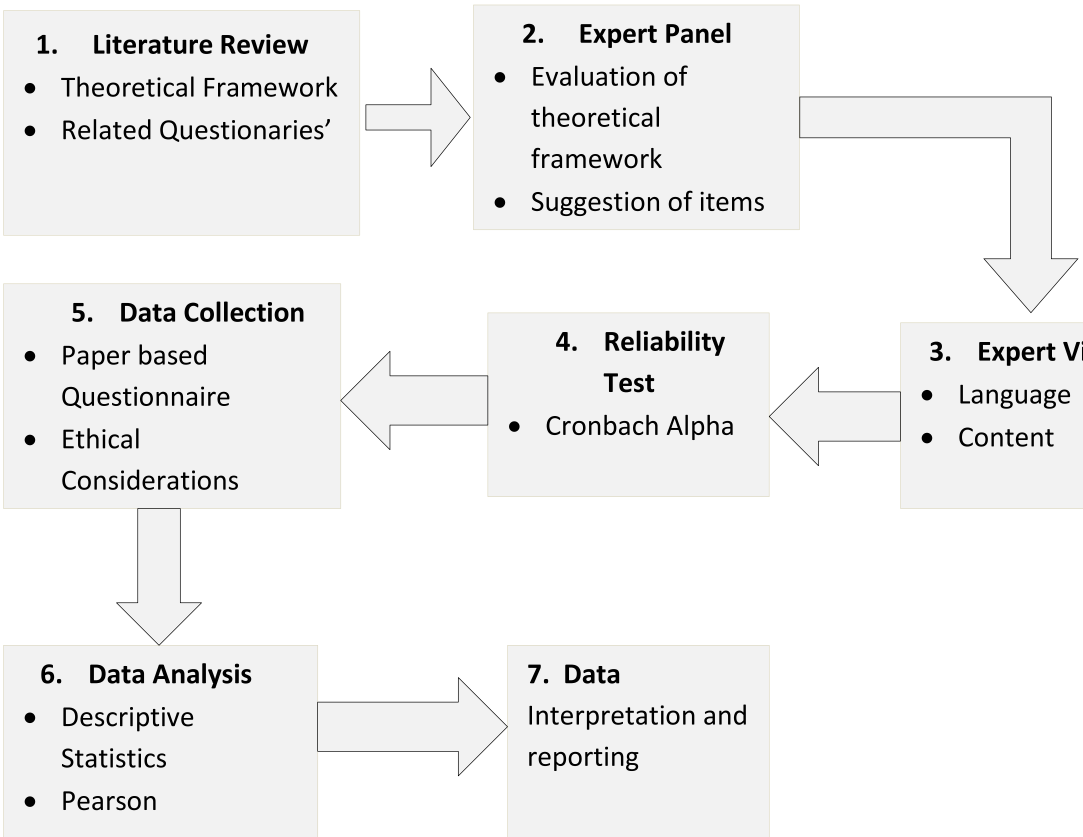


**Figure 4.3:** Research procedure

Table 4.3 below shows the summarized steps taken by the researcher in conducting the study. Each step is shown against the time frame it took. The entire study was completed in 26 weeks between the end of the spring and fall semester of the year 2018. The methods of analysis adopted are thus given;

1. Content analysis, particularly of resources which students create (such as essays).
2. Discourse analytics, which is used to capture meaningful data on student interactions which (unlike social network analytics) aims to explore the properties of the language used, as opposed to just the network of interactions, or forum-post counts, etc.

3. Analytics of social learning, which is aimed at exploring the role of social interaction in learning, the importance of learning networks, discourse used to sense make, etc.
4. Analytics disposition, which is involved in the capturing of data for the learning of the student.

**Table 4.3:** Thesis research schedule

| TASK | DURATION (WEEKS) |
|---|---|
| Literature Review of Study Area | 4 weeks |
| Research Proposal | 3 weeks |
| Compiling questions for questionnaire | 2 weeks |
| Expert Review | 1 week |
| Pilot study | 2 weeks |
| Data Collection | 8 weeks |
| Data analysis | 3 weeks |
| Data interpretation and reporting | 1 weeks |
| Thesis review and corrections | 2 weeks |
| Total | 26 weeks |

### 4.6 Gantt Chart for the Study

Figure 4.4 below illustrates a Gantt chart of the study. This is a diagrammatic illustration of the various steps that were done during the study against a timeline. Dependencies are clearly shown and it gives a better view of how the steps were related and which steps occurred concurrently as well as which steps had to be completed prior.

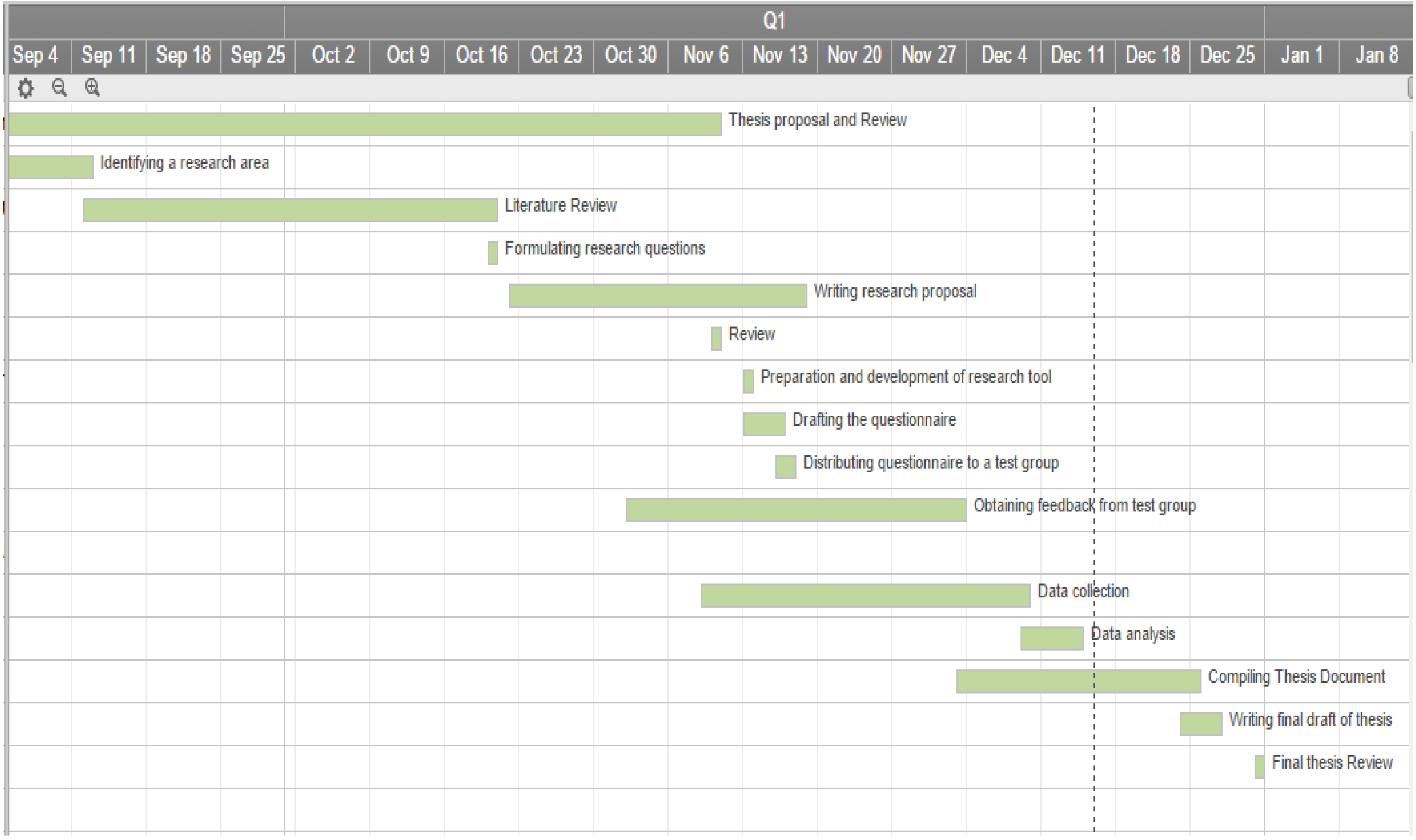


**Figure 4.4:** Gantt chart of the study

# CHAPTER 5

# RESULTS AND DISCUSSIONS

This chapter provides results of the study. Data collected from research participants was analyzed and results discussed in this chapter. Findings are compared with previous research findings to gain a better understanding of adoption of learning analytical tools in higher education.

## 5.1 The Relationship between Performance Expectancy (PE) and Technology Use Intention

**H1:** Performance Expectancy (PE) will have a positive effect on Technology Use Intention on the adoption of learning analytic tools in higher education.

A Pearson Correlation was computed in order to understand the nature of the relationship existing between the independent and dependant variables. Table 5.1 below is tabulated with the results. There was a weak negative correlation between Performance Expectancy and Technology Use Intention as shown by the following values; $r=-.075$, $n=718$ and $p=.044$. Since $p \le 0.05$, we accept the hypothesis and conclude that there is a relationship between the two aforementioned variables. This means that if students are aware of how a technology operates and if it satisfies their requirements, they will be ready to adopt learning analytics into their education. In addition, Figure 5.1 below shows the relationship in a scatter graph.

Similar results were also found by Batta et al. (2018) who conducted a study in Soweto in South Africa among university students staying in that town. Results also showed that performance expectancy affects ones intention when it comes to using learning analytics. The researchers outlined that in the interviews conducted the students emphasized that if the new technology will make them perform better in school they are willing to adopt it. Sarrab et al. (2016) also found similar results in India among 27 students who participated in the study to investigate acceptance levels of learning analytics at University of Dehli, results also showed a positive relationship between the two aforementioned variables implying the need to develop tools and technology that address needs of students for successful adoption.

**Table 5.1:** Showing the Pearson Correlation between Performance Expectancy (PE) and Technology Use Intention (TUI)

| | | Performance Expectancy (PE) | Technology Use Intention |
|---|---|---|---|
| Performance Expectancy (PE) | Pearson Correlation | 1 | -.075** |
| | Sig. (2-tailed) | | .044 |
| | N | 718 | 718 |
| Technology Use Intention | Pearson Correlation | -.075** | 1 |
| | Sig. (2-tailed) | .044 | |
| | N | 718 | 718 |

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

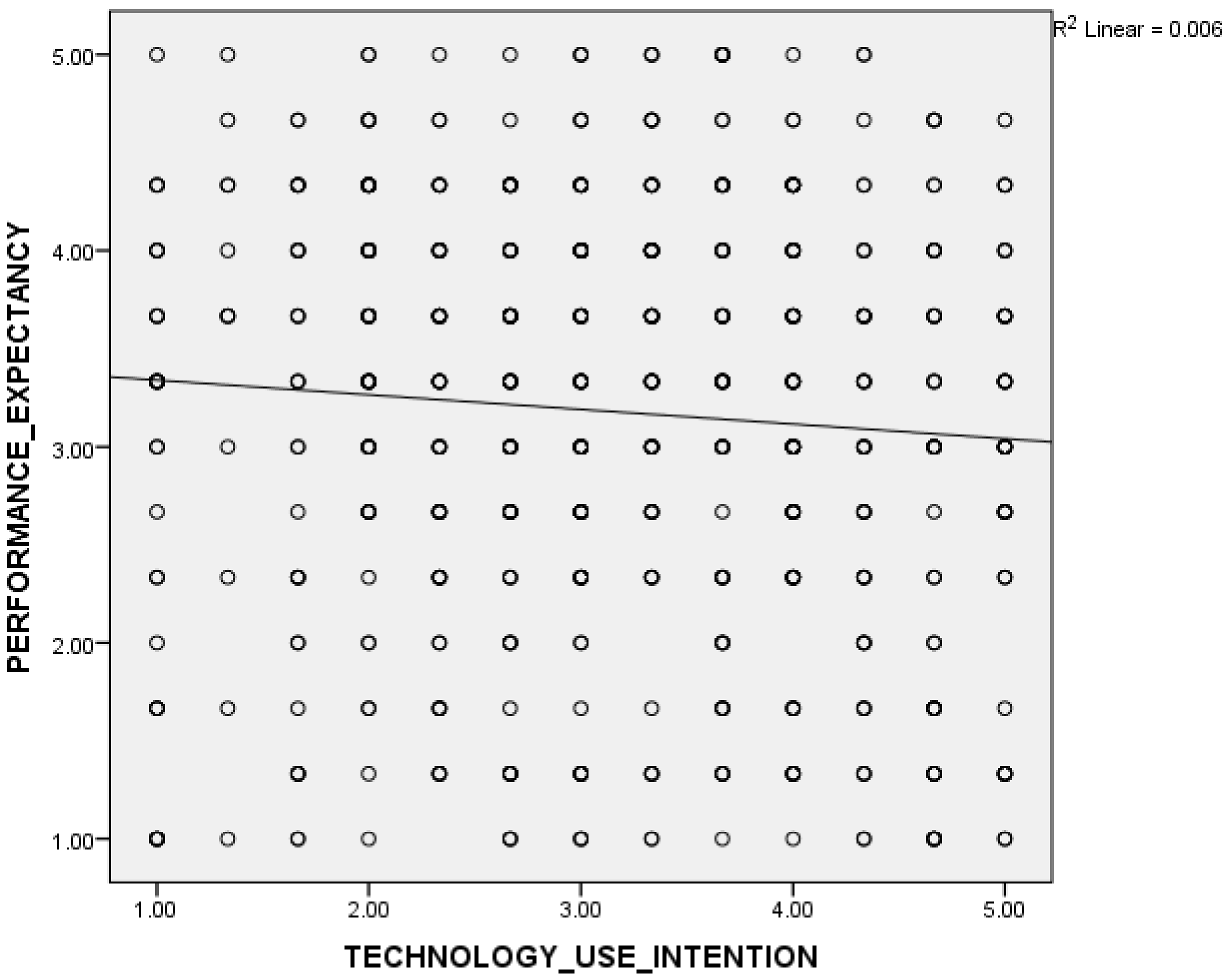


**Figure 5.1:** Scatter graph for relationship between PE and TUI

## 5.2 The Relationship between Effort Expectancy (EE) and Technology Use Intention

**H2:** Effort Expectancy (EE) will have a positive effect on Technology Use Intention on the adoption of learning analytic tools in higher education**.**

A Pearson Correlation was computed in order to understand the nature of the relationship existing between the independent and dependant variables. Table 5.2 below is tabulated with the results. There was a weak negative correlation between Effort Expectancy and Technology Use Intention as shown by the following values; $r = -.197$, $n=718$ and $p=.000$. Since $p <= 0.05$, we accept the hypothesis and conclude that there is a relationship between the two aforementioned variables. This implies that when students perceive that little or no effort is needed for one to master learning analytics, they are keen on adopting the technology. In addition, Figure 5.2 below shows the relationship in a scatter graph.

A study undertaken by Cheon et al. (2018) in Australia among 18 undergraduate students studying computer science showed that effort expectancy had a positive relationship on intention to use implying if students perceive a technology to be easy to use, requiring less effort they will be willing to adopt it. However other scholars may argue on these results as they were targeted on students in a technical department who are already using technology and these results may not be ideal when looking at novice users. Alssabaiheen and Love (2017) also found contrary results in a study in investigating acceptance of learning analytics among first year university students, results showed that there was no relationship between effort expectancy and intention to use. Such differences could be attributed to the fact that the majority of the first year students had not been exposed to such technology before and for this reason they were anxious to try new technology.

**Table 5.2:** Showing Pearson correlation between Effort Expectancy (EE) and Technology Use Intention (TUI)

| | | Effort Expectancy (EE) | Technology Use Intention |
|---|---|---|---|
| Effort Expectancy (EE) | Pearson Correlation | 1 | -.197** |
| | Sig. (2-tailed) | | .000 |
| | N | 718 | 718 |
| Technology Use Intention | Pearson Correlation | -.197** | 1 |
| | Sig. (2-tailed) | .000 | |
| | N | 718 | 718 |

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

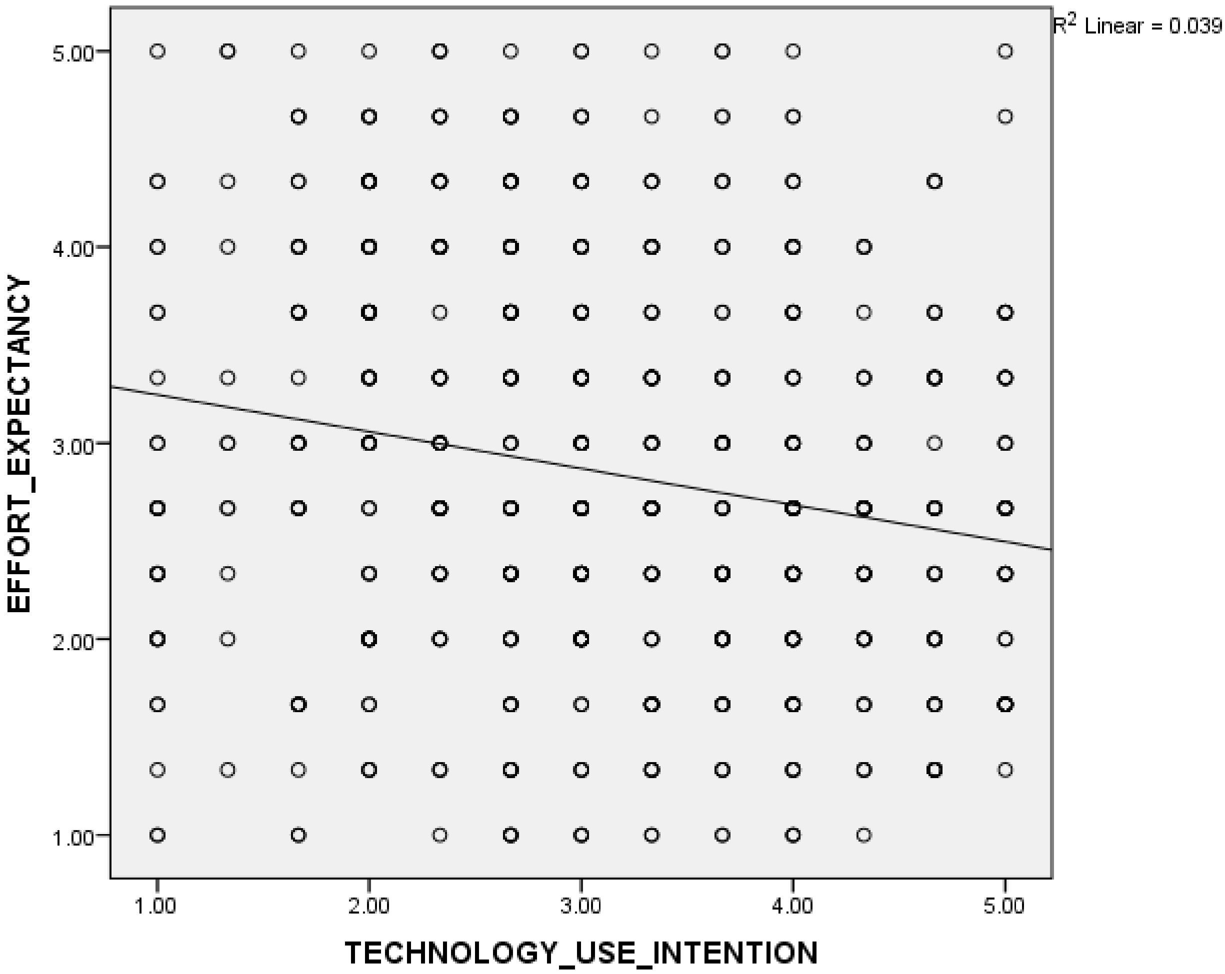


**Figure 5.2:** Scatter graph showing the relationship between EE and TUI

### 5.3 The Relationship between Social Influence (SI) and Technology Use Intention

**H3:** Social Influence (SI) will have a positive effect on Technology Use Intention on the adoption of learning analytic tools in higher education.

A Pearson Correlation was computed in order to understand the nature of the relationship existing between the independent and dependant variables. Table 5.3 below is tabulated with the results. There was a weak positive correlation between Social Influence and Technology Use Intention as shown by the following values; r= .045, n=718 and p=.224. Since p > 0.05, we reject the hypothesis and conclude that there is no relationship between the two aforementioned variables. This means that friends and family have no say as to influence ones decision when it comes to using learning analytics, it is ones independent decision. This mean that even if peers are using learning analytics tools in their studies one may still decide not to use, close associates have no influence. In addition, Figure 5.3 below shows the relationship in a scatter graph.

Different results were found by many researchers in the literature (Ching-Yi et al., 2017; Rahim & Athmay, 2018; Sutana et al., 2017) who found out that there was a positive relationship between social influence and intention to use learning analytics. The researchers argue that close associates such as friends and family have a positive influence in the technology that one uses. If fellow friends and family members are already using learning analytics for their studies they are most likely to influence non-users who will eventually adopt to the new technology. Further investigations may be required to understand variations in results.

**Table 5.3:** Showing the Pearson Correlation between Social Influence (SI) and Technology Use Intention (TUI)

| | | Social Influence (SI) | Technology Use Intention |
|---|---|---|---|
| Social Influence (SI) | Pearson Correlation | 1 | .045** |
| | Sig. (2-tailed) | | .224 |
| | N | 718 | 718 |
| Technology Use Intention | Pearson Correlation | .045** | 1 |
| | Sig. (2-tailed) | .224 | |
| | N | 718 | 718 |

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

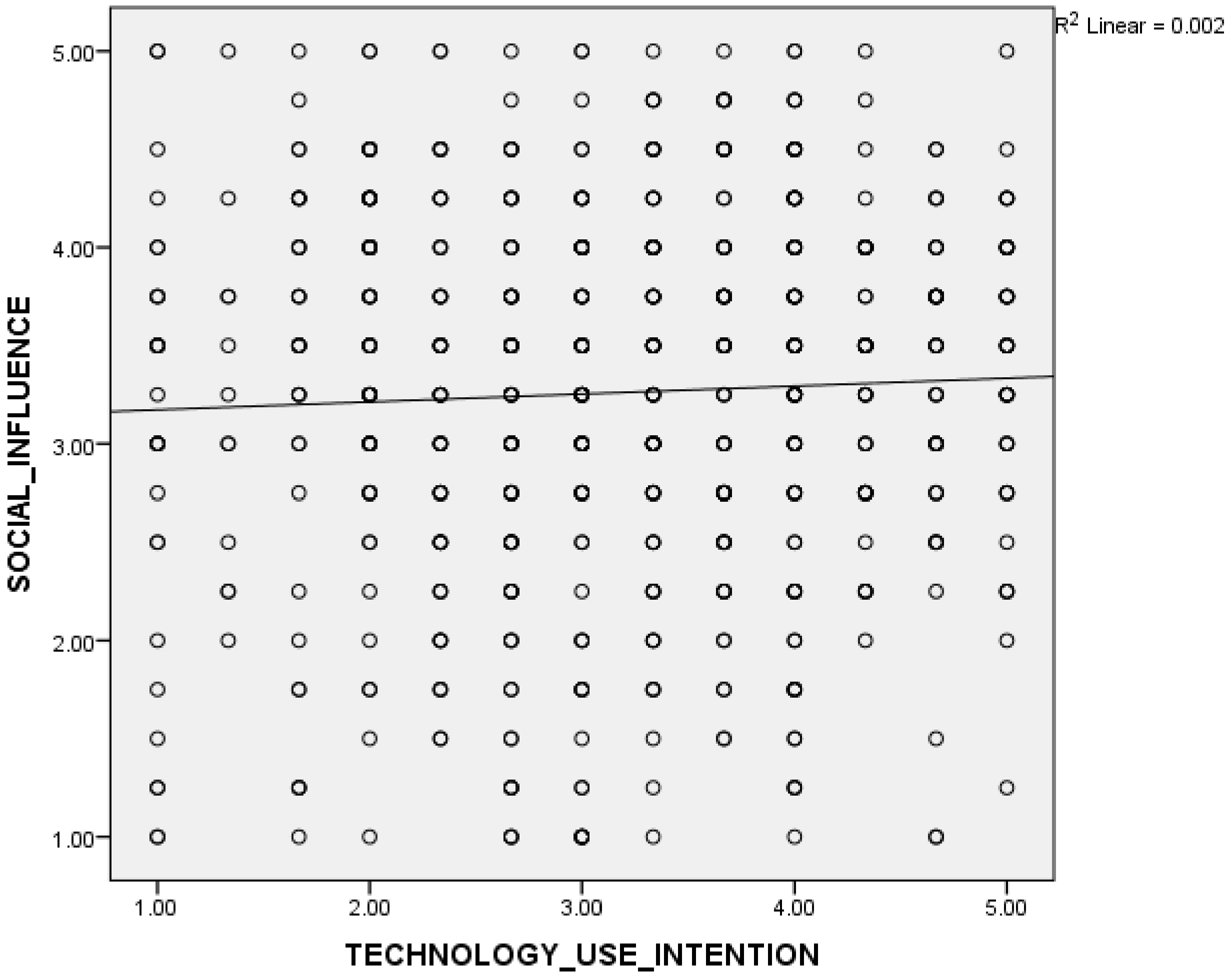


**Figure 5.3:** Scatter graph showing relationship between SI and TUI

### 5.4 The Relationship between Technology Use Intention and Technology Use Behavior

**H4:** Technology use intention will have a positive effect on Technology Use Behavior on the adoption of learning analytic tools in higher education.

A Pearson Correlation was computed in order to understand the nature of the relationship existing between the independent and dependant variables. Table 5.4 below is tabulated with the results. There was a weak negative correlation between Technology Use Intention and Technology Use Behavior as shown by the following values; r =-.179, n=718 and p=.000. Since p <= 0.05, we accept the hypothesis and conclude that there is a relationship between the two aforementioned variables. This mean that one’s behavior towards using learning analytics is strongly determined by his or her intention to use the technology now or in future.

When students intend to use learning analytics they show a positive behavior towards the technology whereas when one does not intend to use the technology they tend to show negative attitude. In addition, Figure 5.4 below shows the relationship in a scatter graph.

Christensen and Knezek (2018) also found similar results in their study on learning analytics and social media adoption in education. The research comprised of university students at 5 universities in Italy a total population of 1186 had results analysed. Results showed that a weak positive correlation between Technology Use Intention and Technology User Behavior implying that the behavior which students exhibit is a clear sign of whether they intend to use learning analytics now or in future. A negative behavior is often associated with students who are not keen on adopting the technology,

**Table 5.4:** Showing Pearson correlation between Technology Use Intention (TUI) and Technology Use Behavior (TUB)

| | | Technology Use Intention | Technology Use Behavior |
|---|---|---|---|
| Technology Use Intention | Pearson Correlation | 1 | -.179** |
| | Sig. (2-tailed) | | .000 |
| | N | 718 | 718 |
| Technology Use Behavior | Pearson Correlation | -.179** | 1 |
| | Sig. (2-tailed) | .000 | |
| | N | 718 | 718 |

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

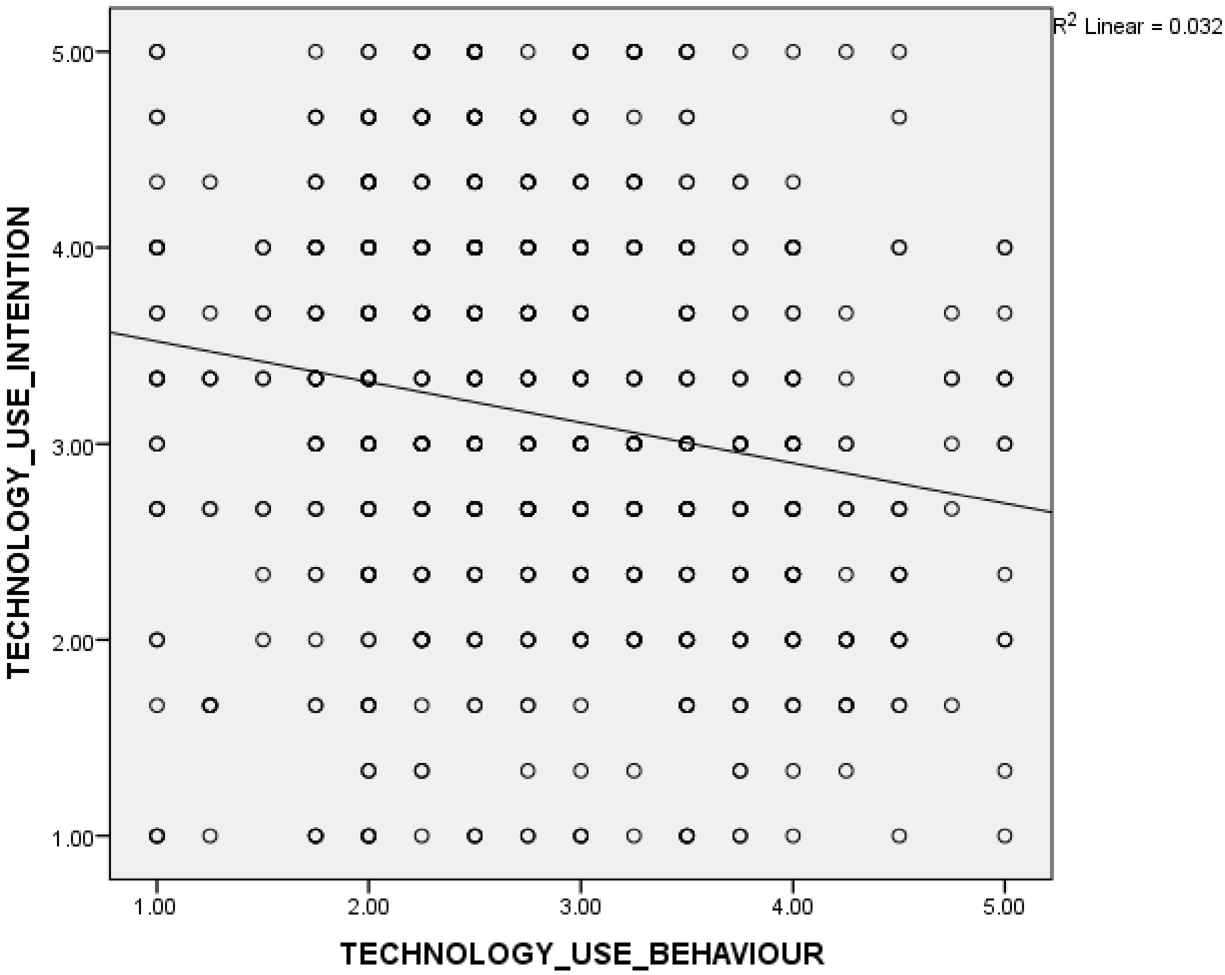


**Figure 5.4:** Scatter graph showing the relationship between TUI and TUB

### 5.5 The Relationship between Facilitating Conditions (FC) and Technology Use Behavior

**H5:** Facilitating Conditions (FC) will have a positive effect on Technology Use Behavior of learning analytics tool adoption.

A Pearson Correlation was computed in order to understand the nature of the relationship existing between the independent and dependant variables. Table 5.5 below is tabulated with the results. There was a strong positive correlation between Facilitating Conditions and Technology Use Behavior as shown by the following values; r = .734, n=718 and p=.000. Since p <= 0.05, we accept the hypothesis and conclude that there is a relationship between the two aforementioned variables. This means that the way a student behaves towards using learning analytics is strongly influenced by other factors that contribute towards accepting the technology such as if they have the resources needed, do they have the knowledge required and will the technology be compatible with other learning tools they are currently using. All these are facilitating conditions that affect user behavior. In addition, Figure 5.5 below shows the relationship in a scatter graph.

In the literature, Rahim and Athmay (2018) also found similar results in their study in Taiwan. The researchers found a strong correlation between facilitating conditions and technology use behavior. This means that several factors should be considered prior to adoption and if all factors considered by the student are considered ideal then their behavior towards the usage of learning analytics change. Suklabaidya and Sen (2015) support the same results and theses researchers go on to say that facilitating conditions can be changed to suit students need and that will result on a positive effect on behavior, for example if one of the factors that students consider as important is compatibility, it is important for educational institutions to make sure that learning analytic tools introduces can easily be integrated into current learning tools.

**Table 5.5:** Showing the Pearson Correlation between Facilitating Conditions (FC) and Technology Use Behavior (TUB)

| | | Facilitating Conditions (FC) | Technology Use Behavior |
|---|---|---|---|
| Facilitating Conditions (FC) | Pearson Correlation | 1 | .734** |
| | Sig. (2-tailed) | | .000 |
| | N | 718 | 718 |
| Technology Use Behavior | Pearson Correlation | .734** | 1 |
| | Sig. (2-tailed) | .000 | |
| | N | 718 | 718 |

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

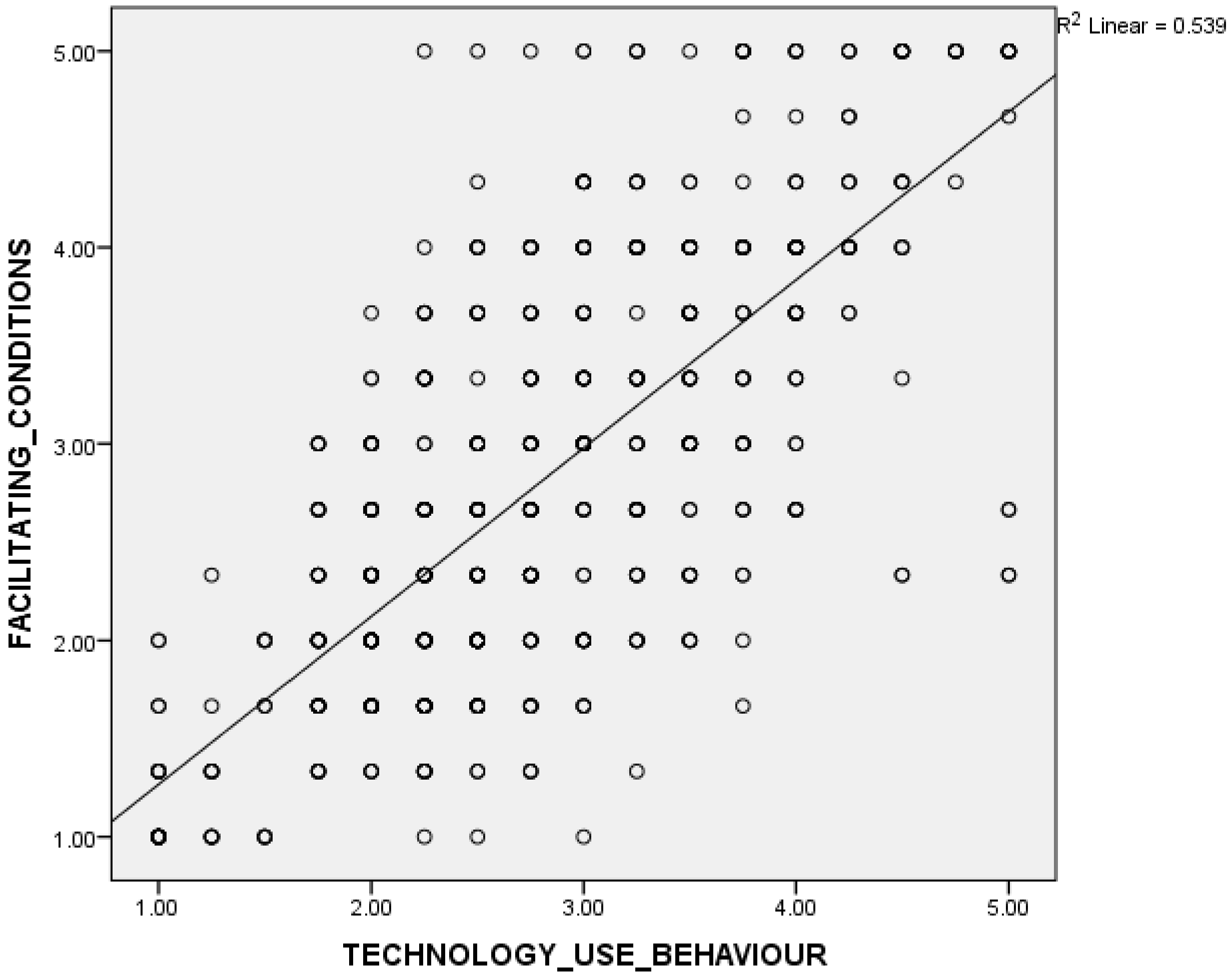


**Figure 5.5:** Scatter graph showing relationship between FC and TUB

### 5.6 The Relationship between Technology Anxiety and Technology Use Behavior

**H6:** Technology Anxiety will have a positive effect on Technology Use Behavior when it comes to learning analytics tool adoption.

A Pearson Correlation was computed in order to understand the nature of the relationship existing between the independent and dependant variables. Table 5.6 below is tabulated with the results. There was a moderate positive correlation between Technology Anxiety and Technology Use Behavior as shown by the following values; $r = .503$, $n=718$ and $p=.000$. Since $p <= 0.05$, we accept the hypothesis and conclude that there is a relationship between the two aforementioned variables. If students are afraid of using technology they tend to portray a negative behavior towards the technology and if they are curious to try the technology then they are likely to portray a positive behavior. In addition, Figure 5.6 below shows the relationship in a scatter graph.

Technical anxiety is defined as a feeling of uneasiness when it comes to the use of new technology (Batta et al., 2018). This feeling is often associated with novice users who are new to technology (Cheon et al., 2018). Sutana et al. (2017) found out the same results that technology anxiety affects user behavior when it comes to adoption of new technology. The researchers encouraged educational institutions to first make students comfortable with using technology prior to adoption that way successful adoption will be achieved.

**Table 5.6:** Showing Pearson Correlation between Technology Anxiety and Technology Use Behavior

| | | Technology Anxiety | Technology Use Behavior |
|---|---|---|---|
| Technology Anxiety | Pearson Correlation | 1 | .503** |
| | Sig. (2-tailed) | | .000 |
| | N | 718 | 718 |
| Technology Use Behavior | Pearson Correlation | .503** | 1 |
| | Sig. (2-tailed) | .000 | |
| | N | 718 | 718 |

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

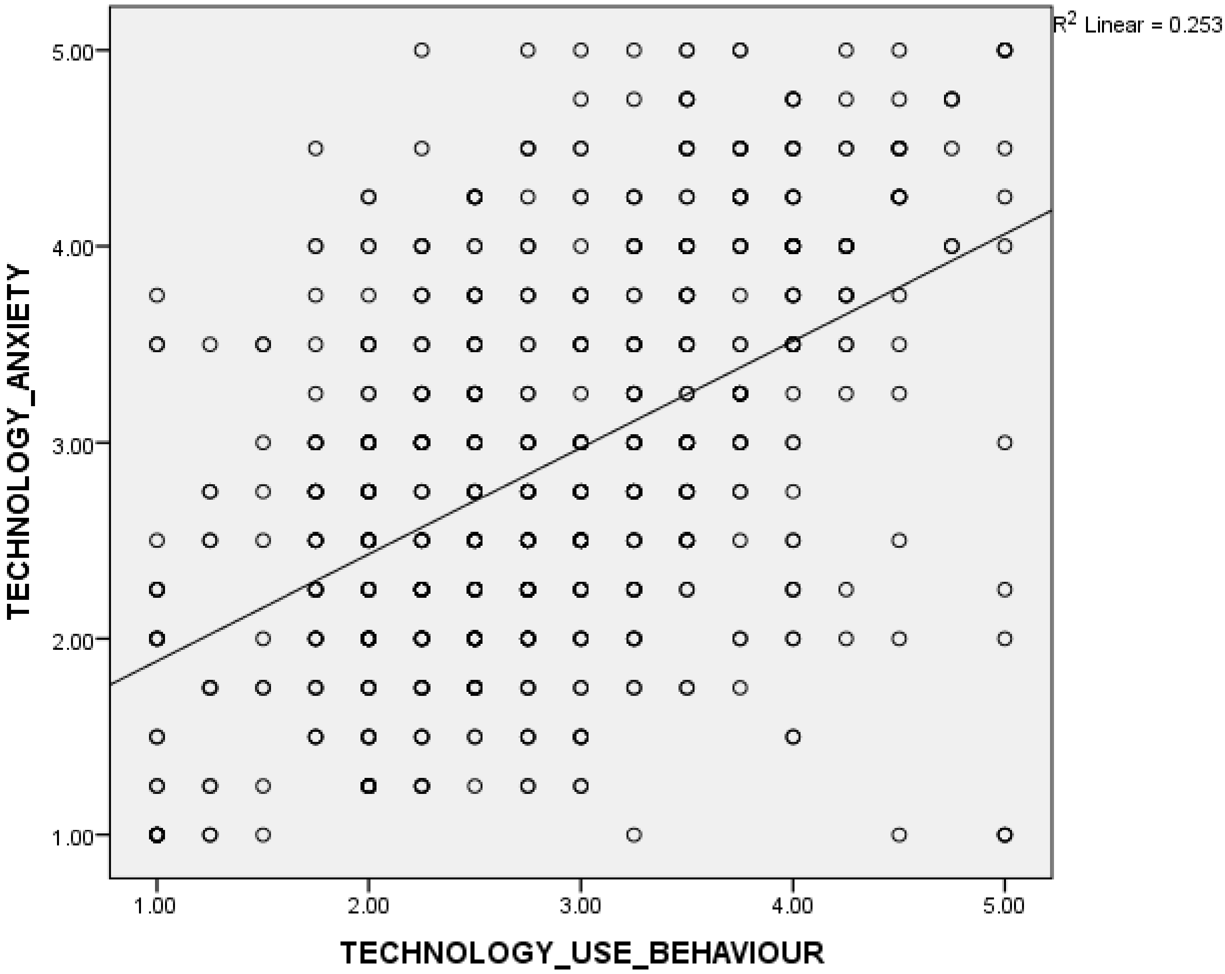


**Figure 5.6:** Scatter graph showing the relationship between TA and TUB

## 5.7 Summary of Findings

In conclusion it is clear that students in North Cyprus are keen on adopting learning analytics. This is so because five of six hypothesis used were supported by the results. Students indicated that they have study applications from Play Store they use with a customized dashboard and reminders on their phones also inform them that it is now time to study and to switch subjects. This is evidence that the small mobile devices already in use can be used even more effectively. It is also crucial for institutions to embark on workshops to educate both students and instructors on the benefits of adopting to this technology.

Table 5.7 below explains how to interpret Pearson Correlation results. The table gives us detailed information of the ranges and interpretations as explained in the literature by Intel (2016).

**Table 5.7:** Showing interpretations of Pearson Correlation results (Intel, 2016)

| Correlation | Meaning |
|---|---|
| -1.0 to -.8 | There is a very strong negative correlation |
| -6 to -.79 | There is a strong negative correlation |
| -.4 to -.59 | There is a moderate negative correlation |
| -.2 to -.39 | There is a weak negative correlation |
| -.01 to -.19 | There is a very weak negative correlation |
| 0 to .19 | There is a very weak positive correlation |
| .2 to .39 | There is a weak positive correlation |
| .4 to .59 | There is a moderate positive correlation |
| .6 to .79 | There is a strong positive correlation |
| .8 to 1.0 | There is a very strong positive correlation |

Table 5.8 below shows the relationship that exists between the independent variables and dependent variables in the study together with the correlation coefficient and the r values stated.

**Table 5.8:** Summary of findings

| Hypothesis | IV | DV | Supported | Correlation coefficient (+/-Positive/Negative) | R value |
|---|---|---|---|---|---|
| H1 | PE | TUI | Yes | Weak - | -.075 |
| H2 | EE | TUI | Yes | Weak - | -.197 |
| H3 | SI | TUI | No | Moderate + | .045 |
| H4 | TUI | TUB | Yes | Weak - | -.179 |
| H5 | FC | TUB | Yes | Strong + | .734 |
| H6 | TA | TUB | Yes | Moderate + | .503 |

Figure 5.7 below illustrates the research model of the study, the r values between each independent and dependent variables. It is clearly seen that 5 of the hypothesis were supported and 1 in red showed that there was no significant correlation between the two variables.

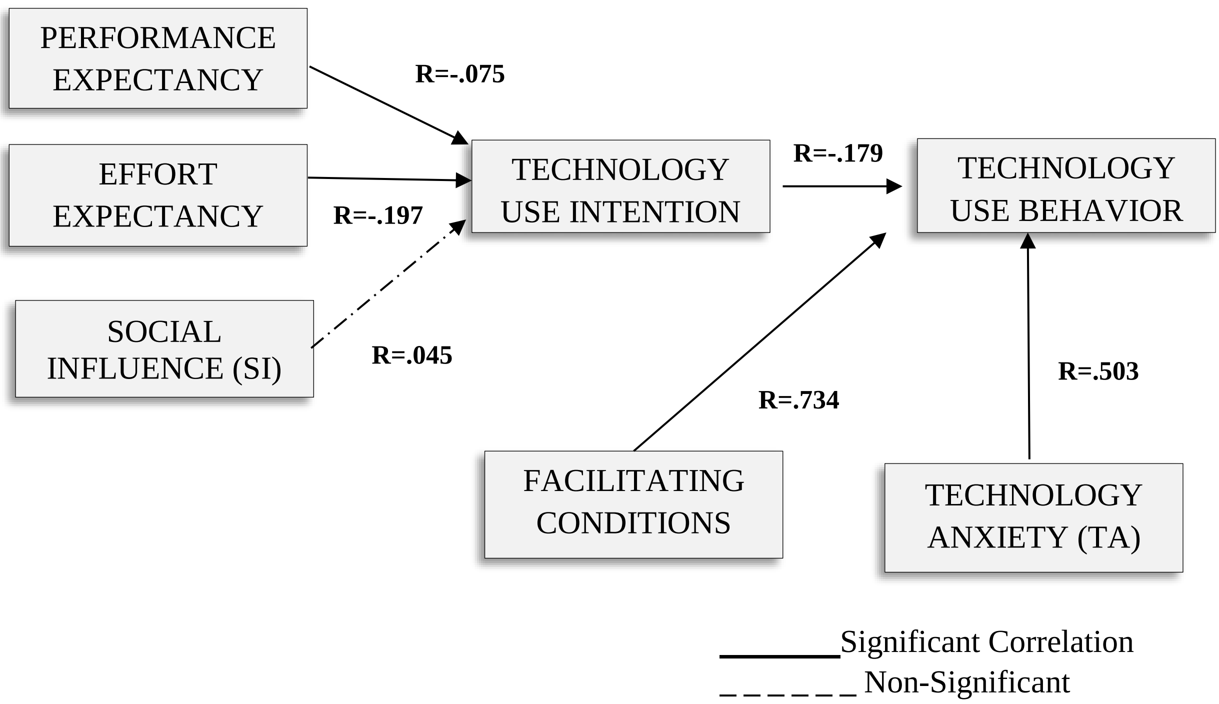


**Figure 5.7:** Summary of findings and correlations

# CHAPTER 6

# CONCLUSION AND RECOMMENDATIONS

This chapter concludes the study by giving a closing summary of the entire study highlighting what results have shown and reasons behind such results and the researcher suggests recommendations for future research that act as guidelines to future researchers who may be interested in the same area under study.

## 6.1 Conclusion

The main aim of the study was to understand the determinants of learning analytical tools by university students in North Cyprus. To achieve the main aim of the study, the researcher tested a number of hypothesis and conclusions were drawn based on the results obtained. The following are the conclusions from the study:

- In conclusion, it is clear that students in North Cyprus are keen on adopting this new technology however anxiety is still an issue as some students are not ready to adopt new technology. However on the other side, upon interviewing a few students, some indicated that they were already using such tools in their study but were not aware of the term, “learning analytics”. Students indicated that they have study applications from Play Store they use and reminders on their phones also inform them that it is now time to study and to switch subjects. This is evidence that the small mobile devices already in use can be used even more effectively. It is also crucial for institutions to embark on workshops to educate both students and instructors on the benefits of adopting to this technology.

- There was a weak negative correlation between Performance Expectancy and Technology Use Intention implying an inverse relationship between the two variables as one variable increased, the other variable decreased. This hypothesis was supported meaning there is a relationship between PE and TUI. When students are aware of how a technology operates and if it satisfies their requirements they will be ready to adopt learning analytics into their education.

- There was also a negative weak correlation between Effort Expectancy and Technology Use Intention implying an inverse relationship between the two variables as one variable increased, the other variable decreased. This hypothesis was also supported meaning there is a relationship between EE and TUI. When students perceive that little or no effort is needed for one to master learning analytics they are keen on adopting the technology.

- There was also a positive weak correlation between Social Influence and Technology Use Intention implying that as one variable increase, the other variable decrease. This hypothesis was rejected meaning there is no relationship between SI and TUI when it comes to learning analytics. This means that friends and family have no say as to influence ones decision when it comes to using learning analytics, it is ones independent decision. This mean that even if peers are using learning analytics tools in their studies one may still decide not to use, close associates have no influence.

- There was a negative weak correlation between Technology Use Intention and Technology Use Behavior implying an inverse relationship between the two variables as one variable increased, the other variable decreased. This hypothesis was also supported meaning there is a relationship between TUI and TUB. This mean that one's behavior towards using learning analytics is strongly determined by his or her intention to use the technology now or in future. When students intend to use learning analytics they show a positive behavior towards the technology whereas when one does not intend to use the technology they tend to show negative attitude.

- There was a strong positive correlation between Facilitating Conditions and Technology Use Behavior meaning as one variable increase, the other variable also increase. This hypothesis was supported meaning there is a strong relationship between FC and TUB. This means that the way a student behaves towards using learning analytics is strongly influenced by other factors that contribute towards accepting the technology such as if they have the resources needed, do they have the knowledge required and will the technology be compatible with other learning tools they are currently using. All these are facilitating conditions that affect user behavior.

- There was a moderate positive correlation between Technology Anxiety and Technology User Behavior. This means that as one variable increase, the other variable also increase. This hypothesis was supported meaning there is a relationship between TA and TUB. If students are afraid of using technology they tend to portray a negative behavior towards the technology and if they are curious to try the technology then they are likely to portray a positive behavior.

## 6.2 Recommendations

The researcher would like to outline a number of recommendations which should be taken into account by fellow researchers in future. The following are recommended:

- The study only focused at a small population of students at three universities only. We strongly recommend a larger population group to be considered in future to really give a better view of the technology and its acceptance levels.

- The study only focused at understanding the determinants of adopting learning analytical tools in education with a strong focus on student perspective. Future research is strongly recommended that will focus on instructors to fully understand both angles.

- Institutions should come up with policies that encourage adoption of such technologies and implement workshops so that it will yield in successful adoption as all key stakeholders will be aware of what is required of them.

- Computer basics are the foundation of understanding how learning analytical tools work. It is therefore crucial for institutions to make such studies compulsory among all disciplines whether technical or non-technical.

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## APPENDIX 1: QUESTIONNAIRE

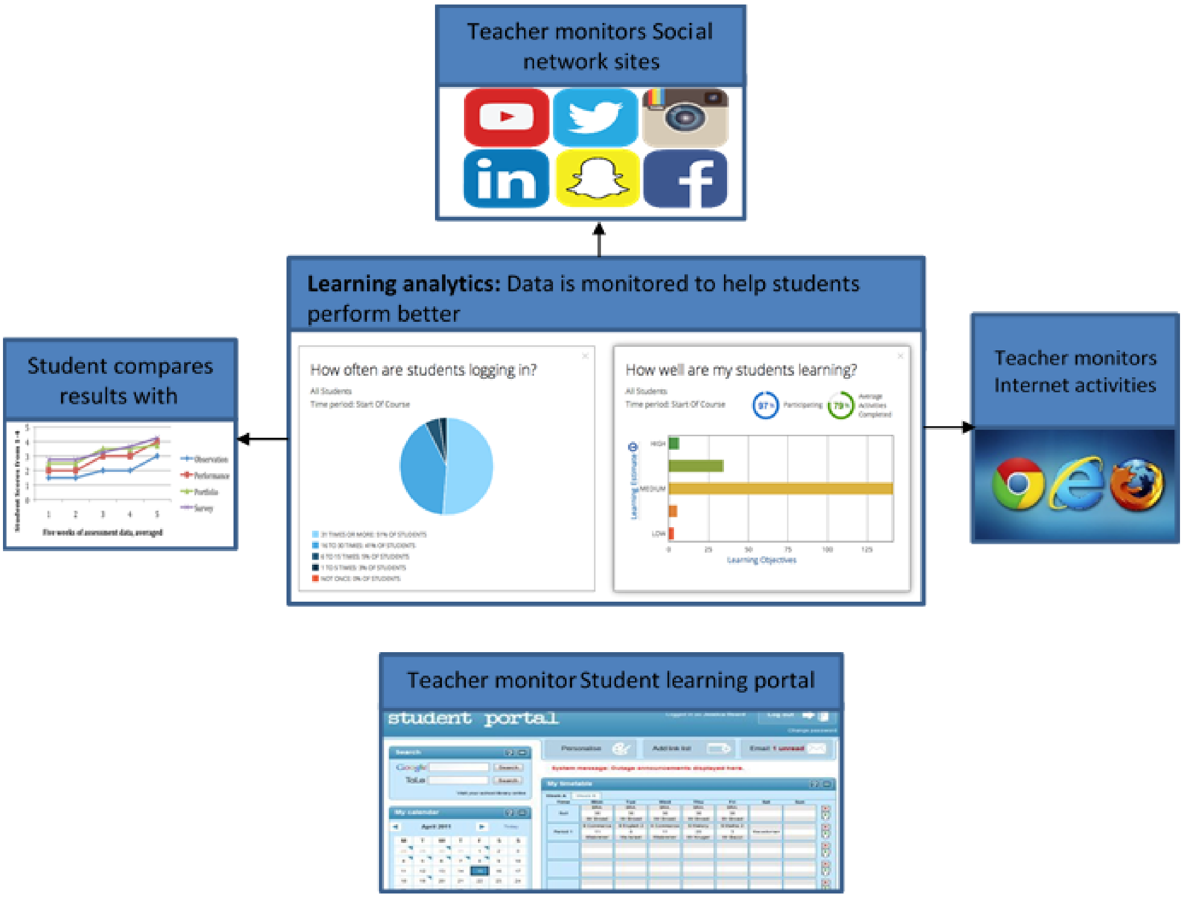
## DETERMINANTS OF LEARNING ANALYTICS TOOL ADOPTION BY UNIVERSITY STUDENTS QUESTIONNAIRE

The questionnaire is a part of MS thesis study and its aim is to investigate **Determinants of learning analytics tool adoption by university students.** Responses to this questionnaire are voluntary and be kept confidential and information will be used for educational purposes only.Questions start on page 2

Please read each question carefully and choose the most convenient for you. You are required to answer all questions, mark X as appropriate in the boxes your participation is greatly appreciated.

**Contact: Ahmad Mohamed Ibrahim Daganni** (20168653@std.neu.edu.tr) phone: 05488331309
**Thesis Supervisor: Assist. Prof. Dr. Seren Başaran**.
Near East University – Department of Computer Information Systems. Nicosia, North Cyprus.

In simple terms, learning analytics refers to a collection of methods that allow teachers and learners to understand what is going on. Learning analytics help teachers understand the student better and come up with ways to help the student improve and perform better in class. Figure 1 below is an example of the different areas that data is analyzed.



**Section I: Demographic information of participant**

**1. Gender:**

◯ Male ◯ Female

**2. In what age group are you?**

◯ 17-26 ◯ 27-36 ◯ 37 and above

**3. Level of Study:**

◯ Undergraduate ◯ Masters ◯ PhD

**4. Department Type** :

◯ STEM (Science, Technology, Engineering, Mathematics) ◯ Other

| **Section II: PERFORMANCE EXPECTANCY** | Strongly Agree | Agree | Neutral | Disagree | Strongly Disagree |
|---|---|---|---|---|---|
| **5.** I think Learning analytics will increase my productivity. | | | | | |
| **6.** I think Learning analytics enables me to accomplish tasks quicker. | | | | | |
| **7.** I think Learning analytics allows me to access more information about my courses. | | | | | |
| **Section III: EFFORT EXPECTANCY** | Strongly Agree | Agree | Neutral | Disagree | Strongly Disagree |
| **8.** Using learning analytics will be easy and intuitive. | | | | | |
| **9.** I find learning analytic tools easy to use | | | | | |
| **10.** I believe it would be so easy for me to become skillful at using learning analytics tools. | | | | | |
| **Section IV: SOCIAL INFLUENCE** | Strongly Agree | Agree | Neutral | Disagree | Strongly Disagree |
| **11.** People who influence my behaviour think I should use learning analytic tools. | | | | | |
| **12.** My supervisors have been helpful in introducing learning analytic tools to me. | | | | | |
| **13.** People who are important to me think I should use learning analytic tools. | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| **14.** I will use learning analytics even if no one I know is using it. | | | | | |
| **Section V: TECHNOLOGY USE INTENTION** | Strongly Agree | Agree | Neutral | Disagree | Strongly Disagree |
| **15.** I predict my university will use learning analytic tools in the next months. | | | | | |
| **16.** My university intends to use a learning analytic tools in the near future. | | | | | |
| **17.** My university plan to use learning analytic tools in the distant future. | | | | | |
| **18.** I intend to use learning analytic tools in the future | | | | | |
| **19.** I predict I will use learning analytic tools in the next months. | | | | | |
| **20.** My university has recently started using learning analytics tool. | | | | | |
| **21.** My university has already been using learning analytics tool for a while. | | | | | |
| **Section VI: TECHNOLOGY USE BEHAVIOR** | Strongly Agree | Agree | Neutral | Disagree | Strongly Disagree |
| **22.** I often access learning analytics tools using the internet. | | | | | |
| **23.** The university has been of help in enabling me to use learning analytics. | | | | | |
| **24.** I am willing to use learning analytics in my studies. | | | | | |
| **25.** Using learning analytic tools will lead to a better overall learning experience | | | | | |
| **Section VI: FACILITATING CONDITIONS** | Strongly Agree | Agree | Neutral | Disagree | Strongly Disagree |
| **26.** I have the resources necessary to use learning analytics. | | | | | |
| **27.** I have the knowledge necessary to use learning analytics. | | | | | |
| **28.** Learning analytic tools are compatible with other learning tools I use. | | | | | |

| **Section VIII: TECHNOLOGY ANXIETY** | Strongly Agree | Agree | Neutral | Disagree | Strongly Disagree |
|---|---|---|---|---|---|
| **29.** I feel apprehensive about using learning analytic tools. | | | | | |
| **30.** It scares me to think that I could lose a lot of information using learning analytic tool by hitting the wrong key. | | | | | |
| **31.** I am hesitant to use learning analytics for fear of making mistakes which I cannot correct. | | | | | |
| **32.** Learning analytic tools are somehow intimidating to me. | | | | | |

**Thank you for participating.**

## APPENDIX 2

## ETHICAL APPROVAL LETTER

YAKIN DOĞU ÜNİVERSİTESİ

**BİLİMSEL ARAŞTIRMALAR ETİK KURULU**

11.12.2018

Dear Ahmad M.I.Daganni

Your application titled **"Determinants of learning analytics tool adoption by university students"** with the application number YDÜ/FB/2018/39 has been evaluated by the Scientific Research Ethics Committee and granted approval. You can start your research on the condition that you will abide by the information provided in your application form.

Assoc. Prof. Dr. Direnç Kanol

Rapporteur of the Scientific Research Ethics Committee

Direnc Kanol

**Note:** If you need to provide an official letter to an institution with the signature of the Head of NEU Scientific Research Ethics Committee, please apply to the secretariat of the ethics committee by showing this document

**APPENDIX 3**

**SIMILARITY REPORT**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## ÖZET

Öğrenme analitiği sistemik bir süreç olup ölçme, toplama, analiz ve öğrenenlerin verilerinin raporlanarak en iyi öğrenme ortamlarını anlamak ve verim oranını artırmayı hedeflemektir. Bu çalışmanın amacı Kuzey Kıbrıs'daki üniversitelerdeki öğrencilerin öğrenme analitiğininin belirleyici etkenlerinin araştırmasıdır.

Çalışmada kullanılan katılımcılar Kuzey Kıbrıs'daki 3 ünüversiteden oluşturulmuştur. Yapılan araştırma sonucunda Performans Beklentisi ve Teknoloji Kullanma Niyeti arasında negatif bir ilişki olduğu görülmektedir. Öğrenciler teknolojinin nasıl kullanılacağının farkında iseler öğrenme analitiğini kullanmaya hazır görünmektedirler. Efor Beklentisi ve Teknoloji Kullanımı arasında da negatif bir ilişki olduğu görünmektedir.

Sosyal Etki ve Teknoloji Kullanma Niyeti arasında ise zayıf pozitif bir ilişki görünmüş Teknoloji Kullanım Niyeti ve Teknoloji Kullanma Davranışı arasında ise zayıf negatif bir ilişki bulunmuştur. Bu sonuçlarda öğrencinin öğrenme analitiği kullanma niyeti olduğunda teknolojiye karşı pozitif bir davranış içerisinde olduğudur.

Çalışma ayrıca Teknoloji Endişesi ve Teknoloji Kullanım Davranışı arasında orta derecede pozitif bir ilişkinin olduğunu gösteriyor.

Bu çalışmanın araştırmacılar, eğitmenler ve eğitim bakanlıkları kullanımı açısından yararlı olacağı düşünülmektedir.



***Anahtar Kelimeler:*** Yüksek Öğretim; öğrenme analitiği; öğrenme araçları; Kuzey Kıbrıs; Öğrenciler; teknoloji