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PREDICTING STUDENT PERFORMANCE TRAJECTORY BY ANALYSING INTERNET TECHNOLOGY UTILIZATION BEHAVIOURAL PATTERNS: CASE OF KENYAN UNIVERSITY STUDENTS

Khakata Esther Nyokabi Gathenya

Submitted in total fulfilment of the requirements for the Degree of Doctor of Philosophy in Information Technology at Strathmore University

Faculty of Information Technology

Strathmore University

Nairobi, Kenya

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Name: **Khakata Esther Nyokabi Gathenya**

Signature:
Date: **28th June, 2019**

Approval

The thesis of **Khakata Esther Nyokabi Gathenya** was reviewed and approved by the following:

Prof. Dr. Simon Samwel Msanjila
Dean, Faculty of Science and Technology
Mzumbe University, Tanzania.

Dr. Vincent Omwenga,
Senior Lecturer, Faculty of Information Technology,
Strathmore University, Kenya.

Dr. Joseph Orero,
Dean, Faculty of Information Technology.

Prof. Ruth Kiraka,
Dean, School of Graduate Studies.

ABSTRACT

Learning within universities today is continuously being revolutionized by the presence and advancements made on internet technology. The use of internet technology by students in the learning process is greatly influenced by the adoption and utilization of the technology within their learning institutions. However, despite the investments made by the institutions for the provision of internet technology, it is not possible to determine whether the technology positively contributes to better student performance. Similarly, the students expend a certain level of effort in order to use the technology in the learning process. Nonetheless, it is not possible to determine whether their effort contributes to positive performance in their studies. Likewise, taking into account a student's behaviour and the result they expect to achieve at the end of a learning process, it is not possible to determine the degree to which the effort of the student (effectiveness of student effort) contributes to improved performance. Therefore, there is need to develop a student performance prediction model that considers the investments made by institutions, the student effort expended and the effectiveness of student effort in the utilization of internet technology.

The scientific contribution of this thesis involved generation of the student performance trajectory and the development of a student performance prediction model that focuses on student behaviour within a learning environment at a specific instance in time. This model will help educational practitioners to analyse the existing contextual factors within an institution and how the factors influence student performance without carrying out a longitudinal research that will be time and resource intensive.

This research considered three major factors in the prediction of student performance, that is, the investment costs, the student effort and the effectiveness of student effort. Investment costs consider student behavioural costs such as the time budget, the physical costs and the mental budget. Student effort encompasses the behavioural intentions and the actions of the students. The effectiveness of student effort considers the expected outcome from performing an action and the behavioural costs. The time budget was mainly influenced by time spent using internet technology and the

physical costs are determined by the physical environment and general infrastructure in the universities. The behavioural intentions and actions of a student were examined using the capability of the student, the attitude of the student, the relevance of the technology in the learning process, the productivity achieved in using the technology and the knowledge of a student in the use of the technology in the learning process.

The key findings of this research showed that internet technology was a useful resource in the learning process of students and the students had embraced its use in their learning with vigour. The students perceived the technology as easy to use and useful in their studies. They had sufficient knowledge in the use of the technology in learning and they had used the technology to accomplish a number of tasks in their learning process. Furthermore, some universities had invested sufficiently for the provision of internet technology and hence, their students had benefited greatly from the technology.

The study concluded by formulating the input factors based on key research findings that were used in the prediction of the student performance perceptions and the student performance trajectory. These formed the major research output and they could be used in predicting student performance at a given instance in time.

Keywords: Internet technology, internet utilization, Cobb-Douglas theorem, student performance, predictive model, prediction algorithms, decision tree.

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LIST OF ABBREVIATIONS

ACM – Association for Computing Machinery

AR – Auto Regressive

B - Behaviour

BN – Behavioural Intention

CIP – Cognitive Information Processing

CGPA – Cumulative Grade Point Average

CTSM – Continuous Time Stochastic Modelling

CTSM-R – Continuous Time Stochastic Modelling in R

DOI – Diffusion of Innovation

er – Estimation of anticipated Result

ETL – Extraction Transform and Load

FreeSpan – Frequent Pattern Projected Sequential Pattern Analysis

GSP – Generalized Sequential Pattern

IAtt – Individuals Attitude

ICT – Information and Communication Technology

ib – Inspiration to go for Beliefs

i.d.d – Independently and Identically Distributed

Inv - Investment

IV – Independent Variable

KENET – Kenya Education Network

KoI – Knowledge of Internet

LAN – Local Area Network

LMS – Learning Management System

LPM – Linear Prediction Models

LTM – Long Term Memory

m – Number of groups influencing a behaviour

MOOCs – Massive Open Online Courses

MRS – Marginal Rate of Substitution

MRTS – Marginal Rate of Technical Substitution

nb – Number of Beliefs

ODE – Ordinary Differential Equations

OER – Open Educational Resources

OLAP – Online Analytical Processing

pb – Persons Belief

pdb – Perceived Beliefs of other people

PEOU – Perceived Ease of Use

PREFIXSPAN – Prefix projected Sequential Pattern Analysis

PU – Perceived Usefulness

RSS – Really Simple Syndication

SAL – Student Approaches to Learning

SDE – Stochastic Differential Equation

SM – Subjective Norm

SPA – Sequential Pattern Analysis

SPADE – Sequential Pattern Discovery with Equivalence classes

SRL – Self Regulated Learning

STM – Short Term Memory

SVMs – Support Vector Machines

TAM - Technology Acceptance Model

TOE – Technology, Organization and Environment

TRA – Theory of Reasoned Action

TTF – Task Technology Fit

TVET – Technical and Vocational Educational and Training

UNESCO – United Nations Educational, Scientific and Cultural Organization

WEKA – Waikato Environment for Knowledge Analysis

WSPAN – Weighted Sequential Pattern Analysis

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DEDICATION

To my lovely baby boy Shem Charles Gathenya Khakata. Rest in peace Son.

To my ***Simeon Timmothy****, Stella Ruth, Emmanuel John and Immaculate Lisa.*

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Chapter 1: Introduction to the Study

1.1 Internet Technology

Internet technology refers to a universal conglomeration of interconnected telecommunication networks and channels which facilitate the interaction and interoperability of connected information systems and their users (Russian Federation, 2012). This technology has brought a revolution in all aspects of world economies by significantly changing the traditional way in which things are done. Although the internet's growth and development was expected, its immense surge and corresponding impact on different sectors was clearly underestimated. Being the fastest growing technology in the 21st century, the internet has achieved within four years what television revolution achieved in thirteen years. Originally, it was intended for communication within the United States Department of Defence, in case of a nuclear war (Leiner et al., 2014). This initial intention has changed due to the fact that many stakeholders and investors have developed great interest in the technology and expanded the scope of its usage.

Specifically, the business sector, the government sector and the education sector have benefited enormously from the advancements that have taken place on the internet. With its great evolution speed, the field of education has not been left behind either. The revolution has created opportunities for students to be active learners, allowing instructors to be enablers in the learning process. Furthermore, the availability of the internet has contributed immensely in the area of research, teaching and learning (Spennemann, 2007). Access to massive online resources, online management of records as well as digital communication has become the norm in the field of academia. As a result, it is worthwhile examining the different uses of internet technology that are exhibited by students as they use the resource in their learning process.

1.2 Internet Technology in Learning

Institutions of learning, specifically the universities, have gradually embraced the use of internet technology in the learning process. Lecturers and students have greatly embraced the use of the technology in their teaching and learning respectively.

Accessibility to the vast information available on the internet has led learners to be in a position to access vast electronic resources without restrictions. It is now possible to download and share resources with greater ease compared to the past. Consequently, there is need to understand how internet technology has contributed to the learning process of students (Ndawula, 2011).

1.2.1 Usage of Internet Technology in Learning

Internet technology is a unique resource that has brought about immeasurable developments in the 20th century and its usage in academia is unparalleled (Ifeoma & Ifijeh, 2010; Oriogu et al., 2015; Wallace et al., 2017). In the late 1990's, researchers in academia discussed and demonstrated how the newly introduced technology was to be used in improving the teaching and learning process in schools and colleges.

The internet is now a widely adopted technology in the world of academia and it has been shaping new classroom practices around the globe. In the education sector, the internet offers two major benefits to its users: information and communication. As a provider of information, the internet offers a great information warehouse which is used as an avenue for interactive learning and a source of current concepts for the world. As a channel of communication, the internet assists in the sharing of information and ideas among its users around the world.

The availability of internet technology has attracted students to different courses in the universities due to the nature of instruction, collective work and cross institution communication provided by the internet in these institutions. This has led to a growing nature of hybrid learning where learning resources are distributed electronically and these resources are easily accessed with the help of the internet (Courville, 2011).

There has been a myriad immense online educational prospects that remain appealing to the current generation of students. The internet has presented students with a variety of learning tools and methods that help in the assimilation of the presented content (Francom et al., 2011). Online databases, wikis and blogs offer many online resources on the internet. The use of internet in learning has had a large impact in the field of academia and keeps evolving quickly at the same rate as computers and electronic devices

(Galloway, 2015). As a result, the internet has evolved to become a critical tool in the process of learning and teaching (Molnar & Fields, 2014).

The use of the internet as a learning resource provides a platform that enables communication between students and instructors, as it helps in the dissemination, retrieval and access to information. Internet technology has continued to play a major role in the field of education by making the teaching and learning process easier and more flexible for both lecturers and students (Mishra et al., 2005; Oskouei, 2010). It inspires a stimulating academic environment that brings in modernized tools for learning, teaching and research. Universities have equally utilized the resource to ensure access to the vast resources provided by the internet (Arya & Talukdar, 2010). This brings about a complete transformation in the different ways that are used in imparting knowledge on the learners. Universities have embraced the use of internet technology in learning with gusto and this has changed teaching and learning in a great way, more so in the access to educational materials.

Jagboro (2003) assessed the utilization of the internet for academic research work in Nigerian universities. The research established that the internet was used in searching for online journals, previous research dissertations, teaching materials and email communication. Further, the study revealed that there was low utilization of internet technology by graduate students attributed to low connectivity levels in the university and high internet technology access costs in the cyber cafes around the university. Unlike colleges of Orissa where dial up connections were available for class demonstration purposes in engineering courses, the students in Nigeria used dial-up connections at home and at their work places to do their academic research. The research concluded that the institutions in Nigeria needed to invest in more access points to ensure internet connectivity in the universities so that students could have access to the vast academic resources and supplement the available books and journals.

Loan (2011) studied internet utilization by college students in Kashmir Valley across different disciplines. The study revealed that more than half the students did not use the internet at all due to many reasons: lack of access to the internet in the colleges, exorbitantly high charges at the cyber cafes, lack of training on how to use the internet, as well as lack of awareness and interest in the use of internet (Amaoge & Igwebuike, 2016). Majority of the students in arts and in computer science used commercial cyber cafes. Many students used the internet twice or thrice a week primarily for communication, and for informational or educational purposes.

Islam and Habiba (2015) assessed utilization of the internet and e-resources at a university in Bangladesh. The study revealed that majority of the students used the internet daily in the university labs, in the university library and at home. The students revealed that the university had enough computer facilities with internet connection and there was adequate bandwidth to access the internet within the university.

According to Virtič (2012), the usage of internet in the learning process had been necessitated by the need to support continuous learning, creation of new ideas and skills and therefore leading to life-long learning. One of the ways that ensured life-long learning had been seen in the use of E-learning and in Open Educational Resources (OER). E-learning is defined as the use of varied internet technologies in the delivery of a wide range of solutions that are meant to assist in the enhancement of knowledge and performance. From another perspective, e-learning focuses on the use of technology to design, convey, select, oversee and extend learning paradigms (Rosenberg, 2011; Massie, 2018). Siemens (2014) categorizes e-learning into the different courses that are transferred to the online environment, informal learning online events, blended learning environments, online communities, knowledge management activities in organizations and networked learning. Open Educational Resources consist of the tools that are used in the sharing, use and re-use of knowledge. These assist with content and tools for the teaching, learning and research activities (Brown & Adler, 2008; Siemens, 2014). Additionally, OER support open courseware and content, open software tools, open materials for e-learning platforms, learning repositories and free educational courses (Hylen, 2017).

In this study, the usage of internet technology in the learning process has mainly been examined from the point of investments incurred for the provision of the technology, the student effort expended in order to use the technology in the learning process and the degree to which the student's effort assists in the learning process. All these factors are then considered together in order to determine whether the technology that has been made available assists in the improvement of student performance in the learning process.

1.2.2 Utility of Internet Technology in Learning

The utility of internet technology in learning covers its accessibility, availability (access points), purposes and the time spent accessing the technology. Accessibility to the internet checks whether the connection is private to the institutions or is government sponsored; availability checks whether the students access the internet at home, school, from a cyber café or on a mobile device; purpose checks how the student uses the internet, for example, for entertainment and communication; time spent accessing the internet checks on the number of hours a student spends on the internet per week for learning purposes (Singh & Bala, 2014).

In considering the educational aspects of the utility of internet technology, there is great need for all the students to access available materials easily and within low costs. Since the internet is an enormous source of information, its utility is realized by the fact that the information found on the resource can be accessed quickly and with ease. This is achieved by the fact that the internet provides asynchronous education that is accessible anytime and anywhere, regardless of geographical locations. This has greatly widened the learning environment for students who do not have to be confined within library buildings, but rather, they can benefit from the online resources easily and quickly. Additionally, the value of internet technology is realized when the technology serves as a tool for learning about the most recent happenings around the globe as well as getting any kind of information that one may require. As a result, internet technology becomes the basis for the quick dissemination of information to a large audience and without the restrictions of time and space (Dogruer et al., 2011).

A research done by Park and Biddix (2011) revealed that students are considered as passionate users of internet technology, mainly for their social and entertainment needs, and not just limiting themselves to learning activities. However, in as much as the internet assists with social and entertainment needs, its utility is greatly associated with the provision of both academic and scientific information. Therefore, it is critically important to encourage learners to use the technology to get all sorts of information necessary for their academic work because the developments on the internet would be futile if they were not properly used in education. Thus, new digital technologies have been widely used in higher education institutions as well as other sections of education around the world. Internet technology has also been credited for the improvement of the quality of education by bringing numerous positive changes to the teachers and instructors (Laurillard, 2011). In the same way, as affirmed by Dryli and Kinnaman (2011), the internet enables students to find enormous information, leading them to think critically and creatively, becoming collaborative and cooperative workers who assist in solving of problems.

Besides university students living in this new technological era that is defined by new literacies and pedagogies, it is of great importance that their capability to use online and offline databases as well as web search engines be effectively considered (Nentwich, 2013). Internet technology utility can only be well realized when the students are well equipped with the ability to reach the correct information, getting the necessary and most correct information among unlimited bits of data. Once the correct information is obtained, there is then need to organize, structure and evaluate it in order to achieve maximum benefit from it.

1.3 Problem Description

Internet technology is arguably one of the most significant technological developments of the late 21st century. In the recent past, there has been growing interest on the usage of internet technology in higher learning institutions. This is attributable to the exponential development on new and cheaper technologies that support internet technology. Many technologies and applications that support learning through internet technologies have also promoted the growth of internet technology adoption in learning. This is seen in the use of the massive open online courses (MOOCs) and the use of e-learning platforms which have greatly assisted in availing educational content to students across the globe. This educational content is developed by instructors with a wide range of experience in their subject areas and is therefore considered beneficial to the learners (Hughes & Dobbins, 2015; Internet Society, 2017b; Ezen-Can et al., 2015).

The educational characteristics of the learning process have also changed dramatically due to the growth of internet technology. For instance, printed materials have a certain fixity and finitude while texts published via the internet have a much more fluid character. With texts no longer being housed between library or bookshop walls, it becomes impossible to pin-down all or even most of the available materials in a given subject area for archival and classification purposes.

Many learning institutions in the world particularly in developing countries have embraced internet technology in their institutions with vigour and the belief that it will help enhance scholarly activities in their institution. As such, over the years, policies have been formulated to support the integration of the internet technology in these institutions with expectations of improvement on student performance. Chiefly, large sums of budgetary allocations have been made to support the deployment of internet technology in these institutions. Equally, educationists in these institutions have been forced to shift their pedagogies to fit into the new realm due to pressure and conviction that internet technology may provide better tiding for their students. The recipient of these changes, the students, have also not been left behind as they try to adjust to the changing learning ecosystem. They often find themselves compelled to try adopting usage of internet technology in their studies even when their knowledge on the technology is limited. In general, all the shifts taking place in the learning ecosystems in universities in particular, is presumed to lead to enhanced student performance. Consequently, adoption of internet mediated platforms in teaching and learning has become a standard norm in most learning institutions. The fundamental problem addressed in this research could be if indeed the configuration, adoption and utilization of internet technology in higher learning institution has led to corresponding improved student performance.

A study done by Miller & Atkinson (2014) to measure the productivity and effectiveness of the students in performing their tasks within the university did not conclusively reveal if the configuration in terms of availability and accessibility to internet technology translates to achievement of desired outcomes even when students spend considerable amount of time on the internet. They observed a need to investigate why inherent utility of the internet technology does not translate into the shaping of the productivity of the student as measured through student performance. Various studies have also concluded that the generic adoption of a technology does not always lead to the full realization of the benefits of the technology but rather the adoption of the technology contextually is found to be critical (Oliviera & Martins, 2011; Nguyen, 2015). Studies on context-centred technology adoption have also demonstrated the need to contextually analyse and configure the technology in order to effectively support its adoption and utilization (Omwenga, 2016). This therefore calls for the understanding of the learning context in which internet technology is utilized and how its utilization levels can be measured to assess the usefulness of internet technology in learning. Similarly, the effect of internet technology in education can be fully understood if underlying factors like knowledge, effort on how to use internet technology and infrastructural investments on internet technology are considered as they contribute to system processes in learning (Ojokoh & Asaulu, 2005).

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A number of researchers have presented various techniques used in measuring student performance in higher learning institutions. Some of the techniques used include Data Mining techniques (Anjali & Ankita, 2017), Decision Tree techniques (Nguyen et al., 2011) and Factorization techniques (Anderson et al., 2014). Most of these studies have focused on the use of grade points or what can be described as data points as indicative pointers of student performance. Generally, these techniques consider varied performance attributes, which include, the final cumulative grade point average, internal assessments, external assessments, final grades, marks obtained from other courses, high school background, soft skills and extra-curricular activities (Jishan et al., 2015; Mayilvaganan & Kapalnadevi, 2014; Natek & Zwilling, 2014). Unfortunately, system processes that leads to the data point outcomes have not been considered in these techniques.

The growing centrality of internet technology in the social context of the learners has nevertheless pushed students to spend increasingly long times on the internet and become less worried about its effect on productivity and effectiveness in helping them perform tasks. For students in higher learning institutions, this is a real danger. There is therefore need to establish the internet utilization level and associated effects on learning so as to optimize student performance trajectory. The intrinsic effects (perceived enjoyment) and extrinsic motivation (perceived usefulness) on internet usage have been studied by Teo et al. (1999) but assessment on the performance of internet utilization was not tackled.

This study investigated the system process particularly on the usage of internet technology in learning and how it influences student performance in higher learning institutions. Particular focus on the prediction of student performance considered student behavioural aspects while using internet technology in the learning environment. The behavioural pattern analysis techniques were used to study internet utilization patterns by the learners when performing given tasks. The techniques also helped in examining the behavioural characteristics of a student which influences their learning outcomes.

1.4 Objectives

1.4.1 General Objective

To develop a model that can be used in the prediction of the student performance trajectory by analysing the internet technology utilization behavioural patterns of students.

1.4.2 Specific Objectives

i. To analyse the current ways in which internet technology has been adopted in the learning process in Kenyan universities.
ii. To examine internet technology utilization behavioural patterns that exist among Kenyan university students.

iii. To analyse ways in which internet technology influences the learning outcome of students in Kenyan universities.

iv. To develop and validate a model for predicting the student performance trajectory in an internetworked environment.

1.4.3 Research Questions

i. What are the current ways in which internet technology has been adopted in the learning process in universities?

This research question examines the different ways in which internet technology has assisted in evolving the learning process, as well as how it has been adopted and used in the learning process in universities. This objective examines the different technology adoption theories, learning theories and models for adoption of internet in universities.

ii. What are the internet technology utilization behavioural patterns that exist among students in universities?

This research question examines the general theories of utilization that exist and the ways in which internet technology utilization is realized in universities. It also examines behaviour patterns, pattern analysis and student learning patterns on internet technology mediated platforms.

iii. How does internet technology influence the learning outcomes of students?

This research question examines the different measures that influence the learning outcome of students who use internet technology in learning. It also examines the factors that influence learning in an internetworked environment.

iv. How can a model for predicting student performance in an internetworked environment be developed and validated?

In this research question, the model development approaches were examined together with the research conceptual framework. The predictive model structure was developed. The data collected from students was used in validating the model developed.

1.5 Significance of the Study

Understanding internet technology behavioural patterns in students forms the basis for accepting how students conduct themselves while on the internet platform as they conduct their studies. This research will help the students be in a position to optimize the use of the technology and as a result, get the most out it and avoid wasteful mannerisms while using the internet.

Investing in information technology in the universities forms a major portion of these institutions' budgets. Specifically, a lot of resources get allocated to the investment in the provision of internet services to ensure that staff and students get to access the internet. Universities will be in a position to determine the technological investment required for the provision of the internet.

In the field of computing, technology advancements have been made and one of these mainly focuses on the internet as an important resource. Internet-based policy makers will be advised on the best way to advise universities as far as achieving the benefits of the resource is concerned.

This research presents the utilization of internet technology by considering the institutional investment, student effort and the effectiveness of student effort in the learning process. These factors were considered together in the determination of student performance trajectory and student performance perceptions at an instance in time. Therefore, it would be possible to determine students' performance perceptions without considering longitudinal studies which are conducted over a period of time.

1.6 Scope of the Study

This study focuses on students in universities in Kenya. The students are both undergraduate and postgraduate students who have used the internet resource in their learning process. The study was guided by the Cobb-Douglas production theorem which gives the ability to measure the different factors of production in determining the production of a good or service. The factors that were considered included the capital costs in the form of investment costs at an instance in time within the university context, the labour cost in the form of the student effort expended in the utilization of internet technology at an instance in time and the effectiveness of student effort at an instance in time. The factors were represented using stochastic differential equations and this assisted in generating the performance trajectory of students who use internet technology in learning. It was then possible to predict the performance perceptions of students based on the different behaviour patterns.

1.7 Research Methodology

The research process in this study involved the use of both observation and initial information gathering approaches. This mainly focused on the fact that most information was obtained from the literature review. Specifically, prediction model formulation was based on identified theories which identified the variables to be considered and the specific objectives to be addressed. The data collection process involved the use of self-administered questionnaires as the survey tool shown in appendix A. Data was analysed based on the different variables that were being considered in the survey tool as shown on appendix B. The results obtained from the data were then interpreted to give results based on different factors considered.

The research philosophy of this study encompassed building a bridge between the field of information technology, education and economics. The goal was to apply an economics theorem (the Cobb Douglas production theorem) to understand how best to implement and evaluate internet technology usage in the education sector to encourage user acceptance, learning and productivity. The study was grounded on current practical needs of the education sector in order to understand technology needs.

The research design focused on designing the study to assist in data gathering, analysis and getting possible conclusions out of the data. The study setting involved carrying out the research within a natural environment on a normal day. The unit of analysis in this study was mainly the individual respondent who was treated as the main source of information. The time horizon of the study was one-shot since the data was collected once to answer the research objective. Since the research was done in a natural environment, there was minimal interference with normal student operations in the universities during the data collection process.

The research design was also both exploratory and quasi-experimental. The exploratory design assisted in understanding the utilization of internet technology in the learning process. This design assisted with initial research into the problem by providing more details to assist in the problem conceptualization. Information sources were used to provide background information to the research. The approach that was used in the exploratory research involved the use of pilot studies focusing on the use of internet technology in the learning process (Manerikar & Manerikar, 2014).

Data was collected by the use of questionnaire surveys as shown in appendix A. This was adopted since the researcher knew what they needed in the study and how the variables were to be measured. This approach was also less expensive and less time consuming compared to interviews. The questionnaires were administered personally in the different institutions, the groups of students were assembled together and any doubts were clarified for the participants. Since the questionnaire was long, some students would get impatient and abandon the exercise and to avoid loss of the questionnaires, they were filled in and returned immediately.

The questionnaire had a brief cover letter that introduced the respondents to the study and assured them that the data was to be used anonymously and confidentially in the study. Precisely, it checked for background information, knowledge of internet usage, capability of the student, attitude of the student, physical environment, influence to use the technology, utility of the technology, relevance of internet, and the extent of the usefulness of internet. The likert scale used in the questionnaire was a five point scale ranging from strongly agree to strongly disagree. This scale was adopted since it helps in capturing the feeling and attitude of the participants as is the case in this study. The 5 scale was further collapsed into a three scale measure so as to determine what the respondents agree, disagree or are not sure about.

To enhance the response rate, the questionnaire used easy to answer questions and simple wording of questions for the respondents to understand. The pre-testing of the questionnaire involved giving the questionnaire to a group of 25-50 actual respondents (Zikmund, 2003). The concerns raised focused on issues of wording and ambiguities which were both corrected. A pilot survey was also done to detect any weaknesses in the data collection instrument, helping respondents gain familiarity with questionnaire, helping establish response rate and the estimated questionnaire completion time.

The respondents in this case were students from 12 public and 8 private universities who were in their third year of study in a STEM or a non-STEM related course. The students did not need to have used internet technology in their learning process for them to respond to the questionnaire. The sample size given by Slovin's formula assuming a degree of variability of 0.01 and a confidence level of 95% gave a sample size of 1,000 students.

$$n = \frac{N}{1 + N(e^2)} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (1.1)$$

$$= \frac{513819}{1 + 513819(0.01^2)} = 1000\ students$$

where n represents the sample size, N represents entire population, e represents the level of precision.

Out of the 1,000 questionnaires issued, 796 were returned (79.6% response rate) and only 747 of the returned questionnaires were usable. Hence, in this research, the respondents were identified using a variable $\boldsymbol{n}$ which was equal to 747. This value was a constant all throughout the study since it represented the total number of participants who responded to the survey questionnaire. The data collection was conducted between the periods of February 2017 to November 2017. The data was then qualitatively analysed and the results were used in the validation of the prediction model as formulated and discussed in Chapter 5.

The quasi-experimental designs involved the selection of different participants for different conditions in the research from the existing selections of groups available. In this case, the required independent variables were formulated from the data given on the pre-existing values and not created through manipulation by the researcher. The participants in this case self-assigned themselves to the pre-existing groups in the target population. The target population for this research was university students. Since the target population was very large, there was need to use a sampling technique to obtain a smaller set of the population. This led to the use of stratified random sampling. Stratified random sampling is a procedure for selecting a sample that includes identified sub-groups from the population in the proportion that they exist in the population. The sample from the sub-groups was picked using proportionate stratification. With proportionate stratification, the sample size of each sub-group is proportionate to the population size of the disjoint groups. The sample size is determined by equation 1.1.

$$n_k = (N_k/N) \ * \ n \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1.2)}$$

where n_h is the sample size of the sub-group h, N_h is the population size for the sub-group h, N is the total population size and n is the total sample size.

The methodology applied in this research also involved four main phases as shown in figure 1.1. In this approach, each of the phases provided valuable information that was used to inform the subsequent phases in the research. Defining the distinct stages assisted in understanding how they all contributed to the research.

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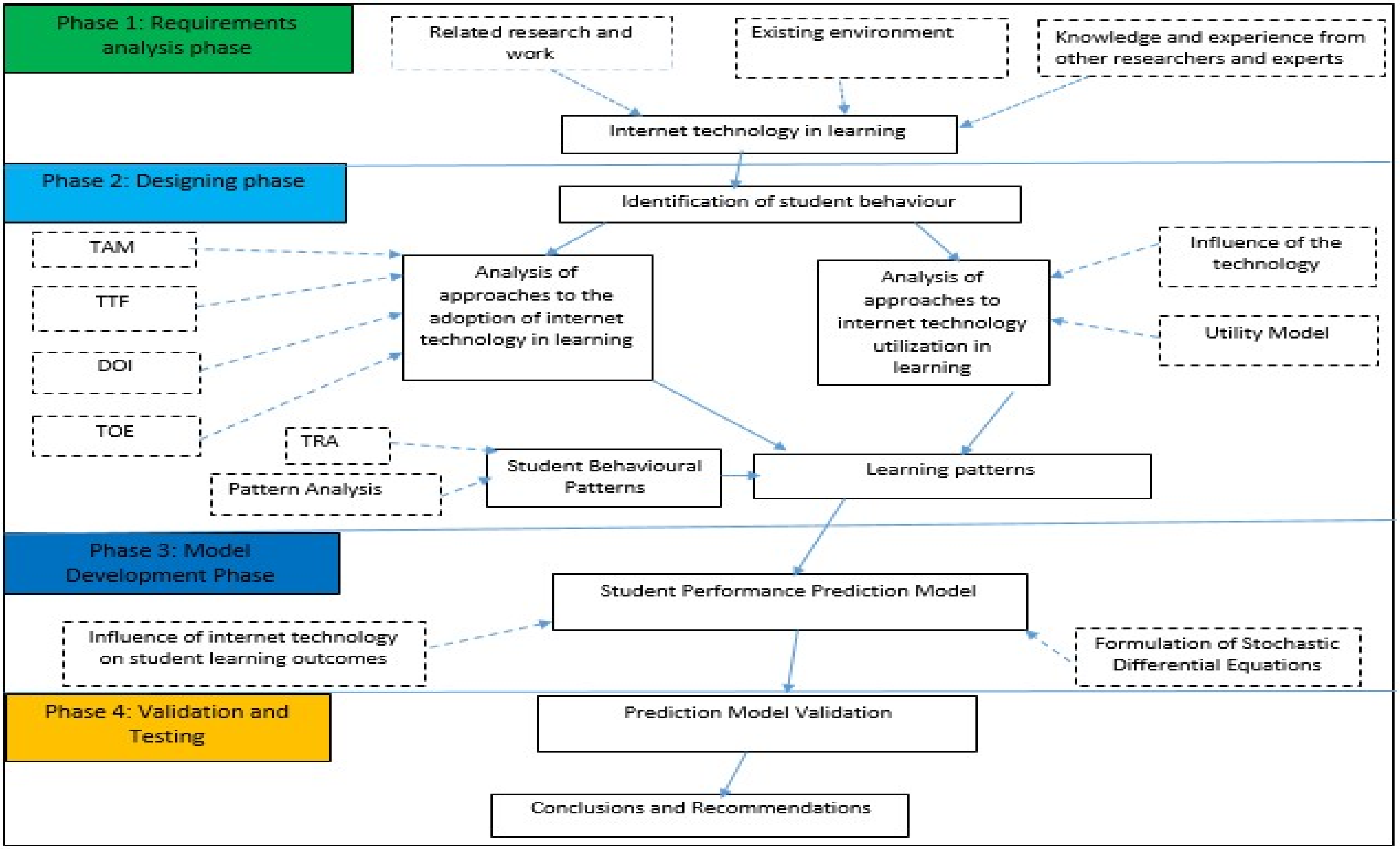

Figure 1.1 *The detailed methodology adopted in this research*

In figure 1.1, the solid-line boxes represent tasks that were performed in the course of this research. The output of these tasks contributed to results that have been extensively discussed in this thesis. On the other hand, the dash-line boxes have been used to represent all the theories, concepts, expert knowledge and research results that have been used in the research. These also contribute to the inputs required in the research.

Phase 1 involved looking at research related to the use of internet technology in the learning process, the contextual nature of the institutions that use the technology in learning and what other researchers have found out about the use of the technology within the learning environment.

Phase 2 used the results of phase 1 to focus on the identification of the student behavioral patterns by analyzing the adoption of the technology in their universities based on various theories. Specifically, the technology acceptance model (TAM), the task technology fit model (TTF), the diffusion of innovation theory (DOI) and the technology, organization and environment (TOE) framework were applied. This phase also considers the concepts of the utilization theory in the learning process by examining existing knowledge and the Cobb-Douglas production theorem. In this phase as well, student behavioral patterns were examined using the theory of reasoned action (TRA) and pattern analysis techniques. Hence, the student learning patterns on an internet mediated platform were generated.

Phase 3 focused on the student behavioral patterns identified in phase 2 to develop the student performance prediction model that was based on the influence of internet technology on student learning outcomes and the formulation of the stochastic differential equations (SDEs).

Phase 4 concentrated on the testing and validation of the model developed in phase 3. This phase uses data collected to check on the accuracy of the model, to verify the student performance trajectory and to check on the margin curve generated using the classification algorithm.

Chapter 2: Internet Technology Adoption in Learning

2.1 Introduction

This chapter examines how internet technology has contributed to the evolution of the learning environment and how the technology has been adopted in the learning process. It examines the different technology adoption theories that exist as well as the theories of learning. It also presents different models that have been adopted for implementing internet technology with a look into internet adoption in universities. Finally, it also presents the research findings based on the effect of internet technology in predicting student performance in Kenyan universities.

2.2 Evolution of the Learning Environment

There has been a remarkable evolution in the learning environment due to the advent of internet technology in the learning environment. Internet technology is a continuously expanding phenomenon in terms of its reach and its penetration into different societies and cultures, but especially in terms of how it affects human relationships (Glassman & Burbidge, 2014). The internet has taken directions and created actions and trajectories that were mostly unanticipated a decade ago. Future developments are unforeseen and unpredictable. There has been extraordinary development of the internet's infrastructure, as well as the continuous flow of new applications, each one seeming to surpass the last one in possibilities and increased user capabilities (Glassman, 2012). The internet has changed society by changing how people relate to each other and to the world around them (Blum, 2012).

Hence, the availability of the internet technology as a resource and its implication on society are two major aspects that have seen internet technology being embraced in the education sector. In the beginning, learning was mainly seen from a traditional classroom perspective. This comprised of a teacher who would deliver lectures to students. This was later modified to ensure that the teacher could deliver lectures to a number of remote classroom locations simultaneously. This led to the inception of distance learning which was dependent on internet technology. However, it was expensive and mostly limited to one-way transmission. This invention succeeded in extending academic opportunities to more students. However, it also produced an educational value subtract, particularly with regard to the frequency of interactions among students and teachers. Nonetheless, this in itself was a significant development in learning since technology ensured that students could access education remotely.

The technical shortcomings of first generation education systems frustrated students by severely limiting their ability to ask questions to the teacher individually, to offer their own insights to their classmates, to engage in real-time class discussions, or to apply course content in personally meaningful ways. Teachers also suffered the frustrations of this technical limitation as well. The education systems ensured that they could reach more students, but it deprived them of the opportunity to do the informal assessments natural to face-to-face interactions, or to employ more individualized teaching methods (Stephens et al., 2012; Ellore et al., 2014).

The education systems network design was built on a centralized broadcast model, in which end users had only limited ability to transmit information over the network. Content decisions, computer power and transmission capability were all centralized and user locations were primarily set up as receiving stations. This made these networks useful for broadcasting lectures and video documentaries, but not for facilitating activities that depended on interaction or collaboration.

Then came internet technology which was shortly followed by the internet commercialization. Internet technology, by contrast, is a distributed intelligence network with millions of individual computers and computer networks that are interconnected. Its very structure assumes interaction and fosters collaboration (ACM, 2014).

Internet technology complemented the first generation learning systems. The technology provided low-cost widespread interactive connections so much lacking in previous learning systems. It broadened the definition of education from one teacher serving multiple classrooms in different locations, to projects involving various groupings of students and/or teachers who interact and collaborate despite their geographical dispersion. Learning was no longer limited to one-way broadcasts, but could include any electronically mediated educational transactions that overcome a distance limitation.

The internet has therefore greatly contributed to the revolution that has taken place in the field of education. This has been seen in the various transformations that have taken place as far as learning is concerned. This shift from the traditional classroom to online collaborations that span through continents cannot be simply ignored. The internet has therefore made remarkable contribution to learning and also to the learning sphere in a significant way.

2.3 Technology Adoption Theories

For individuals to use a new technology, it is necessary that they accept the new technology in the first place, embrace its use and finally work with it. An efficient technology could be introduced but its usage could get curtailed due to the fact that the users feel that they do not need to use it in their work. This therefore leads to failure in implementing the technology. To this end, it is necessary to examine models that have been proposed to assess the rate at which people adopt a technology. Specifically, two models are considered: the Technology Acceptance Model (TAM) and the Task Technology Fit (TTF) model.

2.3.1 Technology Acceptance Model (TAM)

The technology acceptance model (TAM) introduced by Davis (1989) as shown in figure 2.1 posits that the intention to use a system is based on the perceived usefulness of the system and the perceived ease of use of the system. A system's perceived usefulness defines the degree to which the system at hand enables its user to enrich their performance at work. Consequently, the perceived ease of use of a system defines the belief that use of the system will be effort free. Davis (1989) considers that the attitude of a user towards a system was a major determinant of whether the user would actually use or reject the system. In turn, the attitude of the user is also influenced by the two major beliefs highlighted earlier on, namely: perceived usefulness and perceived ease of use of the system.

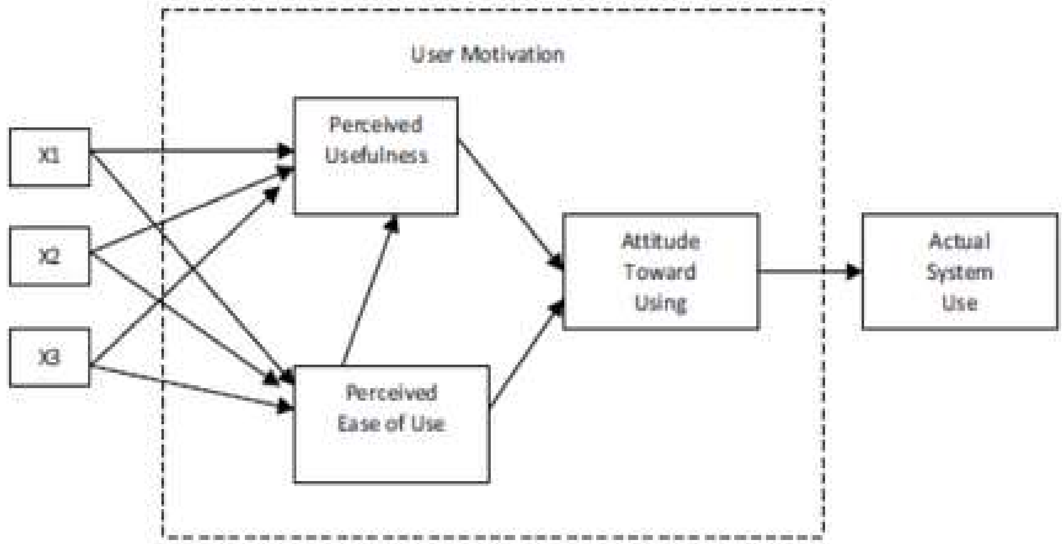

Figure 2.1 Original Technology Acceptance Model (Adopted from Davis (1989))

Since TAM has further been tested and refined by researchers in explaining the behaviour of students in using technologies, it can also be used as shown in figure 2.2 in examining the motivation in the use of a technology, still based on the perceived usefulness of the technology, perceived ease of use of the technology and the attitude of the user towards the technology (Davis et al., 1989; Lai, 2017).

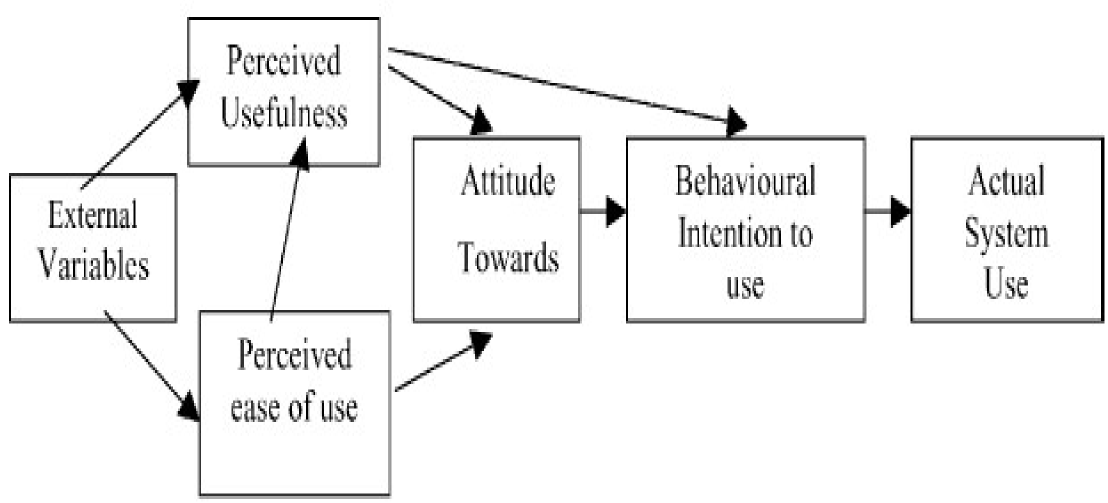

Figure 2.2 *Modified Technology Acceptance Model (TAM) (Adopted from Davis et al. (1989))*

Mathieson (2000) used TAM to explain the intention of students who used spreadsheets in their studies. This study explained why many of the students intended to use Microsoft office in their class assignments. According to Gentry and Calantone (2002), TAM was used to explain students' behavioural intention in the use of internet shop-bots. Taylor and Todd (2005) concluded that TAM was a very useful model in its ability to predict the business school student's ability to use available resources in their computer resource centres. Venkatesh and Morris (2000), added that the use of TAM ensures that the perception of a user towards a technology is well addressed. However, user's experiences with other related technologies could also be put into consideration before their perceptions were considered.

TAM was originally designed to apply only to computer usage behaviour but this has since changed. Research shows that the explanatory power of TAM has yielded consistency in the behaviour of the information technology users. A great number of researchers have confirmed the competence, usefulness and rationality of TAM across a wide range of domains. TAM has also been used in explaining people's attitude towards technologies and systems, computer self-efficacy and internet self-efficacy.

Most recently in a study conducted by Hussain et al., (2016), TAM was used to examine the perception of usefulness, ease of use and enjoyment in the introduction of an application that would assist users in interacting with mobile maps. The study went further in validating the TAM model and concluded that perceived usefulness, perceived ease of use and perceived enjoyment had a very significant impact in the acceptance of the new technology.

Nguyen (2015) has applied TAM in studying consumer behaviours in mobile games. The study examines intrinsic factors like perceived enjoyment as one of the factors that greatly affects the use of gaming applications in the learning context. The study concluded that there were three main factors that affected the perceived enjoyment of a technology; that is, design aesthetic, perceived ease of use and novelty.

Applying the variables considered in TAM in this research involves examining the usage of internet technology among students with perceived usefulness of internet technology being based on whether the students find the technology useful in their studies or not and the time that students spent on the internet. The perceived ease of use checks whether the students find the internet easy to use in the learning process, especially if they have prior experience in using the internet for other non-academic activity. Students also use their course web site more if they perceive the site to be useful in their studies and easy to use. In this study as well, TAM is helpful in assessing the behavioural intention of a student to use a technology. This mainly comes in when the attitude of the student is examined in light of the need to be accomplished while using the technology. The attitude was based on the perceived usefulness and perceived ease of use in embracing a new technology.

2.3.2 Task-Technology Fit (TTF) Model

According to Goodhue and Thompson (1995), the task-technology fit (TTF) model shown in figure 2.3 focuses on individual impact. In this view, individual impact emphasizes improved efficiency, effectiveness and higher quality. Goodhue and Thompson (1995) assume that for good fit to exist between a task and a technology, there is need to increase the likelihood of usage of the technology in order to have maximum benefits on the task being worked on. This model is best used when considering the actual usage of a technology especially when checking for feedback on the usage of a new technology (Lai, 2017).

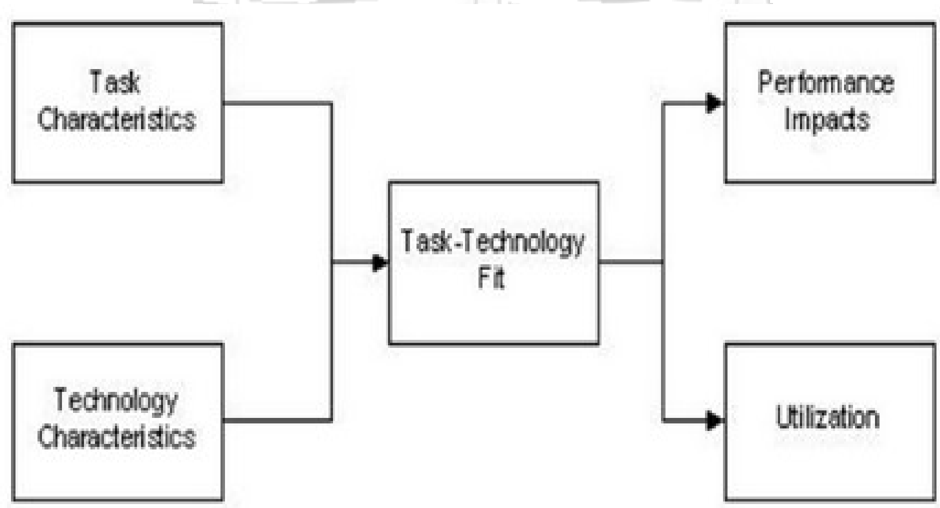

Figure 2.3 *Task-technology fit model (Adopted from Goodhue and Thompson (1995))*

Chen (2013) examines the task-technology fit (TTF) model and posits that information technology has a positive effect on individual performance. If the technology matches the tasks, user's performance gets better. This model also describes that task, technology and individual affect task-technology fit. Moreover, performance is affected by user evaluation and task-technology fit. Therefore, task-technology fit is the most important factor in this model. Task-technology fit consists of eight factors: quality, authorization and compatibility, ease of use/training, production timeliness, systems reliability and relationship with users. Each of the factors is measured with responses on a seven point scale ranging from strongly agree to strongly disagree.

TTF has been applied in diverse range of information systems, especially in electronic commerce systems and when examining individual as well as group uptake of technologies in tasks. In many cases, the model is combined with other models or is used to extend other models in order to formulate an outcome, such as in the case of the technology acceptance model (TAM).

Applying the variables considered in TTF to this research involves identifying the various tasks characteristics required in the learning process of a university student. The tasks depend on the different disciplines pursued by the students. In the case of students, the tasks could involve assignments, research projects, personal studies and the final student performance (Chen, 2013). The technology characteristics in this research aim at examining the features of the technologies that the students needed to use in order to accomplish the tasks given to them. Here, there is need to check how students utilize internet technology in their learning process. Finally, once the students utilize the technology in order to perform different learning tasks, there is need to check whether the same students manage to perform better. This therefore involves checking if the tasks given in the learning process were accomplished using the technology available, hence leading to better performance.

2.4 Theories of Learning

Theories of learning have been used to a great extent in the field of pure sciences, especially in the facilitation of learning within a society or as attributed to an individual teacher. Theories of learning define how a person learns based on their behaviour, their cognitive aspects and their constructivist ideas. Over the past century, educationists have tried to explain how individuals get to acquire, assimilate and use knowledge and skills. New emerging trends in the learning process of students have contributed greatly to a revolution in the education sector. Students are always presented with a large information base which they are required to assimilate in order to learn the theory behind concepts. Learning theories have been organized as behaviourist learning theories, cognitive information processing learning theories and cognitive constructivist learning theories (Burns, 1995).

The behaviourist learning theory dates back to the late 1800s. This theory looks into the history of behaviourism as supported by John Watson in 1913. Later in the 19th Century, similar views to those of Watson were developed as the Gestalts movements in psychology. The Gestalt psychology focuses on the fact that perception is determined not by elements of sensation but by laws of similarity, continuation, closure or symmetry. In the 20th century, behaviourism came as a result of the developments in cognitive revolution and in the 21st Century, research has been undertaken in the field of behaviour analysis.

Ivan Pavlov was the original behaviour theorist. He is the founder of classical conditioning, an automatic type of learning in which a stimulus has the capacity to evoke a response that was originally evoked by another stimulus. John Watson then came in and introduced behaviourism. He studied how different levels of stimuli led different organisms to make responses. This led him to conclude that Psychology is only an objective observation of human behaviour. The concept of behaviourism led to more studies being carried out in different fields: for example, in the 1940s, the principles of behaviour and behaviourist principles in society were studied (Clark Hulls in 1943 and B. F. Skinner in 1948 and 1971).

Behaviourism can be defined as the learning process that involves the use of actions that can be observed and measured. In the behaviourist learning theory, elementary laws of learning are derived and these get extended to explain more complex scenarios. Assuming that the laws of learning are universal, then, mannerisms observed in lower organisms were extrapolated and used on humans. This theory is also based on some associations in the learning process. These associations are the association of ideas, association between senses and impulses and association and reflexology.

In the association of ideas, it is assumed that understanding simpler forms of learning leads to understanding more complex phenomena. This leads to the conclusion that the use of associations of ideas in learning leads to a situation where all ideas acquired become connected to each other or associated through experience. Consequently, the more frequently an association is encountered, the stronger the associative bond. In the associations with sensations and impulses, the learning process takes place when an action has a satisfying consequence. This principle helped in modifying the principle of association and also had significant benefits on behaviourism. In association and reflexology, Pavlov established a learned reflex where there exists a relationship between an appropriate stimulus (food) and an inappropriate one (the trainer). In this case, a relatively neutral stimulus is associated with something that causes a response until the neutral stimulus also causes the response (classical conditioning).

Skinner (1971) brought in the idea of predicting and controlling observable behaviour. Learners are seen as coming to the learning environment already conditioned by their previous environments. This simply meant that by controlling the learners' environment and behaviour penalties, it was then possible to predict and control their behaviour. In addition, by providing positive consequences for behaviour and controlling how the consequences are delivered, it is possible to control and shape behaviour. Behaviour is more likely to recur if it has been rewarded or reinforced and less likely to recur if its consequences have not been compensated. This is referred to as the contingencies of reinforcement. In order to understand the learning process, it is necessary that one looks at the behaviour of the learner and determines why the learner behaves as they do.

The other learning theory is the Cognitive-Information Processing (CIP) learning theory. In the view of cognitive information processing learning theory, the learner is seen as the processor of the information, like the computer. When learning occurs, information is input from the environment, processed and stored by the learner, and the output becomes the learner's capabilities. In this case, the environment of the learner is capable of modifying the learner's behaviour. However, the information processing ability of the learner is defined as the variable factor.

The information processing models are based on the multistage theory of memory where information received undergoes a series of transformations before it is permanently stored up in memory. The three major components of memory are sensory memory, short-term memory and long term memory (Bransford et al., 2000). Sensory memory is the first stage in information processing. This is the part of memory that is associated with the senses and it holds information in memory very briefly before it is processed further. In this stage as well, the process of selective attention takes place. This refers to the ability of the learner to select and process certain chunks of information while ignoring other chunks concurrently. This ability to select what to focus on is based on the meaning of the task at hand, similarity between competing tasks, the task complexity and the learner's ability to control attention.

In short-term memory (STM), further processing is done on the available information ready for long term storage. In this stage, long term memory (LTM) gets activated in order to make sense of the incoming information. STM or working memory acts as a store of a certain amount of information and only for a short period of time. In order to encode information into long-term memory, the learner can either use rehearsal and chunking or encoding techniques. Rehearsal occurs when an idea is repeated over and over again and gets engraved on the long term memory. Chunking involves subdividing the data at hand into smaller groups to aid in the retention of the data. Encoding ensures that the incoming data relates to what already exists in long term memory and hence more memorable. This moves the data from STM to LTM. The learners enact their own organisation of materials, for example, imagery and mnemonics in order to learn them in the best way that fits them (Baddeley, 2001).

Long-term memory (LTM) is characterised by a permanent warehouse for storing information. Once data is moved from STM to LTM, it is always available and never deleted completely. LTM retains an innumerable amount of information though retrieval of the information can be an issue to the learner. The retrieval process from LTM takes place to enable a learner understand some new output or give a required response at an instance.

The Cognitive-Constructivist Learning Theory is based on several research traditions. This theory suggests that knowledge is based on knowing the parts that make up something and how the parts are related. This further implies that learners do not interpret the information presented to them as separate pieces, which ensures that there is order in the world. The numerous pieces of information available to the learner all contribute to the learning process of the student. The learners adapt to the environment they are presented with and they learn how to organise and present the information given to them. In the learning process as well, learning is a socially mediated experience where learners construct knowledge based on the interactions with their social and cultural surroundings (Poerksen, 2004).

2.5 Models for Adoption of Internet Technology in Learning Institutions

The use of internet technology has become universally accepted as an essential tool that has been assisting students in their learning process (Oliviera & Martins, 2011). Internet technology has been accepted since it has had significant effects in the learning process of students. It would be necessary therefore to understand the different determinants involved in the adoption of a technology. With this in mind, two major technology adoption models are reviewed, namely: the Diffusion of Innovation Theory (DOI) and the Technology, Organisation and Environment (TOE) framework.

2.5.1 Diffusion of Innovation Theory (DOI)

The Diffusion of Innovation Theory (DOI) is a theory that explains the reasons, the different ways and the rate at which individuals and institutions adopt new ideas and technologies. The innovations are communicated through specific channels over time and within allowed social systems. The process involved in the communication of the innovation through the varied channels within an institution is commonly referred to as the diffusion process. Different individuals possess different degrees of willingness in adopting innovations and as a result, those who adopt a technology are approximately normally distributed over time. The core idea in DOI is that any technology adoption is influenced by four main elements, namely: the time and social system, the innovation itself and the communication channels regarding the technology at hand. The process of adopting a technology as shown in figure 2.4 involves five main stages: knowledge, persuasion, decision, implementation, and confirmation. It results in six categories of users: innovators, early adopters, early majority, late majority, laggards and the leap-floggers (Sharma & Mishra, 2014).

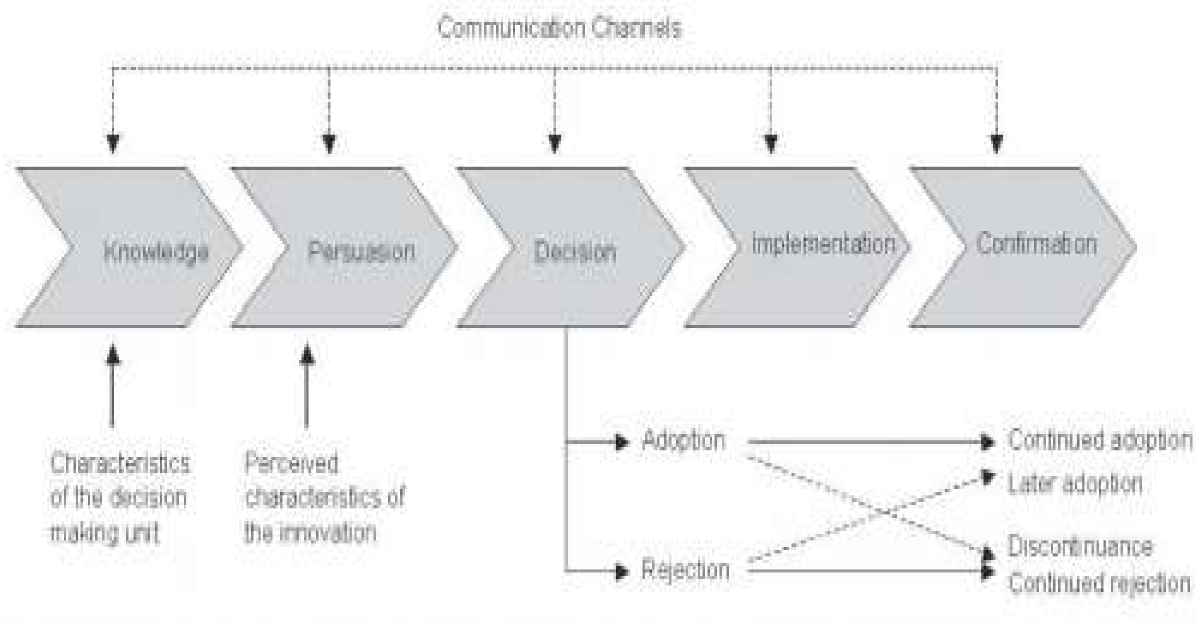

Figure 2.4 *Diffusion of Innovation Model (Adopted from Rogers (2003))*

Applying the DOI model to internet technology adoption process, stages similar to those shown in figure 2.4 are embraced. Users of the technology require an acceptable level of knowledge based on internet technology before they can adopt its use. This is followed by the users' appreciation of the different features found in the technology. The users then make a decision either to adopt or reject the technology. Once the decision to adopt the technology is made, the implementation process begins and the different users get to learn about the technology. Finally, at the confirmation stage, the use of the technology becomes widespread around the institution and all parties are allowed to learn and use the service (Sharma & Mitra, 2014).

DOI theory brings into perspective the S-shaped curve of adoption. According to this curve, the spread of a technology is slow at first, then at mid-range of the curve, the spread of the technology accelerates and finally, the rate of spread tapers off as shown on the S-shaped curve in figure 2.5.

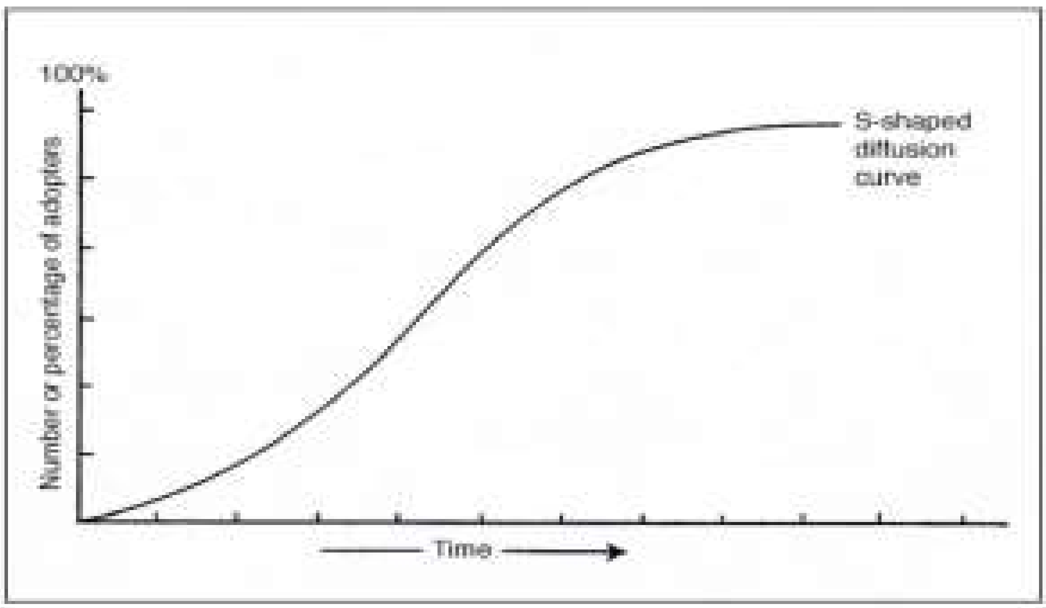

Figure 2.5 *S-shaped diffusion curve (Adopted from Sharma and Mitra (2014))*

In the S-shaped diffusion curve in figure 2.5, the new technology gets introduced from a different environment at an instance in time. This results in a situation where only a few people are introduced to the technology at the beginning. As the few initial users of the technology start accepting it, they introduce it to other people who in turn introduce the same to more people. This leads to an increase in the rate of spread of the technology. Eventually, the technology becomes accepted and usable by many people within the environment and the rate of rapid spread declines. At an instance in time, all persons use the technology and there are none left to accept the technology. At this point, the adoption to the technology stops completely.

Though the S-shaped model mainly applies to technologies and innovations that are introduced from time to time, its application is of special importance when examining the adoption of a communication technology such as internet technology where it is referred to as Metcalfe's law. In this environment, the value of the innovation is enhanced as more and more people use the innovation at hand since each additional user has a positive value on the existing users. According to Sharma & Mishra (2014), the same curve has also been used over the last decade and a half to explain the adoption of internet technology in the learning environments.

2.5.2 Technology, Organization and Environment (TOE) Framework

The Technology, Organisation and Environment (TOE) framework identifies some aspects of an institution that affect the way in which an institution adopts and implement a technology. These are the technological context, the organisational context and the environmental context. The institution's technological context describes the internal and external technologies available in the environment. This also describes the available equipment in the firm and the current practices of individuals within the institution (Oliviera & Martins, 2011). The organisational context focuses on the attributes of the institution at hand, for example, its management structure, size and scope. The environmental context focuses on the environment in which the institution conducts its business, specifically, the industry and competitors.

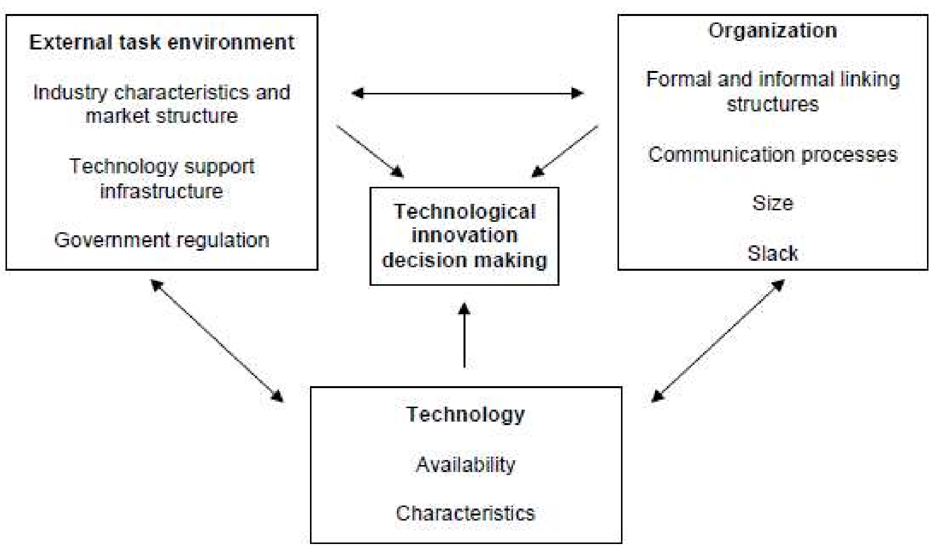

Figure 2.6 Technology Organization Framework (TOE) framework (Adopted from Starbuck (1976))

The TOE framework in figure 2.6 provides a suitable investigative framework that can be used while reviewing the adoption and assimilation of the varied kinds of technologies and innovations in information technology. The framework has a concrete theoretical basis, well laid down practical support and a great potential in fitting innovations in technology and innovations in different studies.

This framework integrates well with the DOI theory in which Rogers (2003) emphasized individual features and internal and external features of an organisation as the key components in institutions' adoption of internet technology. The DOI features are similar to the technology and organisation context in TOE but TOE also brings in the environmental aspect of the technologies to be used in the institutions (Hsu et al., 2006).

2.6 Review of the Effect of Internet Technology on Student Performance

A study carried out by Ogedebe (2012) focusing on the internet usage and students' academic performance in Nigerian tertiary institutions: a case study of University of Maiduguri, checked on the use of internet technology, the time of use of internet, the reasons for using the internet, the benefits associated with the use of internet, the contribution of internet technology to their academic performance and the relevance of the information on the internet in their learning process. The study concluded that internet technology was an important resource in the learning process of the students and if its services were to be fully exploited, the general academic performance of students would greatly improve.

In a study carried out at the University of Nairobi by Waithaka et al. (2013) on internet use among university students in Kenya, it was revealed that internet technology was seen to be a major contributor in the academic success of the students. This particular research only focused on the student level of awareness about the presence of internet technology in the university. It put emphasis on the basic computer and internet skills possessed by the student and how they used the resource in the learning process. Therefore, the students agreed that the technology assisted them to access quality and up-to-date information, which contributed to speeding up the completion of their class assignments. As far as communication with lecturers was concerned, the students indicated that the use of internet technology assisted them to communicate effectively with the lecturers, which enhanced their learning process by ensuring they had a learning forum out of the lecture room.

A study by Stanciu and Tinca (2014) gave a critical look on the student's internet use – an empirical study. In their study, there was focus on their usage abilities, the frequency of use of internet technology, and the different ways in which the students used the technology (email, chats, blogs and research, browsing and gaming). The conclusion made in this case was that the internet was a very important source of information for learning purposes. The instructors needed to know how best to assist the students in using the information available to them on the internet.

Dorji (2015) focused on the impact of internet on academic performance of the students at the tertiary level of education in Bhutan. The study checked on the education level of the students, the number of hours spent daily on academic research, the hours spent on social networking sites, the hours spent on online gaming, the rate of disruption in the provision of the internet resource and the rate of internet coverage within the university. The study recommended that there was need to check the quality and functionality of the internet in order to ensure that the resource benefited students in their learning process. There was need to maintain and support the already existing connectivity levels for the sake of the learners in the institutions.

Ivwighreghweta and Igere (2014) also carried out a research on the impact of internet on academic performance of students in tertiary institutions in Nigeria. In their research, the focus was on the level of computer literacy in the students and how the students made use of the internet. Specifically, the study checked the frequency of internet access, the specific ways that the internet assisted the students in learning and their general performance after using internet technology in learning. The study highlighted the challenges faced by the learners while using the technology in the learning process. The research concluded that there was need for the institutions to invest more in the provision of internet services within the university premises.

Internet technology provides great opportunities for the field of academia. In a research done by Emeka and Nyeche (2016) assessing the impact of internet usage on the academic performance of undergraduate students, the research primarily focuses on the frequency of use of the internet, the most preferred locations for internet usage, the purposes for browsing the internet, the most commonly used search engines, the influence of internet on student's academic performance and the challenges encountered in the use of internet services. The study concluded that there was need to have information literacy and sensitisation forums where students could learn how best to use the resource for their learning activities.

Similarly, Jibrin et al. (2017) focused on the effects of internet on the academic performance of tertiary institutions in Niger state. The findings in the research revealed that internet technology was a beneficial tool in the academic pursuit of students. The study checked the frequency of use of the internet, the rating of use of internet, the usefulness of the internet in academic activities, the most commonly used search engine on the internet, the influence of internet on student performance and the problems encountered in the use of internet services. The study concluded that there was need to sufficiently train instructors on the need of the technology in learning. The institutions also needed to invest adequately in the provision of the technology in the learning process.

In another study by Shahibi and Rusli (2017) on the influence of internet usage on student's academic performance, the study checked academic performance in relation to Facebook usage, internet usage, educational online media usage, non-educational online media usage and student interest. The study concluded that there was no relationship between Facebook usage and academic performance. However, there existed a strong relationship between educational and non-educational online media usage with student's academic performance since, students who used internet services well without wasting time on non-beneficial things end up achieving more while using the resource in their learning activities. Hence, it was possible to increase students' academic performance when internet technology was used in the right way.

All of the above studies laid great emphasis on the contribution of internet technology in the academic performance of students. The studies checked the frequency of internet usage and the specific ways in which the technology had been used in the learning process. Notably as well, the studies also mentioned the challenges faced by individual students and individual institutions in the access and use of internet technology in the learning process. These factors have all been used in the determination of the level of success or failure as far as the use of internet services in learning is concerned.

2.7 Internet Technology Implementation in Higher Learning Institutions in Kenya

There has been remarkable effort in Kenya to ensure that the information and communication technology (ICT) policy framework and implementation strategy is completed with measurable outcomes and time frames. This process has been supported by officials and stakeholders in different government ministries and entities. Conversely, the implementation of the strategy remains a challenge due to lack of adequate resources, lack of a national ICT infrastructure and even lack of electricity supply in rural Kenya. The general availability of mobile phones in the Kenyan population has rapidly increased the number of people using internet connectivity to communicate or access internet sites.

Accessibility to ICT infrastructure in Kenya to assist in internet connection still remains a challenge. In considering the state of learning in Kenyan higher learning institutions, internet connectivity still remains too expensive and poorly managed. Most of the institutions pay much more than their counterparts in developed countries. Institutions have in place ICT policies, some are developing the policies but the implementation has been hindered by a great lack of resources. In order to slowly change the situation, there has been considerable effort in establishing national research and educational networks. In Kenya, there exists the Kenya Education Network (KENET) that was established to develop sustainable communication and networking among educational institutions. This helps in facilitating wide use of internet technology in learning, teaching, sharing of resources and research at an affordable cost to the entire population. This initiative has ensured that higher learning institutions in Kenya have been provided with reliable, high speed and sustainable internet connectivity (Farrell, 2007).

KENET has also been charged with the responsibility of establishing internet infrastructure in the educational institutions in the country. This enables the institutions to enjoy lower tariff costs compared to the rates they receive from other service providers. The institutions also benefit from access to technical support and staff training sessions. KENET is also required to develop human resource in educational content generation and information management.

The use of internet in the learning, teaching, research and management processes in Kenyan universities has recently increased by a significant percentage. This is due to the rising importance of internet technology in these institutions in Kenya. This has greatly been influenced by the revolution that has taken place in ICTs, specifically in the use of internet technology (Musa et al., 2005; Macharia & Nyakwende, 2009).

Research has shown that the future of universities globally depends on their ability to embrace and use emerging technologies, especially the internet, to make sure that they remain relevant in their markets. This trend will need to be embraced by universities in Sub-Saharan Africa where the adoption and use of ICTs is still very low. As a result, students in these countries are enrolling for many courses from the developed world. This is mainly because university students are increasingly demanding for ways in which they can acquire more knowledge, manipulate the knowledge acquired and apply the knowledge with greater access to internet-based resources.

According to Manduku et al. (2012), the adoption and use of internet infrastructure in Kenyan learning institutions is yet to be fully realised in order for the technology to be used in teaching, learning and management as intended. Although many universities are adopting and using blended learning in their mode of instruction, there lacks a great skill set and infrastructure to enable the institutions to adequately use the e-learning platforms and maximise on their numerous benefits to the universities. E-learning, which has innumerable benefits, is yet to be utilized to its maximum for the good of students in the higher learning institutions (Tarus et al., 2015; Takalani, 2008; Khan et al., 2012).

Since internet technology has not been fully adopted within the Kenyan universities, there is need to examine the current state and position of the institutions as they try to use the technology in the learning process. The technology adoption theories discussed in section 2.3 play an important role in determining how users adopt the usage of internet technology within the context of the Kenyan universities.

The Technology Acceptance Model (TAM) discussed in section 2.3.1 states that, for an individual to have the intention to use a technology, they need to perceive the technology as being useful and easy to use. The perceived usefulness (PU) of a technology is the belief held by a user that the technology will assist in accomplishing the required tasks. The perceived ease of use of a technology (PEOU) considers that the use of the given technology will be free of effort. Therefore, it will not be necessary to spend much effort in order to use the technology in order to accomplish a task.

Within the Kenyan universities, the perceived usefulness of the internet technology was examined by considering how the technology assisted in improving the performance of the individual students as shown in table 2.1.

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Table 2.1 *PU and PEOU of internet technology*

Perceived Usefulness	**n**	**Disagree**	**Neutral**	**Agree**
The internet allows me to increase my productivity in my studies	747	4.2%	9.8%	86.1%
The internet has led me to rely less on hard copy text for my studies	747	10.3%	19.1%	70.5%
The internet has enhanced the quality of the work I do in my studies	747	3.5%	17.8%	78.7%
The internet gives me a great sense of accomplishment after using it for learning purposes	747	4.4%	18.5%	77.1%
The internet has enhanced my performance in my studies	747	4.7%	16.5%	78.8%
I find internet useful in my studies	747	2.4%	9.5%	88.1%
Using the internet enables me to accomplish tasks more quickly	747	3.1%	12.4%	84.5%
I feel that using internet resources gives me a great deal of opportunity for my studies	747	3.7%	15.8%	80.5%
I find that I have fewer challenges with my studies than my course mates/friends due to use of the internet	747	10.4%	25.3%	64.3%
I can competently complete any assigned task using internet	747	4.7%	15.8%	79.7%
Perceived Ease of Use	**n**	**Disagree**	**Neutral**	**Agree**
I find the internet easy to use and enjoyable	747	2.9%	12.3%	84.7%
Using the internet is a pleasant experience for me	747	3.6%	15%	81.4%
The internet is a necessary tool in my academics	747	4.8%	11.4%	83.8%

Source: Primary Data (2018)

Specifically, the study checked whether internet technology allowed the learner to increase productivity in their studies. In this case, 86.1% of the respondents agreed that the use of internet in their studies had assisted them to increase productivity in their studies. In checking the use of hard and soft copy reference materials, 70.5%of the respondents affirmed that they used internet technology to access their study material and not hard copy books, hence they had a preference for using the technology rather than library books. In the same way, when checking the quality of output of the work done using internet technology, 78.7% of the respondents affirmed that the technology assisted them in ensuring that quality work was done in the learning process.

Equally, 77.1% of the respondents agreed that internet technology gave them a great sense of accomplishment after using the technology for learning purposes. In the same population, 78.8% of the respondents confirmed that the technology enhanced their performance in their studies and 88.1% of the respondents affirmed that internet technology was useful in their studies. As far as accomplishing tasks more quickly was concerned, 84.5% of the respondents admitted that the use of the technology assisted them to accomplish their tasks more quickly, 80.5% of the respondents felt that the technology gave them a great learning opportunity in their studies and 79.7% of them felt that they competently accomplished and completed any assigned task using internet technology. Notably as well, 64.3% of the respondents confirmed that they had fewer challenges with their studies than their classmates due to the use of internet technology in learning.

Perceived ease of use checked whether the student found internet technology easy to use and enjoyable to use in their studies. This study showed that 84.7% of the respondents found internet technology easy to use in their studies and enjoyable to use as well. At the same time, 81.4% of the respondents admitted that the use of internet technology in their learning activities was a pleasant experience for them and 83.8% of the respondents agreed that internet technology was a necessary tool in their academics.

Additionally, after performing feature selection on the factors that affect perceived usefulness and perceived ease of use of technology, further data analysis was done on the data obtained. This involved subjecting the factors obtained to factor analysis on the SPSS platform. Factor analysis is normally done to reduce a large number of variables into a smaller number of factors. In this case, using the correlation matrix, any factor that had a correlation value less than 0.5 to the output factor was further discarded and not used in the final computation of the factor means. The results obtained are shown on table 2.2 and table 2.3.

Table 2.2 *Correlation matrix for perceived usefulness of internet technology*

Correlation Matrix[a]

		B5	B43	D26	D28	D30	D31	D32	D33	D39	PU
Correlation	B5	1.000	-.033	.034	-.002	.026	-.009	-.003	-.034	.025	.389
	B43	-.033	1.000	.233	.333	.342	.308	.289	.285	.194	.492
	D26	.034	.233	1.000	.424	.366	.365	.319	.317	.296	.594
	D28	-.002	.333	.424	1.000	.536	.489	.386	.406	.368	.669
	D30	.026	.342	.366	.536	1.000	.612	.544	.460	.307	.706
	D31	-.009	.308	.365	.489	.612	1.000	.525	.503	.336	.692
	D32	-.003	.289	.319	.386	.544	.525	1.000	.468	.276	.643
	D33	-.034	.285	.317	.406	.460	.503	.468	1.000	.346	.624
	D39	.025	.194	.296	.368	.307	.336	.276	.346	1.000	.561
	PU	.389	.492	.594	.669	.706	.692	.643	.624	.561	1.000

Source: Primary data

From table 2.2, it is clear that some of the factors considered showed a high level of correlation to the final output of perceived usefulness of internet while others had a low correlation value hence further dropped out. As a result, the factors inputs used were highly reliable in the computation of the final output for this specific factor.

Table 2.3 *Correlation matrix for perceived ease of use of internet technology*

Correlation Matrix[a]

		D34	B6	B7	B8	B31	B32	B33	B34	B35	PEOU
Correlation	D34	1.000	.138	.265	.245	.232	.123	.267	.252	.297	.507
	B6	.138	1.000	.435	.315	.183	.095	.215	.155	.177	.536
	B7	.265	.435	1.000	.506	.217	.189	.295	.224	.272	.627
	B8	.245	.315	.506	1.000	.297	.220	.242	.298	.278	.620
	B31	.232	.183	.217	.297	1.000	.379	.515	.482	.309	.647
	B32	.123	.095	.189	.220	.379	1.000	.444	.240	.264	.555
	B33	.267	.215	.295	.242	.515	.444	1.000	.557	.448	.709
	B34	.252	.155	.224	.298	.482	.240	.557	1.000	.540	.653
	B35	.297	.177	.272	.278	.309	.264	.448	.540	1.000	.633
	PEOU	.507	.536	.627	.620	.647	.555	.709	.653	.633	1.000

Source: Primary data

From table 2.3, it is clear that all the factors considered showed a high level of correlation to the final output of perceived usefulness of internet. As a result, these factor inputs were highly reliable in the computation of the final output for this specific factor.

While considering technology adoption within institutions, another model considered in section 2.3.2 was the Task Technology Fit (TTF) Model. This model takes into consideration the task to be accomplished and the technology available. In a situation where the technology available was used in undertaking a task, then, the technology was found to be useful and the individual performance improved. In this study, the task to be undertaken was the learning process and the technology to be used was internet technology. The use of internet technology in the learning process was examined by checking the different ways the learners needed to use the technology in order to perform better as shown in table 2.4.

***Table 2.4** Task-internet technology fit*

Tasks-internet technology fit	**n**	**Irrelevant**	**Not Sure**	**Relevant**
Source of updated academic information	747	6.4%	6.6%	87%
Access to learning materials through an e-learning portal/learning management system or to upload my assignment through the portal	747	7.9%	6.8%	85.3%
Exchange of ideas through chats/instant messaging platforms	747	9.5%	10.7%	79.8%
Email communication with lecturers	747	22.6%	5.4%	85.4%
Use other online tools (Instant Messenger, Facebook, etc.) to contact lecturers about my studies	747	18.7%	14.2%	67.1%
Email communication with classmates	747	12.4%	9.9%	77.6%
Blogs/websites for sharing academic ideas with other students	747	11.6%	11.6%	76.7%

Blogs/websites for sharing academic ideas with other internet users	747	16.7%	12.4%	70.8%
Access to other learning materials for example, you tube videos	747	8%	7.8%	84.2%
Avails news prompts on the recent happenings in academia and technology	747	6.8%	13.4%	79.8%
Source of free online courses that have assisted me in a variety of disciplines	747	10.3%	11.9%	77.8%
Search online for available part time job opportunities for students	747	10.4%	11.9%	77.6%
Collection of a variety of online information good for my studies, then organizing it in files to be retrieved when I want	747	7.9%	11.2%	80.9%

Source: Primary Data (2018)

This focused on the particular ways that the students used the resource in order for them to learn in a better way. In considering the use of internet technology in the acquisition of learning materials, 87% of the respondents confirmed that the technology provided them with updated academic information and 79.8% affirmed that the technology assisted them in accessing prompt and recent happenings in the academic field and the technology field. In accessing learning materials from an e-learning portal or a learning management system provided by the university, 85.3% of the respondents agreed that the portal assisted them in accessing learning materials and in uploading some of their class assignments. When considering the communication between lecturers and students in aid of the learning process, 85.4% of the respondents confirmed that they used email communication with their lecturers to request for assistance in learning and 67.1% of the respondents used other online tools (for example, instant messengers and chat forums) to contact their lecturers about their studies.

As far as exchanging academic ideas with their peers, 79.8% of the respondents confirmed that they exchanged learning ideas through chat forums and instant messaging platforms, 77.6% of the respondents used email communication with their classmates to exchange learning ideas, 76.7% used blogs and websites to share academic ideas with their classmates, 70.8% used blogs and websites to share academic ideas with other internet users and 84.2% accessed other learning materials (for instance, you tube videos) to accomplish their learning activities. With the provision of learning resources on internet technology, 77.8% affirmed that they accessed free online courses that assisted them greatly in a variety of disciplines and 80.9% of the students agreed that the technology assisted them in collection of a variety of online information useful for their studies. The technology also assisted them in organizing the information into files that they could always retrieve whenever they needed to. During their vacation breaks away from the university, 77.6% of the respondents agreed that they used internet technology to search for available part time job opportunities and they used the same technology to ensure that the work assignments were also accomplished.

Furthermore, after performing feature selection on the factors that affect the task-technology fit, further data analysis was done on the data obtained. This involved subjecting the factors obtained to factor analysis on the SPSS platform similar to what was done with task-technology fit. The results obtained are shown on table 2.5.

***Table 2.5** Correlation matrix for task-technology fit*

Correlation Matrix[a]

		D11	D12	D13	D14	D15	D16	D17	D18	D19	D20	D21	D22	D23	TTF
Correlation	D11	1.000	.533	.364	.310	.160	.309	.152	.104	.275	.304	.294	.238	.339	.521
	D12	.533	1.000	.331	.374	.182	.231	.242	.216	.234	.317	.387	.342	.335	.568
	D13	.364	.331	1.000	.393	.478	.280	.410	.385	.326	.398	.316	.292	.341	.655
	D14	.310	.374	.393	1.000	.328	.408	.315	.324	.238	.323	.377	.280	.347	.614
	D15	.160	.182	.478	.328	1.000	.304	.400	.358	.236	.288	.312	.318	.331	.603
	D16	.309	.231	.280	.408	.304	1.000	.430	.404	.177	.247	.335	.218	.316	.580
	D17	.152	.242	.410	.315	.400	.430	1.000	.633	.343	.327	.399	.366	.358	.673
	D18	.104	.216	.385	.324	.358	.404	.633	1.000	.360	.381	.376	.344	.329	.655
	D19	.275	.234	.326	.238	.236	.177	.343	.360	1.000	.452	.378	.384	.388	.581
	D20	.304	.317	.398	.323	.288	.247	.327	.381	.452	1.000	.475	.410	.422	.648
	D21	.294	.387	.316	.377	.312	.335	.399	.376	.378	.475	1.000	.509	.515	.697
	D22	.238	.342	.292	.280	.318	.218	.366	.344	.384	.410	.509	1.000	.511	.643
	D23	.339	.335	.341	.347	.331	.316	.358	.329	.388	.422	.515	.511	1.000	.676
	TTF	.521	.568	.655	.614	.603	.580	.673	.655	.581	.648	.697	.643	.676	1.000

Source: Primary data

From table 2.5, it is clear that all the factors considered showed a high level of correlation to the final output of task-technology fit of the internet. As a result, these factor inputs were highly reliable in the computation of the final output for this specific factor.

Given the findings above, it is worth noting that the results confirm the technology acceptance model (TAM) and the task technology fit model (TTF). In TAM, it was evident that, since the students found internet technology useful in their studies, they accomplished more in their learning process and they consequently performed better in their academics. This was affirmed by their view that the use of the technology had enhanced the quality of output in their academic work and led to increased productivity in their learning process. The students also confirmed that they found internet technology pleasant, enjoyable and easy to use in their learning process. This perception therefore led to a better learning experience for the students, leading them to perform even better in their studies. On the other hand, the TTF model showed that the students managed to use internet technology to accomplish the tasks assigned to them. The students managed to use the technology to retrieve learning materials required in their studies, consulted with their instructors and shared learning resources with their peers. Therefore, the technology assisted them to achieve their learning objectives and hence perform better.

2.8 Chapter Conclusion

Internet technology adoption in the learning process has been a process that has been characterised by changes in the education sector. The evolution of the learning environment has seen a tremendous change in the delivery of class lectures by use of internet technology, hence accommodating more students in the learning process. The technology adoption theories revealed that users of a technology are affected by a series of factors before they adopt the use of a given technology. Most precisely, the learners need to perceive the technology as useful, easy to use and relevant in fulfilling their ordinary day-to-day learning activities.

In order for a technology to be adopted and used appropriately, there is need to examine the behaviour of the users of the technology. Based on the behaviourist learning theory and the cognitive information processing theory, individuals are able to learn how to use a technology within their environment based on the actions they observe from their environment. Based on an individual's cognitive abilities, students are allowed to input information available in their environment, process the information and finally achieve an output which is mainly in the form of their capabilities.

Finally, in view of the adoption of internet technology, literature revealed that the adoption of internet technology takes an approach similar to the adoption of any other technology. This is characterised by different stages until all users of the technology are comfortable with its use. In the institutions of higher learning, policy frameworks exist in the implementation of the technology around the country. The adoption of internet technology in the learning process is seen to have a great influence on the performance of students. Students identify internet technology as easy to use, useful in the learning process and relevant in their studies.

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Chapter 3: Internet Technology Utilization and Student Behavioral Patterns in Learning

3.1 Introduction

This chapter discusses the theory of utilization, specifically the Cobb-Douglas production theorem and its utility function. It offers an analysis on the influence of internet utilization in the learning process. Highlights on existing student behavioral patterns and the student learning patterns are also discussed. The concept of identification of patterns in the learning process has also been examined with a particular focus on analysis of these patterns.

3.2 Cobb-Douglas Theorem and the Concept of Utilization

This section discusses the Cobb-Douglas production theorem and the concept of utilization that are used to explain the production process.

3.2.1 Cobb-Douglas Theorem

The Cobb-Douglas production theorem is an econometrics theorem that focuses on the production process where different inputs in the production process generate outputs in the form of goods and services. Since the production process involves the use of inputs in order to get an output, there is need to understand the right input variables.

According to Rodrigues (2004), the production function is a scientific illustration that is used to represent different factors that are used in the production process. The proper usage of the production function involves the determination of the factors of production in a system. These factors of production may be the resources that are used in the production of goods and services. In general, the production function is written as

$$Q = f(L, K) \qquad [3.1]$$

where ***Q*** is the quantity produced, ***L*** is the amount of labour required in the production process and ***K*** is the capital required to produce the goods.

From equation 3.1, the amount of goods produced solely depends on the quantities of labour and capital used. Equation 3.1 therefore gives the relationship between input variables denoted by $\boldsymbol{f}\ (\boldsymbol{L}, \boldsymbol{K})$ and the output variable denoted by $\boldsymbol{Q}$ generated from the entire process (Rasmussen, 2013). The inputs are the resources that are combined together to produce the finished products, for example, land, capital and raw materials. Outputs describe the quantities of goods produced by the firm. Thus, the production function may be used by institutions to determine the quantity of output to be produced with a corresponding quantity of inputs used in the production process.

Another way to understand the application of the production function is to look at the cost of production in a system or a firm. The desire of any institution is to maximise the marginal revenue while minimising the marginal costs of production. To minimise the marginal costs, the focus should be on minimising the input variables and fixed costs. On the other hand, to maximise the marginal revenue, the cost incurred in the production process must be at the minimum level. Therefore, the desirable levels of the production function will be achieved when the marginal revenues are higher compared to the marginal costs of production. Otherwise, an equilibrium state may be attained when the marginal revenue equals the marginal production costs.

In the recent past, technology has been seen as one of the key input factors in production (Caves & Barton, 2010). The technological improvement is seen to have a direct and better shift in the production process of an institution, hence influencing the production costs and the marginal revenue of the firm.

From equation 3.1, the production costs are represented by production variables denoted by $\boldsymbol{L}$ (that is, the amount of labour required in the production process) and $\boldsymbol{K}$ (that is, the capital required to produce the good). Therefore, in an ideal situation, $Marginal\ revenue\ (Q) > Marginal\ costs\ (f\ (L, K))$. This means that if $Q > f(L, K)$ then, the production function has decreasing marginal costs and increasing returns. However, when $Marginal\ revenue\ (Q) < Marginal\ costs\ (f\ (L, K))$ then, the production function has increasing marginal costs and decreasing returns. Correspondingly, if $Q = f(L, K)$ then the production function has constant returns (Shekhat, 2004).

In modelling library services using the Cobb-Douglas production function, Hayes (2005) considers demand for the services to be an output variable while staff and capital investment are considered as input variables. The presumption in this study is that increased staff and capital investments are always required to cater for increasing demand in the library services. The focus in this case is to have optimum allocation of the input variables involved in the provision of the library services.

In other applications in different scenarios, Cobb-Douglas production function has been modelled to take other different forms. These forms include the Leontief production function and the linear production function (Miller, 2008). The Leontief production function relates to the production processes where inputs are used in fixed proportions. It assumes that, if the use of one factor input is increased and the other factor is not increased, outputs produced do not change. This presents an extreme case in the production process and hence cannot be used in modeling the output expected from a series of inputs in production of services. The Leontief production function is given by

$$Q = \min \ (aK, bL) \quad where \quad a, b > 0 \ \ldots\ldots\ldots \ [3.2]$$

where $\boldsymbol{Q}$ is the quantity of output, $\boldsymbol{K}$ is the amount of capital and $\boldsymbol{L}$ is the amount of labor used in production and $\boldsymbol{a}$, $\boldsymbol{b}$ are scaling parameters.

Figure 3.1 illustrates the Leontief production functions where the isoquants are L-shaped.

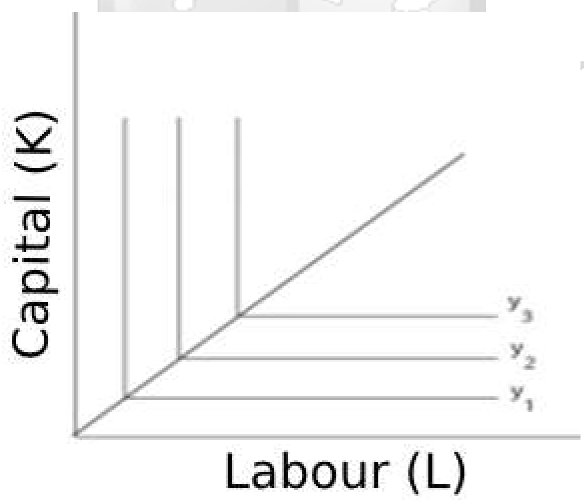

Figure 3.1 *Leontief production function curve (Adopted from Miller (2008))*

From figure 3.1, the percentage change in a factor input (also called elasticity of substitution) denoted by σ is as a result of change in the marginal rate of technical substitution (MRTS). MRTS measures the percentage rate of change when labour is substituted with capital while holding the total quantity produced as a constant on the isoquant. Hence, σ is calculated as

$$\sigma = \frac{\%\ \Delta\,(\mathrm{K/L})}{\%\ \Delta\ MRTS} = \left[\frac{d(K/L)}{dMRTS}\right] * \left[\frac{MRTS}{(K/L)}\right] = \frac{\delta \ln(K/L)}{\delta\, MRTS} \quad \text{[3.3]}$$

where σ the elasticity of substitution measures the marginal returns as one of the inputs increases relative to the other input (Nelson, 1964).

Minimal or negligible changes in the elasticity of substitution leads to minimal or negligible changes in the MRTS hence minimal or negligible changes in the factors of production. Therefore, in figure 3.1, $\sigma = 0$ since, changes in MRTS does not have any effect on the factors of production and maximum output is achieved when the inputs are used in fixed proportions. The elasticity of substitution, σ in the generation of products or services is used to determine the ease with which one factor input can be shifted with another input, specifically for labour and capital. In this research, σ was used in section 5.4.4 to represent the MRTS when institutional investment and student effort were substituted with each other in the process of predicting student performance with the utilization of internet technology.

The linear production function assumes that for every single unit of input used, a firm produces a single output. Hence, the output increases proportionally to increase in inputs. In this case, labour and capital are perfect substitutes to each other. The linear production function is therefore given by

$$Q = aK + bL \quad \text{[3.4]}$$

where ***Q*** is the quantity of output, ***K*** is the amount of capital, and ***L*** is the amount of labor used in production, ***a*** and ***b*** are constants. Figure 3.2 illustrates the case of a linear production function where the isoquants are straight lines. Applying equation 3.4 into the linear production function in figure 3.2 gives $\sigma = \infty$.

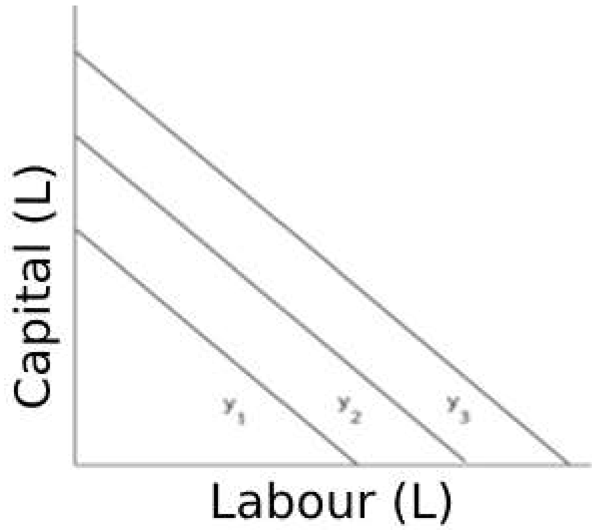

Figure 3.2 *Linear production function curve (Adopted from Miller (2008))*

In general, the Cobb-Douglas production function in all forms assumes that, for an output to be generated, the least total number of factor outputs needed should be relatively equal to the combination of the inputs. Thus, equation 3.1 can also be written as

$$Q = A \; K^{\alpha} \; L^{1-\alpha} \quad \text{...} [3.5]$$

where ***Q*** is the quantity of output, ***A*** is a constant parameter, ***K*** is the amount of capital, and ***L*** is the amount of labor and α determines the returns to scale on factor inputs. Equation 3.5 can graphically be represented as shown in figure 3.3. The isoquants in this case are slightly convex shaped and $\sigma = 1$.

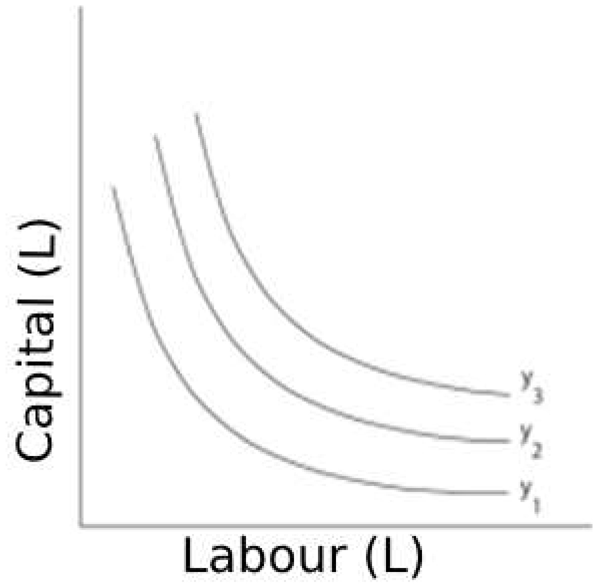

Figure 3.3 *Cobb-Douglas production function curves (Adopted from Miller (2008))*

In order to apply Cobb-Douglas production function in economics, various factors other than labour and capital can also be considered. Therefore, it is possible to remodel equation 3.5 as shown in equation 3.6 to capture more input factors in order to give more accurate results. This is shown as

$$P(L, K) = b\ L^{\alpha}\ K^{\beta} \quad \text{[3.6]}$$

where ***P*** can be used to represent the total monetary value of all the goods that are manufactured in a year, ***L*** is the total man-hours that are used in the year, ***K*** is the total value of all capital investments in the production process (buildings, machines, equipment), ***b*** is the total factor of productivity, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ represent the output elasticity of labour and capital respectively.

The parameters that measure the output elasticity in equation 3.6 ($\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$) are used to determine total change of the output to a change in the levels of capital and labour, assuming that all conditions are held constant. For instance, if $\boldsymbol{\alpha} = 0.15$, a 1% growth in the labour input would lead to a 0.15% growth in the output levels. Additionally, if $\boldsymbol{\alpha} + \boldsymbol{\beta} = 1$, then the production function has constant returns, meaning, if ***L*** and ***K*** inputs are each increased by 30%, then, the output ***P*** would also be increased by the same value, 30%. Hence, the returns to scale are used to determine the change in output followed by a proportional change in all inputs (assuming that input increases by a constant).

In general, the different values of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ lead to various return to scale scenarios. For instance, when output increases by less than the proportional change in inputs, this results in decreasing returns to scale, that is, if $\alpha + \beta < 1$, there are decreasing returns to scale. Similarly, when output increases by more than the proportional change in inputs, this results in increasing returns to scale, that is, $\alpha + \beta > 1$ there are increasing returns to scale.

Applying the Cobb-Douglas production function in this research, the performance of a student is considered as an output variable which is dependent on the utilization of internet technology in their learning process. The utilization of internet in learning is also dependent on a number of factors. These factors include capital investment made by the university on the internet technology deployment and the effectiveness of student effort in the utilization of the internet technology in the learning process. Student effort, in this case represents the labour component; where a student's decision to use internet technology, is influenced by their behavioral intention and their actions towards the technology. The other factor that has been considered is the effectiveness of the student effort which has been presented as the difference between two possible action strategies; a student's preference for one action as compared to their preference for another action. Therefore, the general form of the Cobb-Douglas function representing student performance given the input variables identified above can be given by

$$P_t = I_t^a (K_t E_t)^b \qquad [3.7]$$

where $\boldsymbol{P_t}$ is the student performance level at an instance in time **t**, $\boldsymbol{I_t^a}$ is the investment incurred, $\boldsymbol{K_t}$ is the effort expended by a student while using internet technology in the learning process and $\boldsymbol{E_t}$ is the effectiveness of student effort while using internet technology in the learning process for some arbitrary but fixed student investment cost $a \in (0, 1)$ and $b = 1 - a$. The application of equation 3.7 is discussed in section 5.4.4.

3.2.2 Cobb-Douglas Utility Function

The Cobb-Douglas utility function is an important concept that assist in understanding how the demand for a given resource is dependent on the ability of its user to utilise a resource based on a given budget. This specifically checks on the income level of the user and the different prices presented on the given resource. In this case, there are two input variables being considered, that is, (x, y). The prices of the input variables are captured as (p_x, p_y).

The Cobb-Douglas utility function is derived from the general form of a utility function denoted by $U(x, y)$ with two variables $\boldsymbol{x}$ and $\boldsymbol{y}$. It is given by

$$U(x, y) = x^a \; y^{1-a} \quad [3.8]$$

where $a \in (0, 1)$ is a scaling constant parameter.

The desire is to maximize the utility function in order to get

$$U = U(x, y) \quad [3.9]$$

subject to the existing constraints

$$B = p_x x + p_y y \quad [3.10]$$

Unless there is a corner solution (where one of the variables may be considered and not the other), the solution to the maximization problem will occur where the highest indifference curve is tangent to the constraint equation given by equation 3.10. Therefore, the marginal rate of substitution (MRS) in the case of goods equals the price ratio given by

$$MRS = \frac{p_x}{p_y} \quad [3.11]$$

This rule when combined with the constraint gives the solution to the utility maximization problem.

For instance, if the utility function is

$$U = x\,y \quad [3.12]$$

then

$$MRS = \frac{y}{x} \quad [3.13]$$

Similarly, considering a special case of the Cobb-Douglas utility function, equation 3.12 will take the form

$$U = x^a y^b \qquad [3.14]$$

where $\boldsymbol{a}$, $\boldsymbol{b}$ represent constants. In this case therefore, the MRS for the Cobb-Douglas utility function is given by

$$MRS = \left(\frac{a}{b}\right)\left(\frac{y}{x}\right) = \left(\frac{ay}{bx}\right) \qquad [3.15]$$

regardless of the values of a, b.

In using the general form of Cobb-Douglas as given in equation 3.14, MRS as given in equation 3.15, the constraint as given in equation 3.10 and the price ratio p_x/p_y, then utility maximization yields

$$MRS = \frac{p_x}{p_y}$$

$$\frac{ay}{bx} = \frac{p_x}{p_y}$$

$$y = \frac{b}{a}\frac{p_x}{p_y}x \qquad [3.16]$$

Substituting into the constraint gives:

$$B = p_x x + p_y\left(\frac{b}{a}\frac{p_x}{p_y}x\right)$$

$$B = p_x x + \frac{b}{a}p_x x$$

$$B = \left(\frac{a+b}{a}\right)p_x x \qquad [3.17]$$

Using $\boldsymbol{x}$ as the subject gives,

$$x = \left(\frac{a}{a+b}\right)\frac{B}{p_x} \qquad [3.18]$$

In a similar way, $\boldsymbol{y}$ can be given as,

$$y = \left(\frac{b}{b+a}\right)\frac{B}{p_y} \qquad [3.19]$$

The solution of $\boldsymbol{x}$ and $\boldsymbol{y}$ are called the consumers demand functions.

3.3 Influence of Internet Technology Utilization in Learning

The presence of internet technology in the learning environment has positively contributed to a better learning experience within the universities. Internet technology is a useful tool which has been adopted specifically in the education sector where it is being used to improve the learning experience of students (Shivaraj et al., 2013). The technology offers more information than the largest libraries in the world and as a result, it has become an essential part in many educational institutions. Specifically, as seen earlier, internet technology plays a vital role in meeting information and communication needs of students, teachers and institutions.

In the field of education, the technology has assisted educators as a great tool for use in learning. Internet technology is used to connect students in disparate countries and allows them to share ideas that improve their learning experience (Sharma & Maleyeff, 2013). The technology seems to be a virtually perfect instrument for learning that offers convenience to students while offering endless possibilities to innovative learning. The internet reaches non-traditional students, provides interaction with industry experts, and seems to provide a self-paced, convenient learning environment.

The emergence of the internet, particularly the World Wide Web, as a new medium of information storage and delivery represents a revolution, which has contributed to a lasting impact on the publishing and information delivery system in the 21st Century. It is highly effective and efficient in providing instant and comprehensive access to users at their end, irrespective of time and space. The internet is relatively fast, it is readily accessible and any one can use it from where they want (Shivaraj et al., 2013).

There are various ways that have been specifically highlighted as far as the utilization of internet technology is concerned. These include utilization of the technology in classroom instruction, its utilization on the e-learning platforms, its use in social software that aid in the learning process, as well as in the learning management systems found in different universities.

3.3.1 Classroom Instruction

The use of internet technology in classroom instruction has become the norm all around the world. It has not only allowed learners to access and connect to their peers, but it has ensured that they are part of a larger and more diverse culture. University students use the internet resource on a daily routine basis since they have grown up with computers. They are therefore early adopters and heavy users of the internet compared to the greater general population. Consequently, the internet has become an ordinary technology and its use in the daily learning experiences of students cannot be ignored (Molnar and Fields, 2014).

The rapid growth rate experienced in internet technology has brought about the era of distributed learning and numerous electronic databases. This has led to the advent of online learning, which has in return revolutionised classroom experiences (Courville, 2011; Galloway, 2015). Academics are constantly urged to utilize internet technology in their daily class activities since the resource holds an incomprehensible depth and breadth of information. It provides a vast set of resources both for the students and the teachers. The lecturers can learn from the experiences of other colleagues in a different part of the globe, which enhances many aspects of knowledge sharing, hence creating a collegiate collaboration via the internet.

The internet allows for growth in the learning experience by providing a means to teach better and reach many students. This replaces the traditional approaches to course delivery. Learning is maximised by the use of the technology, resulting in increase in the content learnt and increase in the quality of learning. Internet instruction provides more motivation with efficient and interesting ways of knowledge dissemination since it integrates the use of media, text, audio, graphics and videos. The instructional materials provide an inter-link among the different subject areas and institutions.

An effective approach in teaching using internet technology involves a number of processes: orientation, inspiration, exhibition, explanation, amplification, consolidation and verification. During the orientation stage, the student is introduced to the content aligned to what they need to capture during their study period. At inspiration stage, the student is motivated to embrace the learning approach introduced and is also encouraged to be creative in the learning process. In this stage, the use of multimedia and images from the internet has been seen to be very helpful. At exhibition stage, the content is presented to the student in a way that helps the student to grasp a few ideologies. At the explanation stage, the instructor steps in to clarify whatever challenges the student faces in order to help the student get some enlightenment in the content provided. During amplification, the student is presented with expounded knowledge on the subject matter to assist them acquire a deeper understanding of the subject. The use of web-based images and diagrams assists the students in gaining a better understanding of the concepts. At the consolidation stage, all the knowledge acquired in the previous stages is linked together and presented as one body of knowledge to the student. Finally, at verification stage, the knowledge acquired is confirmed for the student's and learning takes place at this moment. This is the point when an online assessment can be administered with immediate feedback to gauge the understanding levels of the students. This also involves the use of web-based simulations and tests that can help in the confirmation of the knowledge acquired in the course (Molnar & Fields, 2014). Though the stages discussed apply to classroom instruction on the internet, it is advisable that the student learning process be improved, complemented or extended using a variety of resources on the internet.

Instructors embrace the use of e-mails and messaging applications as they aim at sharing the course objectives and learning outcomes. E-mail communication is used to assist in course progress management by explaining more regarding tasks given in class, emphasizing instructions given earlier on or sharing more course materials. The use of e-mail in class instruction has been seen as a way of ensuring that students remain focused on the course objectives and obligations.

The learning process embraced by students improves and gets complemented through the use of internet technology. The students benefit from exercises and online participatory forums that consolidate learning. Web-based simulations and tests in different disciplines provide insights and valuable knowledge that are not achievable on any other platform. They also give instant feedback on the provided set of data (Molnar & Fields, 2014). E-mail messages sent by lecturers to their students help in increasing communication platforms in the learning process beyond lecture hours.

Internet technology provides an effective teaching and learning tool by enhancing the student learning experience through innovation. The learning process becomes an empowered, active, self-formulated and self-constructed set of steps in which the student secures ideas and concepts based on existing knowledge. A study by Gebre et al. (2014) affirms that the cognitive ability and social engagement of students who have used the technology as part of their classroom instruction is always significantly higher than that of students where the internet was not part of their instruction. The embrace of internet technology in the learning process of students always leads to students who are better and more effectively taught. The use of internet in science, mathematics, engineering and technology disciplines has led to a better understanding of the scientific procedures involved in the other disciplines (Hegedus & Roschelle, 2013; Rutten et al., 2012).

3.3.2 E-Learning Platforms

E-learning platforms refer to learning environments that are enabled and aided through the use of information and communications technologies (ICTs). E-learning also refers to electronically facilitated asynchronous and synchronous communication that aids in the creation and sanctioning of knowledge. This kind of learning has naturally evolved from the distance learning approach to education, and has helped in the restructuring of the education sector (Garrison, 2011; Sangrà et al., 2012). Learning on the e-learning platform encompasses the use of internet technology to provide a varied set of solutions aimed at enhancing knowledge and performance capabilities. E-learning is categorised into synchronous and asynchronous learning. In synchronous learning, both the lecturer and the students are present at the same time while in asynchronous learning, the lecturer and the student need not be present at the same time. The nature of this kind of instruction is dependent on the most suitable approach that fits the students and the lecturer. Learning materials are also available at any time and the student can study at their own pace and time (McCann et al., 2010).

E-learning, also referred to as web-based learning or online learning, is characterised by universal accessibility, the simplicity of editing and updating available content and ease in getting cross-referenced material from a variety of sources. This naturally inclines the students to prefer web-based learning due to flexibility in accessibility of the materials, ease of use of the materials, the advantage of different available practice platforms and freedom in the navigation across different platforms.

According to Ruiz et al. (2006), the use of the e-learning platform in the learning process has a great number of advantages. E-learning offers an immense opportunity for increased learning by turning the learning experience into a personalised set of experiences; the learner learns what they need to learn. The dynamism of the e-learning platform through interactions maintains a high level of interest in the materials provided by ensuring sufficient practice, which enhances the learning experience. Moreover, the ease of access to course materials, making them available anytime and anywhere, leads to a more personalised approach to course instruction. The lecturers can also update the materials provided with ease and they can also distribute them to students with great ease. They are in a position to regulate their content and provide a systematic way of learning for the students. As a result, the instructors facilitate learning and assess the competence of the learners.

Evolution in the field of education has led to a change in the approach to the learning experience of students. Curriculum that has been developed for courses needs to be delivered in a way that meets the needs of the learner with different learning approaches. The student owns the learning process when they feel that they learn most outside class and they can control their own education. E-learning has enhanced better interaction between faculty, learners and peers from around the globe (Divaris et al., 2008). It is also more appealing to learners due to the available graphics, multimedia materials and upgrades in the platform software. Hence, more dynamic information is availed and the possibility of passive content is minimised.

With the introduction of new technologies in the education sector, ICT and e-learning have led to the advent of another form of learning: blended learning. Blended learning is a form of learning that aims at a thoughtful combination of the online learning experiences and face-to-face learning (Garrison & Vaughan, 2008; Balci & Soran, 2009). This form of learning has assisted in revolutionizing the traditional learning experiences that seem not to work for the students in the present day. The learning resources available have been tailored to take care of the unique experiences of individual learners. This mainly includes the flexibility in the time frames involved in the learning process which mainly ensures that learning takes place at the students pace. Research in Kenyan universities shows that many of the institutions have not effectively embraced the use of technology in supporting their teaching, learning and assessment spheres (Manduku et al., 2012). Furthermore, the minimal use of blended learning in these institutions has been due to the fact that there exists inadequate e-learning skills and absence of the technological support infrastructure in these institutions.

The benefits of using e-learning in the student learning process remain unmatched. The students learn how to take personal liability in their learning process by building their knowledge base and self-confidence. The adoption and use of e-learning also ensures that students cooperate with each other in the learning process, motivate one another to keep learning together and ensure that information and other resources are well shared amongst themselves. As a result, they achieve deep learning experiences (Takalani, 2008; Khan et al., 2012).

In the education sector, e-learning is becoming a common approach to the learning process in many universities in the world. This is due to the ease with which learners can now combine the knowledge they have gained in class with the advances that information and communication technologies (ICTs) are offering them. Institutions of higher learning are adopting the use of ICTs and utilising the technologies to ensure that they have access to the best available tools that can help in the universal access to course materials (Wanjala et al., 2011; Khan et al., 2012). Indeed e-learning has played a leading role in the changes being seen in the education sector (Ariwa & Rui, 2005; Bates, 2012).

The adoption and use of the e-learning platform in the education sector provides developing countries with the competence required to become a knowledge economy. It is also being seen as a cost effective method of ensuring that learning for large groups can be actualised using ICT (Berhanu, 2010). According to Tarus et al. (2015), the use of e-learning is cost effective, easily accessible and flexible in terms of time and place. The learning process is never restricted to the time and place where the student and the lecturer are available, hence convenience is always well achieved. Other significant benefits of the use of e-learning as adapted and summarised by Unwin (2008) include: ease of access to information; great possibility in the interactions between students and instructors; location of learning and access to information spans remote areas to the entire world; the learning materials available are timely and reliable and can be re-used; it combines both live interactions in learning and the possibility of access to educational materials when not in the class environment; learning takes place at the student's pace, hence lowering the cost of accessing educational resources; the e-learning solutions are highly scalable; the management of students' learning records and progress records is done effectively.

3.3.3 Blogs, Wikis and Social Networks

With the dawning of the use of blogs, wikis and social networks (social software) in the learning process, educators are realising that there is need to enhance some level of interaction between the different students who participate in their classes. Research shows that the presence of these platforms enhances student-student and teacher-student interactions. The use of social software applications has been on the increase in higher learning institutions (Halic et al., 2010; Top, 2012; Shana & Abulibdehb, 2015). These software applications are helping students to learn together through collaborations, peer-to-peer learning and cooperation by pooling all of them in groups (Kang et al., 2013; Avci & Askar, 2012; Junco, 2015; Koç & Koç, 2016). In these software applications, students are free to share text, audio files, video files and multimedia images (Papastergiou, et al., 2011). Sharing of information resources is also made possible and the various participants contribute to a given topic, allowing a variety of opinions and hence enriching the entire learning process (Conole & Culver, 2010). In this environment, the sharing of information and the collaborations on different topics are all aimed at improving the learning experience of the student (Top, 2012). As a result, students can define their own learning path, regarding their reading and their research work.

Web 2.0 technologies are also called social software tools. These include the use of Facebook, podcast, Flickr, blogs and RSS feeds in the learning process. These internet services encourage internet users, especially students, to participate in the learning process by suggesting ways of building knowledge and sharing it with others. This ends up encouraging students to learn together and the feedback received from the forum creates a great sense of communal learning, hence enhancing student motivation (Avci & Askar, 2012). Web literacy has encouraged students to improve their individual skills as they can get feedback from a wide range of users on these particular communities.

A weblog or a blog is an online journal or an online space where the author can post information on various topics and can edit the information, making the content available to members of the public without need for any web programming or web design knowledge (Papastergiou, 2011). The readers of the information are free to comment on what they have read and they can give a personal opinion on it. The interactive conversation available on blogs is provided by use of internet technology (Sim & Hew, 2010; Kresser et al., 2012). Blogs are better and very different from the traditional classrooms since they offer the users an opportunity to assimilate other members' opinions and engage in open discussions on a topic of interest (Koç & Koç, 2016).

The wide-ranging use of social software applications and tools in the learning process has led to a great sense of community on the internet. The Web 2.0 technology activists find significant value in the education related activities promoted on these applications. Most importantly, the participants share their experiences and accept the comments given (Kang et al., 2011). Blogs and social networking sites have the potential to enhance positive interactions between participants and also ensure that meaningful discussions take place (Pi et al., 2010).

The extensive use of social software in education creates a significant learning atmosphere that caters for the different needs of the learners through giving proper direction to the students and real-world experiences, resulting in student-centred learning. The blogs facilitate collaborative environments, critical thinking and reflection-oriented learning experiences which results in positive learning experiences among the students similar to a class environment (Park et al., 2011; Top, 2012; Li et al., 2013; Kiliç, & Gökdaş, 2014). This approach has been seen to improve the academic performances of students who prefer to learn in groups rather than individually when away from a class environment (Laal & Laal, 2012; Chang & Chang, 2014). They have also been used to increase the spirit of motivation in students in a specific area within specific subjects, especially in challenging topics (Pursel & Xie, 2014; Shana & Abulibdehb, 2015).

The use of social software in learning has been termed as an effective means of transmitting knowledge in the learning process (Koç & Koç, 2016). Fessakis et al. (2008) confirmed that students feel that the online environment gives them a great chance to exchange ideas in depth, which would actually not be possible in a normal class environment. Due to the availability of the internet, students are in a position to carry on a discussion that was left unfinished in a class environment, which acts as a way of challenging them to read more even beyond the class time. Park et al. (2011) argued that social software was only effective when the topics, knowledge and ideas being discussed fell within an area of interest to the students. This was due to the fact that, the users of these applications preferred to use available information in learning as a knowledge acquisition and reflection based process. It was also notable that the software tools enabled students to deal with the information differently from each other.

Due to the collaborative nature of the social software applications, students and other participants involved were in a position to monitor the contributions of other people on a given topic, spend less time trying to figure out an existing challenge and communicate with each other in a more direct way. This leads to better collaboration on ideas, better understanding of a learning outcome and individual responsibility in the learning process. Students perceive the use of social software in the learning and teaching process as a benefiting factor. They posit that the access to data on these applications is easier for them, they benefit from a guided reflection process and the peer interactions ensure timely feedback and equal access to information (Avcı & Aşkar, 2011).

The use of social software in the learning process has also been faced with a number of limitations in the learning process. In some situations, it was not possible to tell the prior abilities of the participants who gave feedback on a subject area. Consequently, a straight conclusion could also be made that learning actually took place in this environment (Hew & Cheung, 2013).

3.3.4 Learning Management Systems

In higher learning institutions, the use of Learning Management Systems (LMSs) (for example, Moodle, Blackboard, Web CT, Claroline, ATutor) has become very popular due to their support for blended learning, distance learning and face-to-face learning processes (Dahlstrom et al., 2014). LMSs offer an internet-based learning platform that facilitates different areas in the management of courses: administration, delivery, follow-up on learning, assessments, communication, registration process of students and planning purposes. They offer great value to institutions by ensuring that their content is well sequenced and the instructors can create their own course structures. According to Gautreau (2011), LMSs can be defined as "a self-contained webpage with embedded instructional tools that permit faculty to organise academic content and engage students in their learning".

This approach to learning provides an online portal where students and lecturers connect off the classroom. It also acts as an avenue for sharing course materials very easily. Due to the availability of internet technology in the universities, the exchange of ideas among peers is possible around the campus environment, in the halls of residence and in the homes. The learning experience common at university level is a two way process: sharing of knowledge with lecturers and students are allowed to contribute by sharing their opinions and thoughts. As a result, the search for more knowledge becomes almost inevitable (Adzharuddin & Ling, 2013). LMSs provide a faster way of communication among teachers and students and as a result, ensure speed and efficiency in educational processes. This can be done effectively by embracing the use of synchronous functionalities of LMSs, for example, chats and online discussions (Hustad & Arntzen, 2013). In this research, the use of LMSs was considered by specifically checking how students utilized internet technology in enhancing their learning process, both within class environments and outside the classroom setups. This partially contributed to the parameters that were used in the generation of the student behavioural patterns.

The core functionalities of Learning Management Systems (LMSs) that support teaching and learning services revolve around course administration, dialogues and discussions, lecture materials, assignment and homework templates, online forums, content uploading, presentation uploads, course assessments and grading of participants. The evolution that has taken place in the world of LMSs has made sure that the learning content is presented in a better way, as it incorporates the use of technology and interaction possibilities (Freire et al., 2012). The usability of LMSs especially focuses on the interfaces and the functionalities developed. Research has shown that not all the developed functionalities are used by the users of the systems and some functions are used more than others (Jaschik & Lederman, 2014,).

In some cases, for example, Blackboard LMSs, the most frequently used functionalities are content uploads, assignment templates and grading applications. This challenge was mainly due to system problems and design flaws (Fathema & Sutton, 2013). Other challenges that have been faced in the implementation and use of LMSs in many institutions include organisational barriers (for example, internet accessibility challenges, inadequate training on use of the resources capped with non-existing institutional policy to support the use of the resource, unavailability of technical, hardware and software support) and personal barriers in faculty members (for example, lack of interest and lack of skills in using the technology) (Holden & Rada, 2011). On the other hand, students are also a major player in the use of the LMSs. They affirm that the resource plays a major role in their studies since it is useful in accessing information. The perceived usefulness, perceived enjoyment and perceived ease of use of the LMSs have greatly contributed to the acceptance and use of the internet-based learning technology by students (Lee et al., 2013).

3.4 Student Behavioural Patterns in Learning

This section highlights the formulation of human behaviour and what affects a specific human behaviour. It then examines the existing student behavioural patterns as seen in different individual students.

3.4.1 The Theory of Reasoned Action

The Theory of Reasoned Action (TRA) primarily focuses on user behaviour that can be seen outwardly and how that behaviour tends to control the individual (Armitage & Conner, 2001). The theory states that any human behaviour is a function of two parameters; their attitude and their subjective norm. TRA works with the assumption that human beings are rational thinkers in nature and they tend to make maximum use of the information available to them. The theory is built on the fact that a behaviour is a free personal choice based on individual preferences. Hence, the use of the TRA framework assists in understanding the behaviour of an individual. Researchers have affirmed the simplicity of using the TRA framework by adding external factors that have assisted over time in the test of behaviour in different environments (Trafimow & Lench, 2015). The same approach of using the external factors was used in this case in order to establish the behaviour of students while using internet technology in the learning process.

According to the TRA framework, an individual's behavioural intention (BN) is the most predominant feature in predicting a person's specific behaviour (B). BN is then directly affected by two major independent factors: the individual's attitude towards the behaviour (IAtt) and the subjective norm (SM). When both parameters are positive, the individual has a more positive intention to use a technology and hence has a specific behaviour. Therefore, the individual performs a behaviour that is acceptable. Research has proven that the major factors that influence the behavioural intention are attitude and subjective norm. Although there may be other factors that influence behaviour, these have only been seen as influencing and indirectly mediating IAtt and the SM. Ajzen and Fishbein (1980) proposed the fundamental relationship of the two variables as shown in equation 3.21. This defines the relationship between the different variables in defining a specific behaviour:

$$B = BN = f((IAtt\ (\omega 1)) + (SM\ (\omega 2)) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3.21]$$

where B represents the specific behaviour, BN is an individual's behavioural intention, $IAtt$ is the individuals attitude towards a specific behaviour, SM is the subjective norm defining if a person want to engage in a specific behaviour and $\omega 1$ and $\omega 2$ represent the relative influence of IAtt and SM on BN. TRA as proposed by Ajzen and Fishbein (1980) was used in this study to assist in understanding how external factors (attitude and behavioural intention) directly influence a student in the use of internet technology in their studies. It is therefore necessary to examine each of the factors that are considered in the equation 3.21.

The specific behaviour of an individual refers to the observable actions of a person that rightfully describe the person. This definition has remained consistent over the years and hence confirms its validity when using the TRA. A specific individual behaviour is additionally defined as a specific use situation, for instance, a student using internet technology in their studies could use the technology for research or for communication. These different types of behaviours occur in different situations and at specific times (Ajzen, 1991).

The behavioural intention of an individual to engage in a specific behaviour, as defined by Fishbein & Ajzen (1975), refers to the individual's position on a subjective possibility involving the relationship between himself and the action. As a result, an individual's behavioural intention defines the probability that the individual will perform a certain behaviour. Therefore, there exists a great correlation between people's behavioural intentions (BN) and their specific behaviours (B). Specifically, BN provides a relative weight by intervening between B and the predicting variables (IAtt and SM). A positive BN that is computed based on IAtt and SM infers a strong specific behaviour, B of the individual at hand (Arvola et al., 2008).

An individual's attitude towards a specific behaviour is defined as a person's feeling of favourableness or unfavourableness towards some stimuli (Fishbein & Ajzen, 1975). An individual's attitude is composed of three different attributes. Firstly, a person's belief (pb) that their specific behaviour will lead to an anticipated result. Secondly, the estimation of this anticipated result (er) and finally, the number of beliefs (nb) held in performing the specific behaviour. The TRA therefore infers that, the attitude of an individual (IAtt) directly affects how a person views a specific behaviour as being favourable or not. It is also worth noting that the attitude of an individual towards a specific behaviour may not be similar to their attitude towards a certain stimulus. Hence, equation 3.22 shows the formulation of an individual's attitude, IAtt as

$$IAtt = \sum_{i=1}^{n} pber \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad [3.22]$$

where $\boldsymbol{IAtt}$ is the individuals attitude, ***pb*** is the persons belief, ***er*** is the estimation of the anticipated result and ***n*** are the number of beliefs in a specific behaviour.

The subjective norm (SM) refers to an individual's view that people who are important to them think they should perform a specific behaviour. This variable is influenced by the perceived beliefs of other people (pdb), the inspiration to go for this beliefs (ib) and perform the specific behaviour and the number of the groups influencing the behaviour at hand (m). Hence, equation 3.23 shows how the subjective norm can be computed in individual cases:

$$SM = \sum_{j=1}^{m} pdb \;\; ib \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad [3.23]$$

where ***SM*** is the subjective norm, ***pdb*** are the perceived beliefs of other people, ***ib*** is the inspiration for the belief and ***m*** are the number of groups influencing the behaviour.

The Theory of Reasoned Action can thus be diagrammatically represented as shown in figure 3.4.

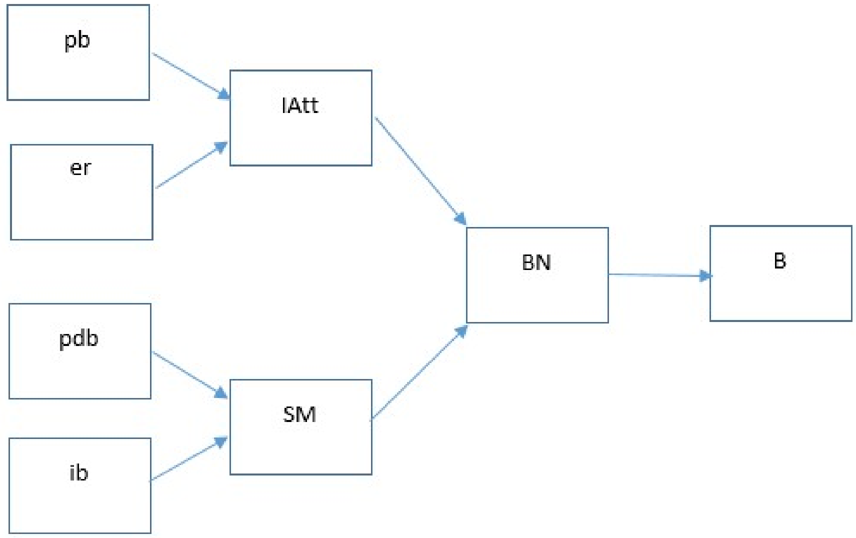

Figure 3.4 *Theory of Reasoned Action*

3.4.2 Student Behavioural Patterns

Student behavioural patterns are described as the mannerisms and actions seen in an individual student. Behaviour, as seen in 3.4.1, refers to the different ways in which a person acts and conducts themselves. Behaviour is observed in the way an individual acts towards other people or towards society in general (Watson, 2018). The behaviour of an individual depends on the identity of the person, the motivation that drives the individual to act in a certain way and their cognitive ability in their way of acting (Bergner, 2011). In cases where behaviour is objectively observed and the behaviour is independent of what the mind does, the concept of Behavioural Psychology or behaviourism is introduced. Behaviourism considers the visible reactions to stimulus and affirms that all behaviours are learned from the environment through conditioning (Phillips & Soltis, 2011).

Behavioural patterns are acquired and learned from an environment. The environment in which an individual finds themselves naturally influences the way in which an individual behaves. While in a new environment, an individual learns new behaviour by classical or operant conditioning (McLeod, 2018). In classical conditioning, the student responds in a specific way to a certain stimulus. Operant conditioning occurs when a response to a given stimuli is reinforced using a feedback system or a reward system.

According to the original work by Watson, behaviourism is divided into two major categories: methodological behaviourism and radical behaviourism. He further asserts that, in methodological behaviourism, the mind is assumed to be born as a blank slate which therefore implies that the behaviour of an individual can be predicted and controlled depending on their environment. This behaviour only forms a part of what the entire disposition of man's behaviour looks like. In radical behaviourism, individuals are born with inherent innate behaviours as a result of their genes and biological configuration. The behaviour of the individual can therefore be predicted and controlled though underlying internal mental events that tend to affect the behaviour seen in individuals (McLeod, 2018).

Shristi (2017) describes the behavioural actions of students as being influenced by a number of factors. In many cases, the behaviour of an individual is influenced to a greater extent by the environment they find themselves in and the people associated with that environment. Individual behaviour also varies with the degree of complexity from simple behaviour to complex behaviour, all being influenced by a large number of factors. Among the common factors that influence human behavioural dispositions are the physical and the psychological factors. The physical factors relate to the circumstances the individual finds themselves in as well as their physical surroundings. As a result, this helps in shaping and influencing the behavioural dispositions of the individual. Human behaviour also varies between different individuals due to the existing individual differences. Consequently, examining the traits of individuals also reveals similarity in their behavioural patterns, explaining why individuals with similar traits behave similarly. Behaviour is usually goal oriented and always purposeful. In this case, an individual embraces a positive goal oriented behaviour or an avoidance behaviour depending on the environment they are in and what they need to achieve from the their set of behaviours.

In the context of this study, the behavioural dispositions associated with the behavioural patterns of an individual student can therefore be categorised into three major categories: consistency, regularity and persistence.

In consistency, the student shows methodological behavioural patterns and it is relatively easy to predict the student behaviour towards a technology. Regardless of a change in environment and physical surroundings, the student tends to show the same consistent behaviour in their approach to learning. As a result, such a set of behaviours tends to assist the student to embrace the use of a technology in their learning process regardless of their location. In regularity, the student tends to embrace a culture of constancy in their behavioural actions. The student will tend to be constant in the use of the technology in the learning process, which will eventually impact the student positively in regard to their performance. The student will also embrace the use of the technology with loyalty and as a result, their behaviour will be greatly influenced by the technology they embrace and use. In persistence, the student tends to embrace the use of a technology with determination and will persevere in using the technology until they achieve the goal they intended to achieve from the initial stages. As a result, this student ends up benefiting from the technology since their persistence ensures that they get the right output from the technology. Consequently, taking a closer look at the behavioural actions of the students assists in understanding how the students will embrace the use of a technology based on their behavioural dispositions.

3.4.3 Factors Affecting Student Behavioural Patterns on Internet Mediated Environments in Kenyan Universities

Student behavioural patterns, as described in section 3.4.2, are the mannerisms and actions shown by individual human beings. These mannerisms and actions influence human behaviour which in turn affects individual's behavioural intentions as discussed in section 3.4.1. The behavioural intention of an individual forms the basis for their specific behaviour within the environment they are exposed to. The specific behaviour refers to all observable actions that assist in describing the person. Behavioural intention is directly affected by two major factors: the attitude of the individual and the subjective norm. The attitude of an individual refers to the sensation shown by an individual in favour of a stimuli or in disapproval of the stimuli. The subjective norm of a person refers to the situation where other persons important to them expect them to behave in a specific way. In this study, the attitude and the subjective norm of the student have both been considered in relation to the use of internet technology in the learning process as seen in table 3.1 and table 3.3 respectively.

The results presented in table 3.1 and table 3.3 were obtained from the analysis of the data collected using the survey questionnaire shown in appendix A. Specifically, data was classified as shown on the specific parameters on appendix B. The respondents in this case were students from 12 public and 8 private universities who were in their third year of study in a STEM or a non-STEM related course. The students did not need to have used internet technology in their learning process for them to respond to the questionnaire. The sample size used in this research was 1,000 students out of which 747 of the returned questionnaires were usable. Hence, in this research, the respondents were identified using a variable n which was equal to747. This value was a constant all throughout the study since it represented the total number of participants who responded to the survey questionnaire. The data collection was conducted between the periods of February 2017 to November 2017. The likert scale used in the questionnaire was a five point scale ranging from strongly agree to strongly disagree. This scale was adopted since it helps in capturing the feeling and attitude of the participants as is the case in this study. The 5 scale was further collapsed into a three scale measure so as to determine what the respondents agree, disagree or are not sure about.

In order to establish the internal consistency or the reliability of the data collected for this study, there was need to subject the data to a Cronbach's alpha test. This test measures how well a test measures what it should. This test checks whether the multiple-question surveys done are reliable and whether they accurately measure the variables required in the survey (Tavakol & Dennick, 2011). The formula for the Cronbach's alpha is given as

$$\propto = \frac{N.\ \bar{c}}{\bar{v} + (N-1).\ \bar{c}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.24)$$

where N is the number of items, c is the average covariance between item-pairs and v is the average variance. Using the algorithm given in appendix J, the alpha coefficient obtained is 0.998 suggesting that the item used in the survey have a relatively high internal consistency and hence very reliable.

The results obtained after considering the different parameters that affect student attitude were represented as shown in table 3.1.

Table 3.1 *Students attitude towards internet technology*

Attitude of the student	**N**	**Disagree**	**Neutral**	**Agree**
I look forward to using internet in my studies	747	2.9%	11.6%	85.4%
The challenge of learning about the internet is exciting	747	8.3%	18.6%	73.1%
I am confident that I can learn internet skills	747	1.9%	8.2%	90%
Anyone can learn to use internet if they are patient and motivated	747	1.7%	6.3%	92%
Learning to operate internet is like learning any new skill – the more you practice, the better you become	747	2.5%	6.6%	90.9%
I am afraid that if I begin to use internet I will become dependent upon it and lose some of my reasoning skills	747	44.7%	22.2%	33.1%
I am sure that with time and practice I will be as comfortable working with internet as I am in working with a library of books	747	6%	16.7%	77.2%
I keep up with the advances happening in the internet field	747	9%	22.2%	68.8%

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I dislike working with internet since it appears like a machine that is smarter than I am	747	68.3%	11.2%	20.5%
I have difficulty in understanding the technical aspects of internet	747	54.5%	21.6%	24%
I hesitate to use internet for fear of getting too much information that requires a lot of sifting	747	62%	16.9%	21.2%
I have avoided internet because it is unfamiliar and somewhat intimidating to me	747	72.7%	9%	18.3%
I seek information from the internet for learning activities e.g. assignments and projects	747	2.1%	9.4%	88.5%
I search for materials from the internet to complete my assignments and projects	747	3.7%	10%	86.3%
I use the Internet as the main source of information for my studies	747	16.9%	23.2%	60%
I use the internet to access the Learning Management System/E-learning portal as part of my learning activity	747	6%	12.9%	81.1%
I seek the latest information online to enhance my knowledge related to the courses taken in the university	747	4.1%	12.9%	83%
I use internet forums to exchange opinions on academic matters with my friends	747	14.1%	19.5%	66.4%

Source: Primary Data (2018)

In view of students' attitude towards using internet technology as shown in table 3.1, 85.4% of the respondents agreed that they looked forward to using internet technology in their studies and 90% of the respondents were confident that they could learn internet technology skills. At the same time, 77.2% of the respondents agreed that, given time and practise, they were comfortable working with internet technology for their class assignments as they were with library books. As far as using internet technology in the learning process, 73.1% of the respondents found the challenge of learning while using internet technology an exciting process and 92% of the respondents believed that anyone could learn how to use internet technology if they were patient and motivated. As far as learning how to use internet technology in studies was concerned, 90.9% of the students admitted that learning to use internet technology was like learning any new skill, that is, the more practice was done, the better a person became.

Bearing in mind the level of dependency on internet technology, 66.9% of the respondents agreed that they were not afraid of using internet technology, although they could end up depending on the technology for all their study needs. While working on their studies using internet technology, 79.5% of the respondents agreed that they liked working with the technology and they did not feel overwhelmed by the fact that the internet appeared as a machine that was smarter than they were. Similarly, 76% of the respondents agreed that they did not have any difficulty in understanding the technical aspects of the technology. As far as attitude towards the available content was concerned, 78.8% of the respondents agreed that they did not hesitate to use the technology for fear of getting too much information that required a lot of sifting while 81.7% agreed that they still used the technology in the learning process without considering the content to be unfamiliar and intimidating to them. While seeking information for their learning activities, 88.5% agreed that they sought information from internet technology for their learning activities, for example, their class assignments and projects; 86.3% of the respondents agreed that they searched for materials from the internet to complete their assignments and projects and 81.1% of the respondents agreed that they used internet technology to access their institutions' learning management system and e-learning portal as part of their learning activities.

However, only 60% of the respondents agreed that they used internet technology as the main source of information for their studies. In seeking for information using internet technology, 83% of the respondents agreed that they sought the latest information using internet technology to enhance their knowledge base in their field of specialization. At the same time, only 66.4% of the respondents considered using forums provided by internet technology to exchange opinions on academic matters with their peers.

After performing feature selection on the factors that affect student attitude, further data analysis was done on the data obtained. This involved subjecting the factors obtained to factor analysis on the SPSS platform. Factor analysis is normally done to to reduce a large number of variables into a smaller number of factors. In this case, using the correlation matrix, any factor that had a correlation value less than 0.5 to the output factor was further discarded and not used in the final computation of the factor means. The results obtained are shown on table 3.2.

Table 3.2 *Correlation matrix for student attitude*

Correlation Matrix[a]

		B37	B38	B44	B45	B46	B47	B48	I Att
Correlation	B37	1.000	.460	.253	.339	.252	.268	.331	.621
	B38	.460	1.000	.238	.305	.299	.276	.367	.636
	B44	.253	.238	1.000	.593	.309	.409	.469	.659
	B45	.339	.305	.593	1.000	.447	.457	.466	.744
	B46	.252	.299	.309	.447	1.000	.358	.308	.661
	B47	.268	.276	.409	.457	.358	1.000	.522	.691
	B48	.331	.367	.469	.466	.308	.522	1.000	.718
	I Att	.621	.636	.659	.744	.661	.691	.718	1.000

Source: Primary data

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From table 3.2, it is clear that all the factors considered showed a high level of correlation to the final output of student attitude. As a result, the factors inputs used were highly reliable in the computation of the final output for this specific factor.

Besides an individual's attitude, the other factor that directly affected the behaviour of an individual was the subjective norm as shown in table 3.3.

Table 3.3 Subjective norm to use internet technology in learning

Subjective Norm	**N**	**Disagree**	**Neutral**	**Agree**
People who influence my behavior (e.g. course mates, friends) think that I should use internet	747	11.2%	25%	63.7%
People who are important to me (e.g. family members) think that I should use internet	747	11.2%	27.2%	61.6%
University	**N**	**Rarely**	**Occasionally**	**Always**
Internet is available in the university all the time.	747	19.7%	22.9%	57.4%
The connection speed is always very good.	747	25.2%	29.6%	45.2%
There are many places from where internet can be accessed in the university.	747	21.7%	19.8%	58.5%
Internet connection is reliable all throughout the semester.	747	26%	24.8%	49.3%
The ICT department has put in place policies that govern the use of internet.	747	17.1%	16.9%	66%
There is available software and hardware that assist with internet access in the university.	747	23.3%	18.2%	58.5%
There exists no access limitations as far as access and use of the internet are concerned.	747	32%	21.3%	46.7%
The university is committed to offering overall support in using the internet.	747	17.4%	23.2%	59.4%

Lecturers in the university have been encouraging the use of internet	747	9.4%	23.2%	67.5%
The university has supported the use of internet	747	6%	18.6%	75.4%
A specific person (or group) is available for assistance should I encounter difficulties with the internet	747	14.5%	23.4%	62.1%
Check the university website for announcements, dates, updates etc.	747	7.9%	7.4%	84.7%
Peers	**n**	**Rarely**	**Occasionally**	**Always**
A lot of teamwork in campus allows me to learn with the internet.	747	14.3%	22.6%	63%
Availability of many types of shareware from my peers has made me learn more about the internet.	747	14.7%	21.2%	64.1%
Sharing of resources with my peers using the internet has made me learn a lot.	747	8.3%	20%	71.8%
My peers have influenced me to positively use the internet especially for learning.	747	12.3%	16.1%	71.6%
My peers are a great source of assistance in overcoming the difficulties involved in learning using the internet.	747	9.8%	18.7%	71.5%
Family	**n**	**Rarely**	**Occasionally**	**Always**
I get a lot of encouragement from my family members to use the internet for learning purposes.	747	25.7%	25.4%	48.9%
I have a personal laptop at home.	747	18.9%	12%	69.1%

I have a smartphone/iPad/tablet at home.	747	9.9%	9.6%	80.5%
I have access to various software applications at home.	747	24%	17.8%	58.2%
I have unlimited internet access at home.	747	31.1%	22.4%	46.6%

Source: Primary Data (2018)

In this study as shown on table 3.2, the subjective norm considered the influence of the institution and different categories of people to the specific behaviour of the student. In the population, 63.7% of the respondents agreed that the people who influenced their behaviour, for example, course mates and friends, thought that they should use the technology in their studies and 61.6% of the respondents agreed that people who were important to them, for instance, family members, thought they should use the technology in their learning process.

While considering the influence of the institution towards the use of the internet technology, 57.4% of the respondents agreed that there was always internet technology service available in their university, 54.8% of the respondents felt that the connection speed was always poor and 49.3% of the respondents felt that the connectivity to the technology was reliable all throughout the semester. Within the university setup, 58.5% of the respondents agreed that there were many places designated where internet services could be accessed within the university. Regarding the use of the technology, 66% of the respondents agreed that their respective ICT departments had in place the necessary policies that governed the use of internet technology within the university and 46.7% agreed that there were always access limitations as far as access and use of internet technology was concerned. Within the same context, 58.5% agreed that there was available software and hardware that assisted with internet access within the university and 59.4% of the respondents agreed that the universities were committed to offering overall support in using the internet. In the same institutions, 67.5% of the respondents agreed that the lecturers in their universities had constantly encouraged them to use internet technology in their studies. As shown by the willingness of the universities to assist the students in the learning process using the technology, 75.4% of the respondents agreed that their institutions had supported the use of the technology in their learning process and 62.1% of the respondents agreed that there was always a specific person or a group of people who were available to offer assistance to the learners whenever they encountered a difficulty while using the internet for learning purposes. Considering access to internet technology around their universities, 84.7% of the respondents agreed that they used the technology to check the university website for any announcements, dates and updates.

The other category of people who influenced the use of internet technology among students were their peers, where 63% of the respondents agreed that a lot of teamwork existed in the university, which allowed them to learn with this technology. This was confirmed by 71.6% of the respondents who agreed that their peers had influenced them to positively use the technology especially in their learning process. Consequently, 71.5% of the respondents also agreed that their peers were a great source of assistance in overcoming the difficulties involved in learning using internet technology. As far as sharing of resources was concerned, 71.8% of the respondents agreed that sharing of resources using internet technology with their peers assisted them to learn a lot from each other and 64.1% agreed that the availability of many types of shareware from their peers assisted them to learn more about the technology.

In considering the influence of the family on the students' use of internet technology, 48.9% of the respondents agreed that they got a lot of encouragement to use internet technology from their family members. In the sampled population, 69.1% of the respondents agreed that they always had a personal laptop at home and 80.5% of the respondents agreed that they had a smartphone or an iPad or a tablet at home. When considering access to the technology, 58.2% of the respondents agreed that they had access to various software applications at home and this really assisted in their studies, while 46.6% confirmed that they had unlimited internet technology access at home and this assisted them in their learning process.

From the above findings, it is worth noting that the theory of reasoned action (TRA) is confirmed. According to TRA, specific human behaviour is influenced by an individual's attitude and the subjective norm. It was evident from the findings that, the respondents in this population had a positive attitude towards the use of internet technology and this had greatly influenced their interactions with the technology. With the right attitude towards the technology, respondents were consistent in their use of internet technology and they performed better since they used the technology with its benefits in mind. Looking at the subjective norm, it was evident that the respondents viewed their peers, their institutions and their families as the key individuals who influenced their use of internet technology. Due to the encouragement accorded to the respondents by these groups of people, they had been persistent and regular in their use of the technology and hence they used the resource to better their academic performances.

After performing feature selection on the factors that affect the subjective norm, further data analysis was done on the data obtained. This involved subjecting the factors obtained to factor analysis on the SPSS platform similar to what was done with student attitude. The results obtained are shown on table 3.4.

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Table 3.4 *Correlation matrix for subjective norm*

Correlation Matrix[a]

		C16	C17	C18	C19	C20	C21	C22	C23	C24	C25	C26	C27	C28	C29	C32	C34	C35	C36	C37	C38	C39	C40	C41	C42	C43	C44	D24	D35	D36	D37	D38	SM
Correlation	C16	1.000	.694	.603	.611	.534	.528	.320	.552	.264	.256	.227	.217	.239	.194	.165	.205	.175	.104	.119	.263	.151	.120	.184	.175	.227	.097	.244	.100	.143	.138	.285	.583
	C17	.694	1.000	.621	.627	.426	.464	.355	.520	.298	.260	.209	.229	.194	.220	.206	.200	.159	.143	.154	.191	.132	.146	.113	.098	.181	.123	.203	.090	.124	.077	.202	.556
	C18	.603	.621	1.000	.612	.508	.502	.259	.491	.260	.261	.286	.224	.250	.163	.188	.232	.190	.176	.205	.216	.179	.035	.171	.159	.211	.129	.195	.139	.156	.164	.325	.579
	C19	.611	.627	.612	1.000	.486	.586	.427	.541	.169	.224	.241	.174	.179	.242	.280	.152	.145	.178	.197	.151	.225	.136	.172	.129	.182	.050	.181	.126	.180	.186	.295	.584
	C20	.534	.426	.508	.486	1.000	.556	.251	.490	.221	.235	.275	.205	.213	.151	.164	.178	.180	.171	.140	.136	.103	.097	.184	.217	.167	.114	.196	.124	.117	.147	.293	.527
	C21	.528	.464	.502	.586	.556	1.000	.407	.627	.209	.296	.296	.161	.228	.220	.287	.163	.179	.198	.181	.173	.162	.135	.207	.166	.190	.127	.137	.134	.168	.206	.299	.589
	C22	.320	.355	.259	.427	.251	.407	1.000	.388	.195	.212	.208	.138	.139	.252	.247	.170	.073	.141	.129	.158	.276	.256	.099	.040	.184	.156	.116	.115	.167	.087	.152	.465
	C23	.552	.520	.491	.541	.490	.627	.388	1.000	.242	.252	.318	.233	.266	.189	.234	.178	.171	.190	.178	.162	.149	.138	.156	.138	.187	.096	.200	.064	.127	.207	.314	.574
	C24	.264	.298	.260	.169	.221	.209	.195	.242	1.000	.710	.499	.546	.462	.301	.100	.363	.303	.265	.263	.277	.171	.181	.262	.285	.313	.222	.193	.119	.171	.153	.184	.565
	C25	.256	.260	.261	.224	.235	.296	.212	.252	.710	1.000	.607	.589	.549	.377	.165	.335	.296	.278	.287	.260	.201	.173	.241	.245	.325	.299	.171	.178	.205	.201	.188	.609
	C26	.227	.209	.286	.241	.275	.296	.208	.318	.499	.607	1.000	.624	.614	.292	.269	.276	.343	.285	.278	.273	.260	.246	.384	.305	.289	.193	.209	.224	.192	.292	.246	.627
	C27	.217	.229	.224	.174	.205	.161	.138	.233	.546	.589	.624	1.000	.657	.328	.127	.394	.339	.268	.344	.272	.164	.215	.271	.319	.337	.241	.195	.132	.174	.175	.141	.575
	C28	.239	.194	.250	.179	.213	.228	.139	.266	.462	.549	.614	.657	1.000	.330	.176	.366	.341	.299	.330	.299	.179	.237	.312	.318	.338	.269	.289	.226	.244	.263	.176	.607
	C29	.194	.220	.163	.242	.151	.220	.252	.189	.301	.377	.292	.328	.330	1.000	.407	.332	.212	.374	.330	.250	.223	.265	.254	.153	.229	.233	.139	.234	.360	.239	.181	.545
	C32	.165	.206	.188	.280	.164	.287	.247	.234	.100	.165	.269	.127	.176	.407	1.000	.109	.138	.242	.191	.097	.130	.173	.146	.080	.127	.090	.084	.190	.224	.157	.139	.408
	C34	.205	.200	.232	.152	.178	.163	.170	.178	.363	.335	.276	.394	.366	.332	.109	1.000	.394	.401	.396	.336	.294	.256	.284	.296	.345	.325	.219	.195	.279	.162	.110	.550
	C35	.175	.159	.190	.145	.180	.179	.073	.171	.303	.296	.343	.339	.341	.212	.138	.394	1.000	.349	.319	.175	.155	.268	.388	.421	.203	.091	.254	.079	.147	.189	.219	.470
	C36	.104	.143	.176	.178	.171	.198	.141	.190	.265	.278	.285	.268	.299	.374	.242	.401	.349	1.000	.625	.321	.335	.252	.362	.275	.313	.287	.194	.186	.274	.278	.184	.546
	C37	.119	.154	.205	.197	.140	.181	.129	.178	.263	.287	.278	.344	.330	.330	.191	.396	.319	.625	1.000	.282	.309	.365	.364	.313	.402	.311	.161	.163	.238	.225	.161	.546
	C38	.263	.191	.216	.151	.136	.173	.158	.162	.277	.260	.273	.272	.299	.250	.097	.336	.175	.321	.282	1.000	.528	.321	.344	.297	.273	.227	.218	.183	.246	.158	.122	.509
	C39	.151	.132	.179	.225	.103	.162	.276	.149	.171	.201	.260	.164	.179	.223	.130	.294	.155	.335	.309	.528	1.000	.414	.365	.235	.237	.300	.126	.182	.203	.204	.166	.485
	C40	.120	.146	.035	.136	.097	.135	.256	.138	.181	.173	.246	.215	.237	.265	.173	.256	.268	.252	.365	.321	.414	1.000	.474	.328	.350	.225	.206	.078	.203	.119	.098	.462
	C41	.184	.113	.171	.172	.184	.207	.099	.156	.262	.241	.384	.271	.312	.254	.146	.284	.388	.362	.364	.344	.365	.474	1.000	.604	.373	.196	.241	.140	.222	.227	.240	.540
	C42	.175	.098	.159	.129	.217	.166	.040	.138	.285	.245	.305	.319	.318	.153	.080	.296	.421	.275	.313	.297	.235	.328	.604	1.000	.419	.247	.233	.121	.199	.192	.254	.491
	C43	.227	.181	.211	.182	.167	.190	.184	.187	.313	.325	.289	.337	.338	.229	.127	.345	.203	.313	.402	.273	.237	.350	.373	.419	1.000	.422	.217	.149	.235	.140	.158	.534
	C44	.097	.123	.129	.050	.114	.127	.156	.096	.222	.299	.193	.241	.269	.233	.090	.325	.091	.287	.311	.227	.300	.225	.196	.247	.422	1.000	.067	.198	.192	.145	.080	.422
	D24	.244	.203	.195	.181	.196	.137	.116	.200	.193	.171	.209	.195	.289	.139	.084	.219	.254	.194	.161	.218	.126	.206	.241	.233	.217	.067	1.000	.160	.184	.307	.283	.408
	D35	.100	.090	.139	.126	.124	.134	.115	.064	.119	.178	.224	.132	.226	.234	.190	.195	.079	.186	.163	.183	.182	.078	.140	.121	.149	.198	.160	1.000	.536	.402	.261	.378
	D36	.143	.124	.156	.180	.117	.168	.167	.127	.171	.205	.192	.174	.244	.360	.224	.279	.147	.274	.238	.246	.203	.203	.222	.199	.235	.192	.184	.536	1.000	.442	.330	.468
	D37	.138	.077	.164	.186	.147	.206	.087	.207	.153	.201	.292	.175	.263	.239	.157	.162	.189	.278	.225	.158	.204	.119	.227	.192	.140	.145	.307	.402	.442	1.000	.492	.442
	D38	.285	.202	.325	.295	.293	.299	.152	.314	.184	.188	.246	.141	.176	.181	.139	.110	.219	.184	.161	.122	.166	.098	.240	.254	.158	.080	.283	.261	.330	.492	1.000	.458
	SM	.583	.556	.579	.584	.527	.589	.465	.574	.565	.609	.627	.575	.607	.545	.408	.550	.470	.546	.546	.509	.485	.462	.540	.491	.534	.422	.408	.378	.468	.442	.458	1.000

a. This matrix is not positive definite.

Source: Primary data

From table 3.4, it is clear that a number of factors considered showed a high level of correlation to the final output of the subjective norm. At the same time, other factors showed a correlation less than 0.5. Such factors were further dropped from the final computation since they did not correlate highly with the factor output, subjective norm. As a result, the factors inputs with correlation values greater than 0.5 were used since they were highly reliable in the computation of the final output for the subjective norm.

3.4.4 Student Learning Patterns

A learning pattern can be described as a conglomeration of all the learning activities that learners engage in, as well as the inspirations and philosophies that govern their learning process. This pattern gives them a unique distinction at a specific period of time. It also provides an interrelationship between a learner's reasoning ability, emotional abilities, and beliefs about learning and motivations in learning (Vermunt & Donche, 2017). The learning patterns structure is based on two research traditions: the Students Approaches to Learning (SAL) and the Self-Regulated Learning (SRL), both of which were done in the late 1970s and early 1980s. SAL focused on the origins of learning by specifically examining the cognitive strategies and inspirations behind the learning process (Marton & Säljö, 1984). This was followed shortly by the study of metacognition which was later developed into SRL. Initially the focus on the learning patterns revolved around children and their metacognition skills. However, this has evolved to focus on cognitive skills and strategies of students in high school and college, as well as adult students in higher institutions of learning.

The outline of learning patterns as shown in figure 3.4 focuses on four major pillars in the ability of a student: conception of learning, cognitive processing strategies, metacognitive regulation strategies and learning motivations. Conceptions of learning examine the opinions and philosophies that learners hold about the teaching and learning process. Cognitive processing strategies are the amalgamations of learning activities that students use in order to acquire knowledge and competence in a specific skill. Metacognitive regulation strategies are the combinations of the available learning activities that students use to organise, keep track, direct and assess the learning processes that have led to a positive learning outcome. Learning motivations include all the activities that exist in relation to the learning process; for example, the objectives, aims, motivations and apprehensions regarding their studies.

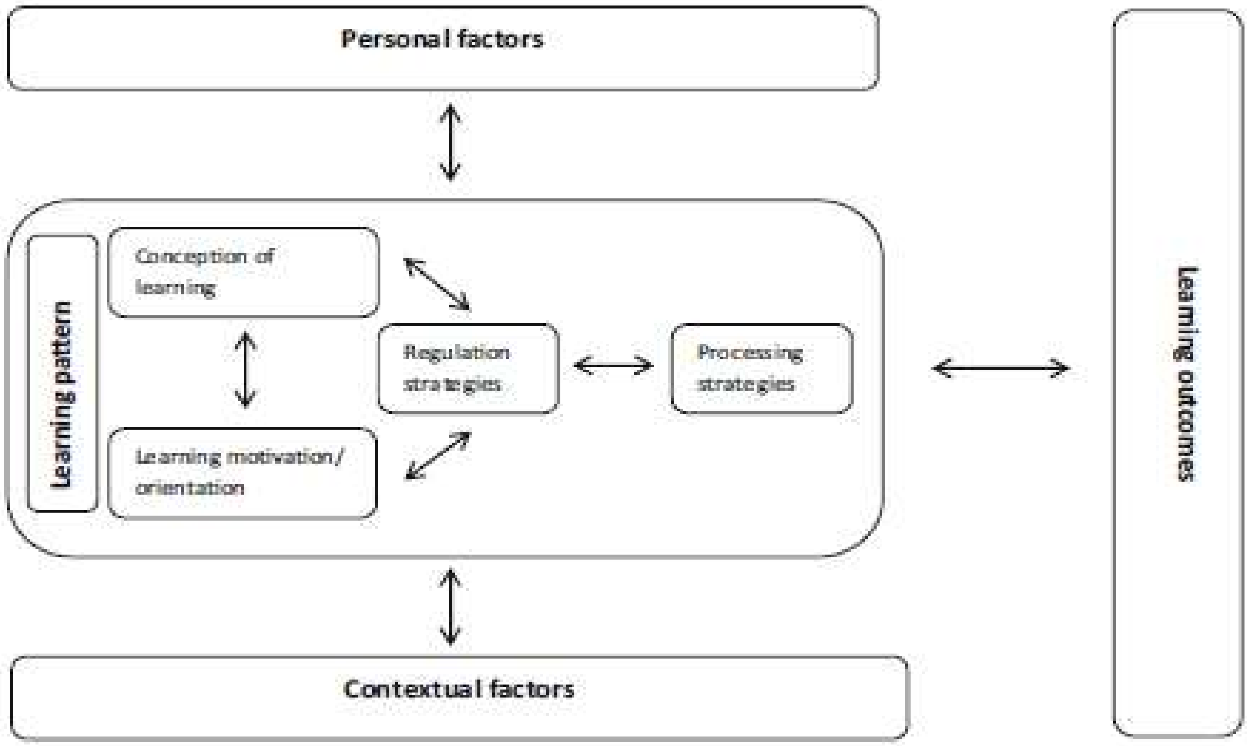

***Figure* 3.7** *A learning patterns model for student learning (Adopted from Vermunt & Vermetten, 2004)*

In figure 3.7, a model of student learning is depicted. The core of the model is formed by a learning pattern. The learning patterns that are used by students in order to understand the subject matter are influenced by processing and regulation strategies which are in turn affected by conceptions of learning and the learning motivations. These learning patterns are then affected by contextual and personal factors which lead to the final learning outcomes of students. The generated learning outcomes could also constitute input for other learning patterns in a different environment. If the context changes, learning patterns may change as well. The model allows a great level of dynamism by having bidirectional arrows on it showing that the learning patterns and the personal factors have the ability to influence each other in generating the final learning outcome of the student. A learning pattern therefore becomes a result that is obtained after combining the personal and contextual factors as shown in figure 3.7 (Vermunt & Endedijk, 2011).

Other studies reveal that students in higher learning institutions depict two qualitative kinds of learning patterns: directed and undirected learning. Directed learning is further divided into application-directed learning, reproduction-directed learning and meaning-directed learning (Lonka et al., 2004). Application-directed learning pattern involves trying to find a meaningful relationship between the ideas learnt and the outside world. Their learning involves finding examples in what is learnt and trying to apply the knowledge acquired in solving real world challenges. The learners attach great importance to knowledge only when they can apply and use it in a meaningful way. The learners also appreciate the acquisition of skills that can enable them become professionally competent or become better in their immediate profession.

Reproduction-directed learning pattern involves a tireless effort to remember what was learnt for the sake of passing an assessment. The learners go through the learning materials in a systematic way trying to commit the content to memory for the sake of the tests. The main motivation for the learners is to pass the tests without much thought on lifelong learning. This approach to learning assumes that the learning process is an intake of facts from a known source and reproducing the facts in the closest similar way. The memorisation of the facts requires a tireless process of rehearsing and analysing the information to ensure that none of it is lost.

In the meaning-directed learning pattern, the students begin by figuring out the importance of what they are learning. They try to find out the relationships that exist between different bodies of knowledge in the subject matter. They then place the subject in the body of knowledge acquired and try to get involved in what they learn. The learning process involves amassing as much knowledge on a subject as possible with no limitations imposed. The learners treat the learning process as a personal way of acquiring knowledge and that their learning depends on how much knowledge they can get on the subject. Oftentimes, the learners are driven by topics of interest to them.

In the undirected learning pattern, students do not have any idea regarding what the learning process should entail. This is a dilemma that faces learners who are in the process of transition from one mode of learning to another or from one kind of educational practices to another different kind. They try to use the learning approaches they had used previously in the former stages only to realise that the approaches do not work, leaving them with no possible way of learning. The learners here experience a lack of direction in the new circumstances. They normally experience uncertainties as pertains to their studies in the new environment and they will hold on to their peers and instructors for a sense of belonging and direction (Vermunt et al., 2014; Vermunt & Donche, 2017).

3.5 Pattern Analysis

Pattern analysis involves the spontaneous recognition of patterns in a dataset originating from the same source (Grenander, 1969). The patterns from the dataset assist in making predictions from a given source. While considering data from many sources, the data could take the form of transactional records, texts or images (Taylor & Cristianini, 2004).

In the learning environment, research work is characterised by some form of output. This output is in the form of data collected using different methods. Once the data is collected, it is usually manipulated in order that valuable knowledge can be extracted from it. Most importantly, knowledge can be extracted from the data to show the relations between the data and the patterns contained in the data. The knowledge gives predictions about the source of the data and helps in giving inferences about relationships contained in the data.

3.5.1 Pattern Definitions

Pattern definitions in pattern analysis are based on data-based or data-driven approaches. Unlike the theory-driven approaches that specify the algorithms that they require, the data-driven approach uses learning systems. These systems use the facts mined from a sample of data to give inferences that can help in solving a problem at hand. This is called learning methodology. This approach to solving existing challenges has become very popular in recent years. Pattern analysis therefore considers applications that use learning methodology to discover eminent patterns in data. Datasets tend to have in them relations that are redundant. These redundant relationships are extracted by mining the data. The results are referred to as patterns. Patterns in data can be approximate or deterministic and exact or only hold when some conditions are met. Hence, patterns are associations existing in a dataset (Duin & Pekalska, 2016).

Depending on the data used in computations, there exists different kinds of patterns that can be defined. These are simple patterns, exact patterns, approximate patterns or statistical patterns (Taylor & Cristianini, 2004).

A simple pattern can be defined as

$f(x) = 0$ for all the data points x.

Assuming a function g that for each data item (x, y) predicts some output values y as a function of a set of inputs x, then the pattern formed can be expressed as

$$f(x, y) = \ell(g(x), y) = 0 \quad [3.25]$$

where $\ell : Y * Y \rightarrow \Re^{+}$ is the loss-function that measures disagreement patterns between the input values. It outputs 0 if and only if the arguments are the same and a positive value if the arguments are dissimilar. An example application of simple patterns is commonly seen when trying to locate common features in a series of letters, words or numbers (SaiKrishna et al., 2012). For instance, in the compression of two distinct files, $\boldsymbol{x}$ and $\boldsymbol{y}$, each file is compressed separately to achieve a certain file size. The two files are then compressed together into one file. The sizes of the compressed files are then given to establish if the files share common patterns.

An exact pattern for a given dataset can be defined as a non-trivial function (non-zero function) $f(x) = 0$ for all the data points x that can arise from a source. This definition only covers exact patterns. Considering the function g defined in equation 3.24 where the values of y are predicted by the input features of (x), then if exact equality cannot be obtained between $g(x)$ and y, the loss function, ℓ, is used to measure the level of mismatch. Consequently, the function gives 0 when the arguments are similar (not necessarily identical) or it also gives small non-zero positive values. An example of the application of exact patterns is always useful in the concept of probabilistic matching when combined with probabilistic patterns (Charras & Lecroq, 2012). For instance, given a text string, ***T***, it is possible to find all the occurrences of a pattern ***P*** in the text string. Taking ***T*** and ***P*** to be presented as

T = AGCCTAAGCTCCTAAGTC and ***P = CCTA.***

Applying the use of exact patterns algorithms reveals that there exists only two occurrences of ***P*** in ***T*** as illustrated: ***AGCCTAAGCTCCTAAGTC***

An approximate pattern for a given dataset can be defined as a non-trivial function $f(x) \approx 0$ for all the data points x that can occur from a particular dataset. In this case, the value obtained at the approximation level is not defined for any specific contexts. Approximate patterns are mainly applied in the area of text searching, computational biology, pattern recognition and signal processing applications (Beaza-Yates & Novorra, 2010). An example of the application of approximate patterns considers a length ***n*** and pattern of length ***m.*** The solution requires that all occurrences of the pattern in the text are established and the edit distance needs to be a value $K \geq 1$. The edit distance between a set of two strings in this case refers to the minimum number of character insertions, deletions and replacements that are required to make the set of strings equal to each other. Pinzon (2006) gives an example that takes ***T*** and ***P*** as follows:

T = "appropriate meaning"

P = "approximate matching"

Checking on the edit distance between the two sets of strings generates figure 3.5.

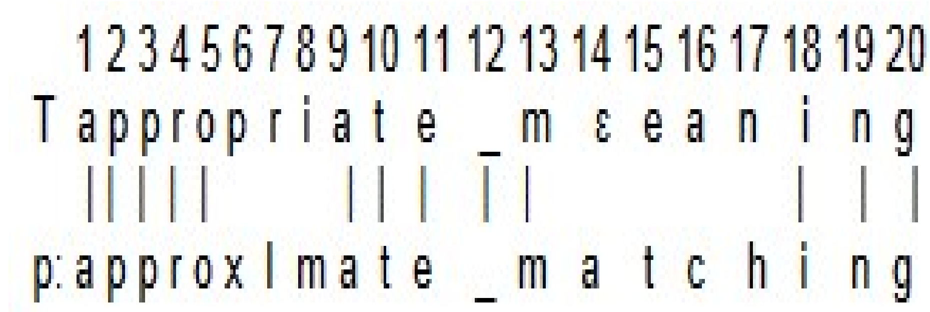

Figure 3.8 *Generation of the edit distance (Adopted from Pinzon (2006))*

Figure 3.8 in this case, shows the edit distance to be δ (t, p) = 7. This is mainly due to the need for character replacements, deletions and insertions of different characters to fit in the given patterns.

In statistical patterns, there exists probability distributions that generate the data used in the patterns. Distinct data items are assumed that they are generated independently and identically (independently and identically distributed or i.i.d). The symbol ε denotes the expectation of some quantity in a dataset. When defining the dataset over which the expectation is derived, the dataset or the expectation is added as an index. In the statistical pattern, the expectation is considered as part of the dataset.

A statistical pattern for a data source generated i.i.d according to an existing distribution (named D) in this case, is a non-trivial non-negative function that satisfies equation 3.25

$$\varepsilon_D f(x) = \varepsilon_X f(x) \approx 0 \quad \text{[3.26]}$$

In cases where the distribution does not satisfy the i.i.d requirement, this means that there are dependencies between the data items generated or there are slow changes in the distribution.

Bearing in mind the different datasets that exist, a fixed set of observations can be obtained according to the underlying distribution. As a result, this set of information loaded on a pattern analysis algorithm identifies all underlying patterns. A pattern analysis algorithm takes a finite set of inputs from data that needs to be analysed and gives an output. The output given indicates that there are detectable patterns in the data or no patterns at all. The patterns detected by the algorithm satisfy the function

$$\varepsilon f(x) \approx 0 \quad \text{[3.27]}$$

where the expectation ε is with respect to the data generated from a definite dataset x. The input data forms the training dataset and the output generated forms the detected patterns existing in the large dataset presented. The expectation value forms the generalisation error expected from the given dataset.

3.5.2 Pattern Analysis Techniques

Pattern analysis techniques are the techniques that are used in identifying the patterns that exist in volumes of data. This also involves the automatic detection of patterns in the data emanating from the same data source. The generated patterns are then used in making predictions in the future with data coming from the same source. This data may originate from images, text, records on transactions, sequential analysis or family trees. The most commonly used pattern analysis approach is the sequential pattern analysis technique.

Sequential pattern analysis (SPA) is a pattern analysis technique that is used to discover similar patterns in the data presented. These patterns are then used to explain the relationships that exist between the data. The pattern analysis technique tries to discover the associations between frequent occurrences in specific order. Once the frequent occurrences are defined, the data can then be used to predict future periodic patterns. Major applications of sequential pattern analysis are in the analysis of customer shopping sequences, medical treatments of recurrent illnesses, predictions of natural disasters, science and engineering processes and the stocks markets. It is also useful in analysis of telephone calling patterns, weblog click streams and analysis of DNA sequences and gene structures (Sharma et al., 2014).

Sequential pattern analysis is divided into two categories according to the way in which the occurrences are generated, tested for frequency and stored (Sharma & Mishra, 2014). There are two types of sequential pattern analysis: Apriori-based and pattern growth based analysis. The taxonomy of sequential pattern analysis shown in figure 3.9 highlights the different approaches to sequential pattern analysis.

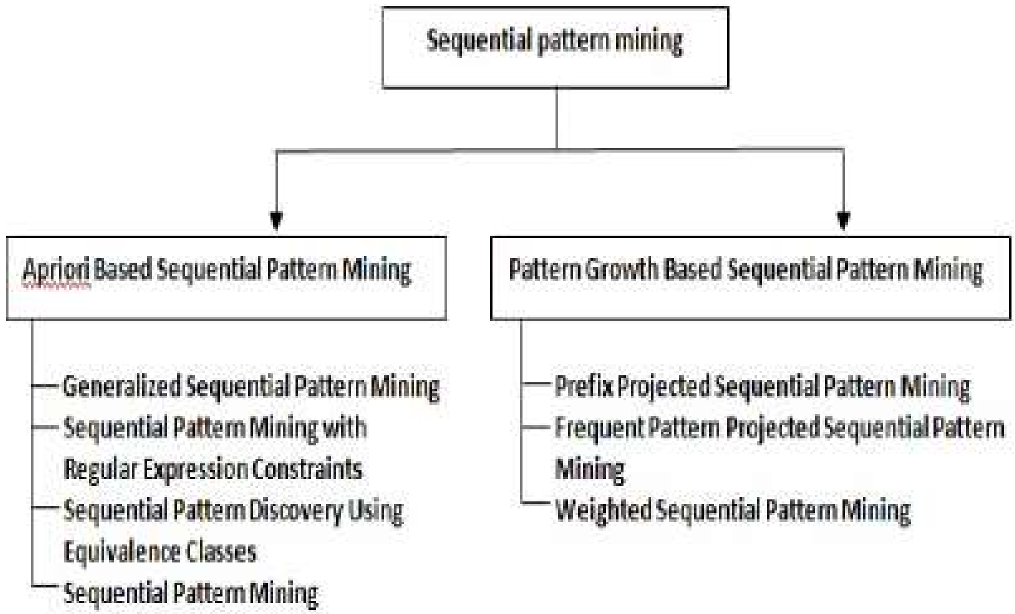

Figure 3.9 *Approaches to Sequential Pattern Analysis (Adopted from Sharma et al., 2014))*

The Apriori based sequential pattern analysis is based on the apriori property. This property states that all nonempty subsets of a frequent item set must also be frequent. This pattern is also defined as monotonic since the frequencies have to pass the minimum support test or otherwise they fail the test. The apriori based method has three major features: breadth-first search, generate-and-test and multiple scans on the dataset. Apriori-based algorithms are defined as breadth-first or level-wise since, during the algorithms iterations, they build k-sequences as they navigate the search space. The generate-and-test feature is a common stage in the early stages of pattern analysis. In this case, many possible occurrences are generated and then each of the generated occurrences is tested further until it satisfies a predefined set of conditions. The apriori based algorithm also allows multiple scans on the dataset given. This mainly ensures that many of the data records available can be used more frequently. However, this can result in high processing time and input-output cost (Mabroukeh & Ezeife, 2010; Boghey & Singh, 2013).

The apriori based sequential pattern analysis technique is divided into four major categories: generalized sequential pattern analysis, sequential pattern analysis with regular expression constraints, sequential pattern discovery with equivalence classes and sequential pattern analysis.

In the generalized sequential pattern (GSP) analysis approach, the downward-closure property is used while adopting a multiple-pass on the dataset and a generate-and-test approach. The algorithm produces as many occurrences as the memory can hold and the dataset is constantly perused to support the occurrences. The sequences that are generated from the data are stored while others are automatically deleted if they do not hold to the criteria set. This continues until all the items of data are counted. At the very beginning, the first pass is established on the dataset based on the items frequency. Consequently, the subsequent sequences are based on what existed in the previous sequences (Ratre & Gupta, 2013) and hence generates a new set of sequential patterns (candidate sequences).

To illustrate the application of the general sequence pattern analysis using an example, consider the table 3.5 as a sample database and table 3.6 as a table of length-1.

Table 3.5 *Sample database*

Sample Database [17]

Seq Id	Sequence
10	<(bd)cb(ac)>
20	<(bf)(ce)b(fg)>
30	<(ah)(bf)abf>
40	<(be)(ce)d>
50	<a(bd)bcb(ade)>

Table 3.6 *Length-1*

Length-1

Cand	Seq
<a>	3
<b>	5
<c>	4
<d>	3
<e>	3
<f>	2
<g>	1
<h>	1

This example requires that all frequent patterns be established in table 3.5. Table 3.5 contains the Seq Id and the sequence of occurrence of different letters. The data in this table is filtered and represented as shown in table 3.6 based on the length-1 condition. The data that does not fulfil the condition cannot pass the threshold without being pruned. The GSP algorithm is represented as follows:

GSP

Begin

1. *Take sequences in form of <x> as length-1 candidates*
2. *Scan database once, find F_1, the set of length-1 sequential patterns*
3. *Let $K = 1$ while $F_k$is not empty do*

   FormC_{k+1}, the set of length – $(k + 1)$ candidates from F_k

   If C_{k+1} is not empty, scan database once, find $F_{k+1}$the set of length-($k + 1$) sequential patterns

   Let$k = k + 1;$

The GSP algorithm benefits from the Apriori pruning since it manages to reduce its search space to a less number of elements on the dataset. The main weaknesses of this algorithm is the fact that its required to perform a multiple number of scans on the database in order to come up with the required solution. It also ends up generating a huge set of candidate sequences that are not necessarily useful in the mining of the patterns.

In the sequential pattern analysis with regular expression constraints, the constraints defined in this pattern analysis technique can be due to many different factors. This can be based on the interactions between attribute values or the patterns generated from the dataset. Pattern templates can also be used as the regular expressions that give the desired forms of what the final patterns will look like. The predefined constraints are used in the analysis procedure to reduce the number of occurrences hence provide a more efficient pattern. In this analysis technique, there is need to use a constraint that ensures that the desired pattern can be generated. There also exists a way of enforcing the required pattern by use of defined algorithms which consider only a few items in the defined dataset (Pies et al., 2002).

In the sequential pattern discovery with equivalence classes (SPADE), the sequential pattern analysis algorithm is based on a vertical format. The original problem to be solved is broken into smaller problems by the help of combination strategies. The dataset at hand is broken down into smaller units that can be administered individually in memory. This approach minimizes the pattern computational costs since it uses different search algorithms for its computations. The vertical format also ensures that there exists different lists which then reduces the number of scans required on the dataset (Kumar, et al. 2012). The challenges with the SPADE algorithm involves huge generation of candidate sets especially when using 2-item candidate sequences. It requires multiple scans on the database, which leads to a situation where the length of each candidate grows by one with every database scan. The approach is not suitable for mining long sequential patterns since long patterns grow up from short patterns and short patterns have an exponential number of short candidates.

Sequential pattern mining uses an algorithm that finds the existing frequent sequences in a dataset. This approach fits a large dataset. A level-wise approach is used to generate the initial occurrences as the search space gets reduced to the required levels. The dataset is stored using a vertical bitmap representation which supports counting as well as a compression mechanism. Implementation of the analysis of the output generated is at times challenging due to the large sizes of the datasets used and hence, getting the frequent patterns proves to be a challenge (Boghey & Singh, 2013).

The other sequential pattern analysis approach is based on the pattern growth based analysis technique. This approach embraces the use of smaller datasets associated with sets of patterns already mined. In this case, instead of using the entire dataset available, smaller datasets are used to come up with the frequent patterns associated with each dataset. Some of the common features in pattern growth based methods include sampling and compression features, candidate sequence pruning, search space partitioning, depth first traversal, tree projection and suffix/prefix growth.

The sampling and/or compression feature is mainly used in reducing the dataset into a small manageable level. This is mainly done at the early stages to establish the required dataset. Another way of ensuring a small dataset is available while analysing sequential patterns is to emphasize on brief illustrations of sequences, for instance, closed sequences. The candidate sequence pruning feature allows the reduction of the dataset at the early stages of pattern analysis, which ensures that the search space becomes smaller and more directed and narrower in the search procedure. The search space partitioning feature allows for efficient memory management since the larger dataset can be partitioned into smaller datasets and the smaller sets can all be analysed in parallel. The level wise traversal feature helps in the early stages of analysis by utilizing even lesser memory and ensuring a more directed analysis on the entire dataset (Peis et al., 2002). Pattern growth algorithms are usually accompanied by tree projections. The entire dataset is represented in the form of a tree data structure which is then traversed using depth first or breadth first techniques. The data reduction mechanism is then based on the apriori mechanism. In the suffix/prefix growth feature, the entire dataset is checked for frequent items. These items are then defined as the suffix or prefix and all the analysis is based on this. The frequent sub-sequences defined greatly reduce the amount of memory required since most of the occurrences share the same suffix/prefix (Khan, 2012).

Pattern growth based sequential pattern analysis is divided into three different categories: prefix projected sequential pattern analysis, frequent pattern projected sequential pattern analysis and weighted sequential pattern analysis.

The prefix projected sequential pattern analysis (PREFIXSPAN) technique starts by exploring the prefixes that exist in the sequential pattern available. The prefix is identified based on the number of growing prefixes available. This approach analyses the entire dataset based using the divide and conquer strategy hence reducing the chances of candidate subsequence generation. The initial scan on the provided dataset generates a set of sequential patterns. Each of the generated sequential patterns is treated as a prefix and the entire set of sequential patterns is subdivided into different subsets of different prefixes. In order to mine the sequential patterns that need to be obtained, the frequent prefixes are extracted and the corresponding postfix sub-sequences are determined using the datasets. This approach uses a projected dataset but the dataset keeps decreasing as the analysis takes place. Prefix projected sequential pattern analysis mines and gives a complete pattern set by reducing the number of pattern occurrences needed. It also greatly reduces the size of the dataset and leads to efficient processing. An example of an algorithm used in the implementation of PREFIXSPAN is as follows:

PrefixSpan $(\propto, i, S| \propto)$

Begin

1. *Scan* $S|\propto$ *once, find the set of frequent items b such that*

    b can be assembled to the last element of $\propto$ *to form a sequential pattern; or* <b> *can be appended to* $\propto$ *to form a sequential pattern.*

2. *For each of frequent item b, append it to* $\propto$ *to form a sequential pattern* $\propto'$ *and output* $\propto'$.

3. *For each* $\propto'$, *construct* $\propto'$*-projected database* $S|\propto'$ *and call*

    PrefixSpan $(\propto',\ i+1, S|\propto')$

    End

The aim in this pattern is to find the relevant sequences existing. The parameters involved here are $\propto$ which represents the sequential pattern, 1 is the length of $\propto$ and $S|\propto$ is the $\propto$ projected database if $\propto \neq <>$ otherwise it is the sequence database S. The advantages associated with PrefixSpan include; no candidate sequences need to be generated. The projected databases keep shrinking and the major cost in this pattern analysis technique is the construction of the projected databases.

In the frequent pattern projected sequential pattern analysis (FreeSpan) the items that occur frequently are used in the projected sequential dataset to generate even smaller datasets. FreeSpan scans the dataset initially, gathers together the support of each item and then tries to find out the items in the data that occur frequently. The frequent items are then listed in a particular order.

Finally, in the weighted sequential pattern analysis (WSPAN) technique, the analysis is based on evaluating the existing relevant patterns between the data and the values in the sequence. The values used in the dataset ought to be discrete and not continuous. This pattern analysis approach is considered as a time series and the output is always closely related. While examining the general sequential pattern analysis techniques, it can be seen that all are based on simple support counting. Introducing an aspect that checks on the weight leads to the computation of better valuable sequential patterns (Yun & Leggett, 2016). When considering general sequential pattern analysis techniques, the same priority is always used for the same pattern. In cases where there are huge datasets, extracting the patterns to be used is not an easy task. However, when the different weights are considered, the generation of patterns becomes more effective and efficient and it also becomes easier to adjust the number of sequential patterns generated. An example of an algorithm that is used in the implementation of the WSPAN technique is as follows:

WSPAN ($\propto, L, S| \propto$)

Begin

1. *Scan* $S| \propto$ *once, count the support of each item, and find each weighted frequent item,* β *in sequences:* β*is a weighted sequential item if the following pruning condition is not satisfied.*

   *Pruning condition: (support * Max W > min-sup)*

   a. β *can be assembled to the last element of* $\propto$ *to form a sequential pattern or*
   b. *<*β*> can be appended to* $\propto$ *to form a sequential pattern*
2. *For each of the weighted frequent item* β*,*

   Add it to $\propto$ *to form a sequential pattern* $\propto'$ *and output*$\propto'$.

   End for
3. *For each* $\propto'$

   Construct $\propto'$ *-projected database*$S| \propto$;

   Call WSPAN ($\propto', L+1, S| \propto'$)

   End for

3.5.3 Learning Patterns on Technology Mediated Platforms

Internet revolution has been greatly felt in the sector of education. The traditional learning environments are slowly being replaced by new emerging technologies and the behaviour of students in these digitized classes cannot be ignored. Learning has mainly shifted into the world of weblogs, wikis and social software applications (Kiyici, 2010). The learning process has greatly been influenced by the technologies at hand, though in all these circumstances, learning still takes place depending on the lifestyle of the students. The new methods have been introduced to aid the learning process. Internet users have greatly contributed to the learning process of their peers through participation on the available online platforms. In order to maximise the use of these platforms for the sake of the online users, it would require that the providers of the services understand the various users of their online environments and the specific activities performed online, their online behaviours, their personalities and the kind of incentives they would like in order that they become loyal users of their services (Selwyn et al., 2005). Appreciating the behaviour of online users ensures that the products developed aim at fitting into their lifestyle and deliver satisfactorily to their needs.

Researchers have investigated the common online activities among many of the internet users. This has revealed that internet users engage in communication, buying and selling of goods and services, searching for entertainment places, downloading software applications and gaming applications and engaging in education related activities (Sahin et al., 2010). According to Colley and Maltby (2008), the most common uses of internet among students in universities centre on communication with peers, acquisition of data and information, searching for news, job search information links and shopping. However, new trends in the exchange of information among students are now shifting to podcasts, wikis, blogs and social software. The students are now in a position to exchange information among themselves by connecting to the internet by use of their mobile devices. Internet revolution has led to situations where people work all round the clock, with typically brief breaks or no breaks at all. There is always an urgency to get to know what is happening and as such internet service providers have been forced to give user support all around the clock.

Understanding the learning patterns that internet users exhibit while online goes a long way in trying to appreciate how the learning process takes place. A deeper look at the student learning patterns on the internet helps an instructor integrate the content of student’s curriculum and the needs of the particular students. The needs of individuals have slowly shifted from what was concrete and tangible a few years ago, to what is virtual and existing only in space; for example, from physical classrooms to online ones and from notice boards to wikis and weblogs (Hsieh & Chyan, 2012).

Patterns, as described by Alexander (1977), occur recursively in everyday life. This happens to give a solution to a problem at hand and the solution provided can be used a number of times without any possible duplicities. Patterns provide solutions for different contexts and they help to resolve problems encountered in different situations. Patterns have been used in the study of human computer interactions, architectural software designs and more generically in software engineering.

According to Caeiro et al. (2014), online learning patterns are classified based on software, learning materials and educational practices. Learning patterns have been successfully used for collaborative learning system designs, especially in the implementation of Learning Management Systems. This has been well adopted in the use and adoption of e-learning systems. The use of learning patterns in educational practices has also been studied in relation to educational theories and instructional disciplines. The patterns have been studied in the use of study groups, classroom environments, seminars and short course programmes. In these different environments, learning patterns are captured to give expert knowledge in the teaching and learning process. The patterns focus specifically on feedback, different approaches in teaching, experimental learning and active learning. The use of patterns in selection of learning materials has also considered the learning experiences of students. These patterns focus on instructional design problems, specifically the content presentation and the specific learning action points. The learning activities are based on specific learning outcomes. Learning patterns relating to wireless and mobile environments in collaborative learning environments have also been used in the study of collaborative learning experiences (Derntl & Motchnig-Pitrik, 2004).

The study of learning patterns has also been developed from a layered pattern language perspective. Pattern language involves the use of patterns to create complex activities and objects. The patterns are studied from high levels to low levels of the pattern generated designs. In order to generate a pattern language for learning, a ranked approach is used. The problem at hand is broken into smaller problems for which solutions exist. This normally takes a top-down approach with the smaller sets of activities being organised to meet the needs of the learners. This is then followed by the definition of the flow of information between the different activities, and for each activity, the actors involved, the specific environment they find themselves in, their interactions and communication levels that they find in the different activities. As a result, a layered approach defined by different activities at each level is embraced. Consequently, this layered approach can be divided into different patterns that can be used in the learning process. These are educational patterns, learning experiences patterns and finally the activity patterns (Caeiro et al., 2014).

Online educational learning patterns involve the learning outcomes and objectives that are specific to every course. Each course has its unique learning goals to be realised. The learning pattern then establishes the fundamentals of the course and why the course needs to be studied. This will require a look at the learning capabilities to be established, the content to be studied and the different applications to be embraced in the course. In studying the learning experience patterns, the designers of the course have to identify the learning experiences to be embraced and the extent to which they will be used. The learning pattern will ensure that the learners achieve their goals, interact with their peers amicably and get the required support from the course instructors. Activity patterns involve all the lower end activities that are required for the learning experience patterns. The learning experience patterns are used to describe the specific approaches while the activity patterns help in filling in the gaps. These describe the specific user interactions in solving specific problems.

3.5.4 Student Learning Patterns in Kenya

Nzesei (2015) carried out a study to establish the relationship between student learning styles and their academic achievements among secondary school students in Kenya. In this study, he classified learning styles into the use of vision, hearing and physical abilities in their learning process. Some students preferred to use one learning style (unimodal style), others used any two learning styles (bimodal style) or all the three styles (trimodal styles). There was need for the class instructors to use appropriate content delivery approaches in order to ensure that the students learned despite their preferred learning style. The study further revealed that the learners' ability to learn was directly influenced by their memory efficiency and the learners use different learning styles depending on their circumstances. There was need to present the content to be learnt using different and diverse multimodal approaches. This was a technique that worked well for the students at that level.

While considering the presentation of the learning content, the same research proposed the use of multiple sensory modalities (vision, hearing and physical abilities) in order to accommodate as many learners as possible. Leveraging on the different learning styles ensured that the learners got a chance to experience an improved learning environment (Morrison et al., 2010).

Adopting the approach to learning patterns discussed in section 3.4.4 led to the consideration of four main components of student learning patterns in the Kenyan environment. These factors include cognitive processing strategies, metacognitive regulation strategies, metacognitive conceptions of learning and learning motivations or orientations (Vermunt & Donche, 2017).

Cognitive processing strategies in this study were considered as the different ways in which students used internet technology to enhance their learning process. This study looked into the different ways that the students used internet technology to enhance their knowledge, understanding and skills level. The use of the technology depended on the capability/self-efficacy of a student when using the technology in the learning process as shown in table 3.3. Specifically, students used the technology as a source of updated information and they used the technology to access learning materials and upload their assignments through an e-learning portal or a learning management system. They used the technology to communicate with their lecturers and classmates on academic matters. The students exchanged ideas with their classmates and lecturers through chats, instant messaging platforms and using other online tools. The use of blogs and websites was also seen as the students exchanged academic ideas with their peers and with other internet users. Students accessed learning materials on You Tube and also enrolled for free courses in various disciplines to improve their academic work. From the data collected as indicated in table 3.3, the cognitive processing strategies were seen to be dominated by use of internet technology as a source of updated information and in accessing learning materials.

Metacognitive regulation strategies examined the mixtures of the different learning activities that assisted the students in planning, monitoring, steering and evaluating their learning process. These strategies ended up affecting the student learning outcomes. As can be seen in table 3.3, the planning stage in the use of internet technology examined the student's willingness to use the technology in the learning process. This checked the relevance of the technology. In monitoring the use of the technology, the frequency and purpose of use of the technology were considered. In the steering of the learning process, this study examined the influence of different parties in the utilization of the internet technology in the learning process. In the evaluation, the students examined whether the use of the technology led them to better performance or whether the use of the technology contributed to their better performance. From the data collected, it can be seen that the planning stage – willingness to use technology, is the predominant factor under the metacognitive regulation strategies.

Conceptions of learning refer to the views and beliefs held by the individual learners about the activities involved in the learning process while using internet technology. In table 3.3, the belief of the student in the importance of the technology was examined. Importance of the technology checked for what purpose a student used the technology in their learning process. Additionally, the attitude of the student towards the use of the technology was examined. This checked the disposition of the students towards using the technology in the learning process. Precisely, this study checked the confidence of the student in using the technology, whether the technology was challenging to the student or not, the fear factor in using the technology, the familiarity of the student with the technology and the outlook of the student towards the technology. From the data collected, it can be seen that under the conceptions of learning, belief in the importance of the technology appears to be a dominant factor. Many students believe in the importance of using the technology in their learning process.

The learning motivations or orientations encompass the aims, goals, motives and worries of students in relation to their studies and they represent the motivational-affective component. In table 3.3, the learning motivations were examined by considering the different parties that directly influenced the students to use the technology in the learning process. These parties involved the university setting, the student's peers and the family members. The motivation of the student is also examined by checking whether the student managed to achieve the expected task and hence performs better. From the data collected as shown in table 3.7, under the learning motivations, the predominant factor was seen to be the use of technology to accomplish tasks.

Table 3.7 *Factors affecting student learning patterns*

Component of student learning in Kenya	n (Sample Size)	Mean	Standard Deviation
Cognitive processing strategies			
Capability/self-efficacy	747	3.94	0.4
Source of updated information	747	4.04	0.7
Access learning materials	747	4.04	0.7
Communication with lecturers	747	3.98	0.9
Exchange ideas	747	3.94	0.8
Metacoginitive regulation strategies			
Willingness to use technology (relevance)	747	4.27	0.6
Frequency of use	747	2.3	1.9
Purpose of use	747	1	0.15
Leads to better performances	747	4.01	0.6
Conceptions of learning			
Belief in the importance of technology	747	3.97	0.5
Attitude towards the technology	747	3.64	0.44
Confidence with the technology	747	3.64	0.45
Learning motivations or orientations			
Influence to use technology	747	3.79	0.6
Manages to accomplish tasks	747	4.04	0.6

The four main components of student learning patterns in Kenya are represented in table 3.7. Each factor takes into consideration its unique characteristics in the learning patterns as can be seen with the use of internet technology in the learning process. Therefore, it is evident that the four factors considered in the Kenyan universities contribute to the student learning patterns within these environments. As a result, it can be seen that students tend to benefit from internet technology in the process of their learning.

3.5.5 Student Learning Patterns on Internet Mediated Platforms in Kenya

The learning patterns obtained from the data collected in this study were generated using a data mining approach. The data mining process involved extraction of hidden information from the dataset obtained in the survey using machine learning and visualization techniques, hence discovering knowledge usable by humans (Jagtap & Kodge, 2013; Han & Kamber, 2011). The data mining process involved a number of steps before the required results were obtained. These included data cleaning, integration, selection, transformation, mining, evaluation and presentation.

This research involved the use of WEKA (Waikato Environment for Knowledge Analysis) version 3.8.3 (c) 1999 – 2018. This is a software written in Java, developed and maintained by the University of Waikato, Hamilton, New Zealand. It is an open application available and used under the General Public License. The WEKA workbench loads a number of visualisation tools and algorithms that are helpful with data analysis and the building of prediction models. It also contains a series of graphical user interfaces that assist with the functionality of the software. WEKA presents a series of machine learning algorithms that assist with resolving day-to-day data mining challenges (Brownlee, 2016).

WEKA allows a standard set of data mining tasks to be carried out within the data provided. It allows for data pre-processing, data classification, data clustering, data visualisation and feature selection. The data used on WEKA is assumed to be a single file with a number of attributes put together, assuming the nature of normal, numeric or nominal attributes. The dataset availed is subjected to data mining process to obtain the required set of results (Aher & Lobo, 2011).

Following the data collection process, data cleaning was done by examining each of the filled-in questionnaires for any inconsistencies. The questionnaires that were found not to give consistent information were all dropped from the dataset. Data integration and selection was done from the same dataset since there was a single data source and this formed the only usable dataset. At the data transformation step, the collected data was combined together into designated classes based on the different aspects that were examined on the survey as shown on appendix B. It is in this stage that feature selection was performed on the dataset.

Feature selection refers to the process of selecting features in the provided data in order to assist in model development (Brownlee, 2016). All the different attribute values in appendix B were subjected to correlation-based feature selection. This approach is considered the most efficient since, in this case, correlations are used to select the most relevant attributes that are needed in a dataset. The aim of the feature selection algorithm is to discard irrelevant and redundant features in a dataset and hence improve the classification accuracy of the data (Vanaja & Kumar, 2014). In this technique, the correlation between each of the model attributes and the output variables was calculated. The attributes selected after the calculation are those that have a value ranging between moderate to high, positive or negative correlation. In our study, only values with positive correlations were considered and any attribute with a correlation ranking below 0.1 was dropped since this alluded to a low correlation. WEKA supports correlation-based feature selection with *CorrelationAttributeEval* technique that requires the use of a *Ranker search method*. The run information obtained for all the eight factors considered is shown on appendix E.

Feature selection algorithms use a filter method that uses attribute evaluation algorithms. These algorithms study the entire dataset and perform categorizations based on the level of relevance of the individual features found on the proposed dataset. The attribute evaluation algorithm provides an individual ranking of all the features on a dataset by assigning a weight to each of the features according to its degree of relevance to the attribute selected. The filter method takes care of all the redundant cases in the proposed dataset. The basic feature selection algorithm takes the following orientation:

Input:

S - Data sample f with features X, $|X| = n$

J - Evaluation measure to be maximized

GS – successor generation operator

Output:

Solution – (weighted) feature subset

L: = Start Point(X);

Solution: = {best of L according to J};

Repeat:

L: = Search Strategy (L, GS (J), X);

X′:= {best of L according to J};

If J (X′) =J (Solution) or (J (X′) =J (Solution) and |X′|
< |Solution|) then

Solution: =X′;

***Until** Stop (J, L).*

As earlier mentioned, the data collected was categorised as shown on appendix B and after feature selection, some of the attributes on the data were discarded. The data used in the generation of the learning patterns of students on internet mediated platforms was still grouped further as shown on appendix B into PU (perceived usefulness), PEOU (perceived ease of use), IAtt (attitude), Inv (investment), KoI (knowledge of internet), SM (subjective norm), TTF (task technology fit), Relevance and Ability (R&A) and Perf (performance). The dataset was subjected to further feature selection and the attribute R&A was dropped due to low correlation value. Hence, only PU, PEOU, SM, Inv, IAtt, SM and Perf were used. These formed the basis for the generation of the learning patterns. In this research, the variables used considered the mean values of the different factors that were used. The mean value gives the central tendency in a given probability distribution. This value computed and was mainly used on the WEKA workbench to help in the data mining process for generation of the student learning patterns.

The learning patterns were generated using WEKA's *Visualise* panel in the form of 2D scatter plots. The *Visualise* panel generated in this case was an eight-dimensional instance space shown in figure 3.10. In the student performance data, there were seven independent variables (PU, PEOU, IAtt, Inv, KoI, SM, and TTF) and one dependent variable (Perf).

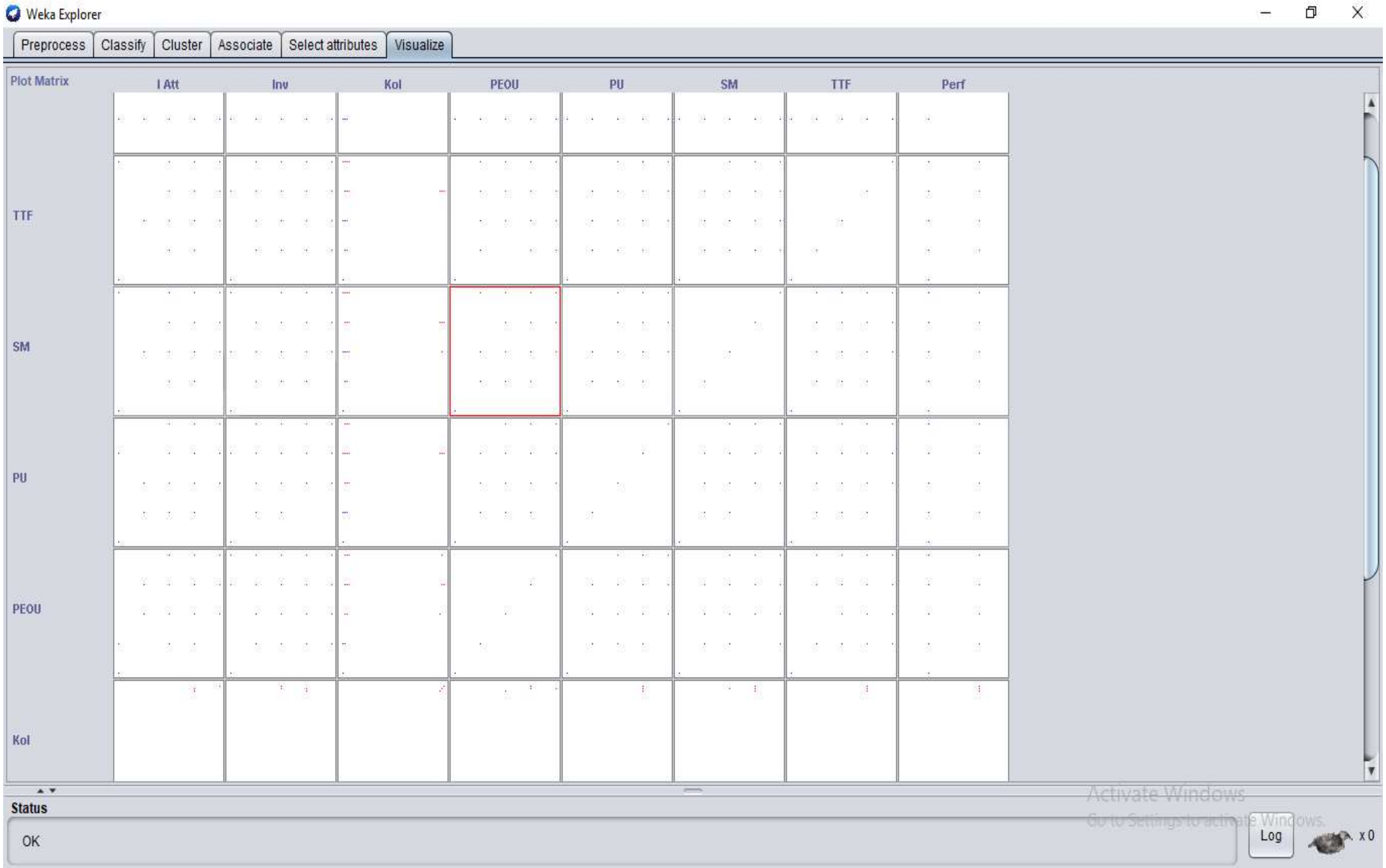

Figure 3.10 *Eight-dimensional instance space*

For each of the visible square areas, different variables were presented as two coordinate graphs showing each variable on either the X or Y axis. To enlarge the square, one is required to click on it and thus generate the scatter plots. The scatter plots show the attributes considered and the colours they assume according to the class selected. Considering that this study focused on student performance, the learning patterns were generated by considering each of the independent variables in relation to student performance.

For instance, considering the pattern generated by examining the individual attitude (IAtt) versus performance (Perf), figure 3.11 was obtained. This figure shows the attitude of individual students on the x-axis and their corresponding performance on the y-axis. On the x-axis, values 1 - 3 represent a tendency to have negative attitude while values 3 - 5 show a tendency to positive attitude. On the y-axis, there are two main sections, *no* and *yes*. The *no* section shows a perception towards poor performance while the *yes* section shows a perception towards good performance.

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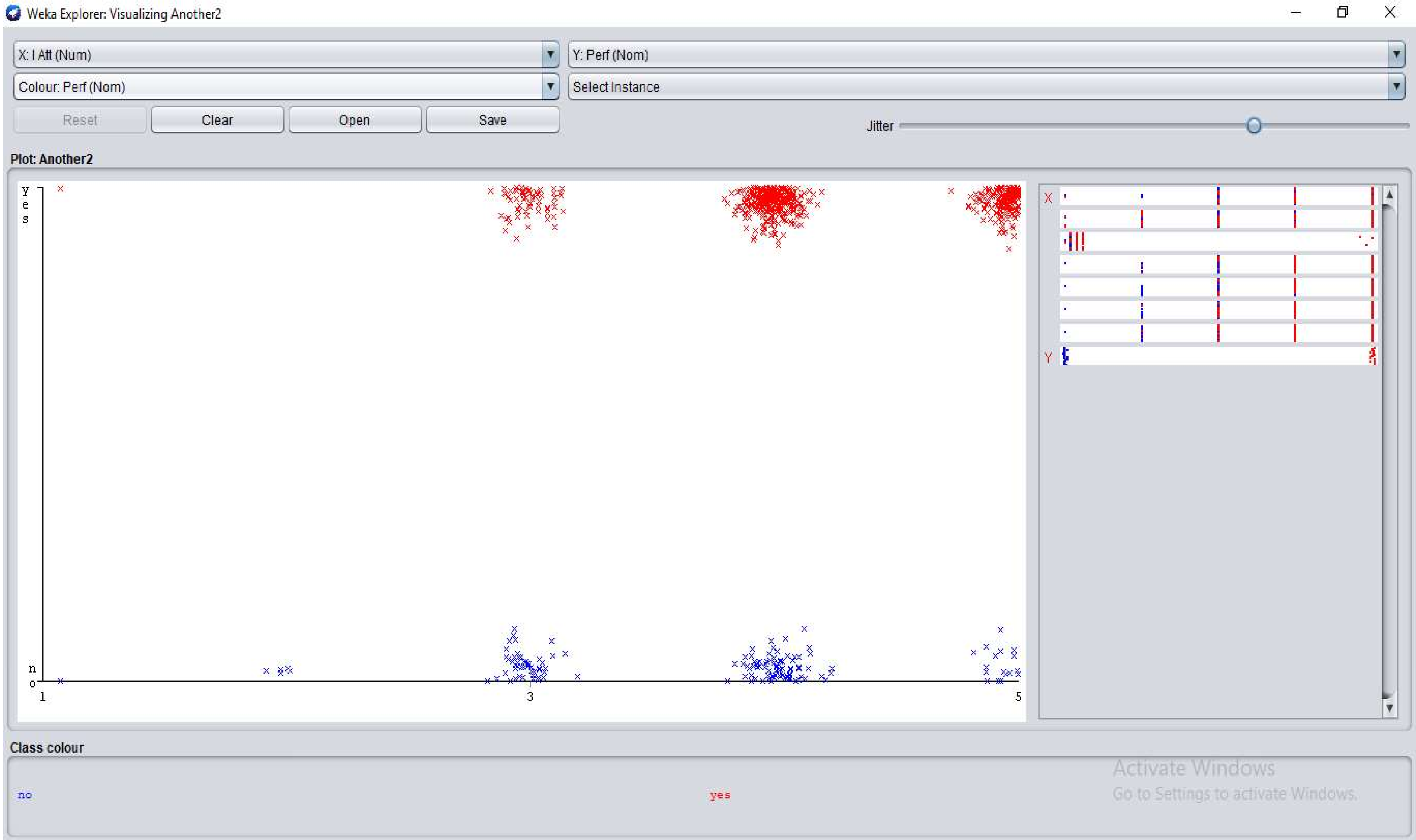

Figure 3.11 Learning pattern examining individual attitude (IAtt) versus performance (Perf)

Hence, the learning patterns generated clearly showed that many of the students had a positive attitude towards the use of internet technology in the learning process and hence they are perceived to achieve better performance. As a result, the scatter plot in figure 3.11 was subdivided into four main sections which were designated at x=2, x=3, x=4 and x=5 (from the left to the right).

At x=2, there exists two kinds of students patterns as shown in figure 3.12.

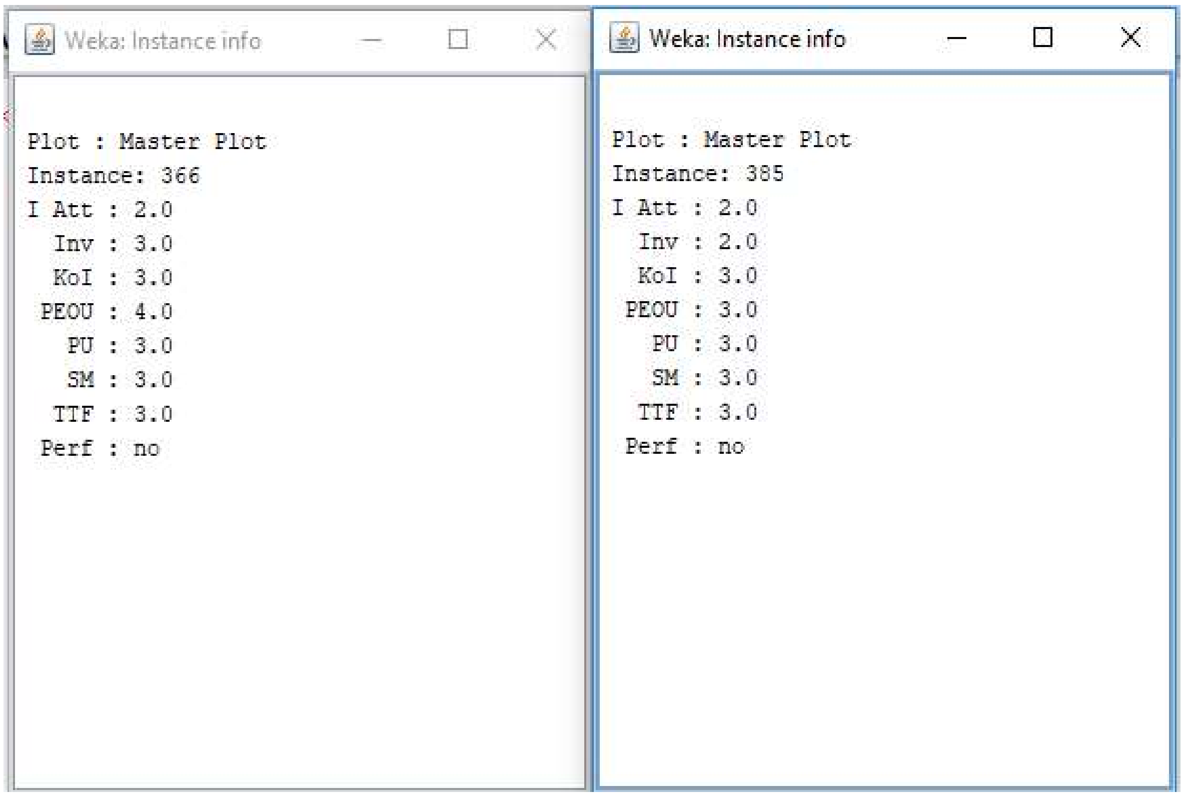

Figure 3.12 *Instances at x=2*

There existed a group of students with negative attitude towards internet technology, since their institutions had not invested in the technology and the students were not sure about their skills in the use of internet technology in the learning process. Although they perceived the technology as easy to use, they were not sure about the usefulness of the technology, they were not sure about the influence of other people in the use of the technology, and they were also not sure about the relevance of the technology in performing academic related work. As a result, the students did not perform well.

On the other hand, there existed a group of students who had a negative attitude towards the use of internet technology and their institutions had not invested in the provision of internet technology. However, the students were not sure about their knowledge levels concerning the use of internet technology in learning and they were not sure about the perceived ease of use of the technology. At the same time, the students were not sure about the usefulness of the technology and its relevance and they were not sure about the influence of others in their use of the technology. As a result, the students did not perform well while using the technology.

At x=3 there existed students with different characteristics as shown in figure 3.13.

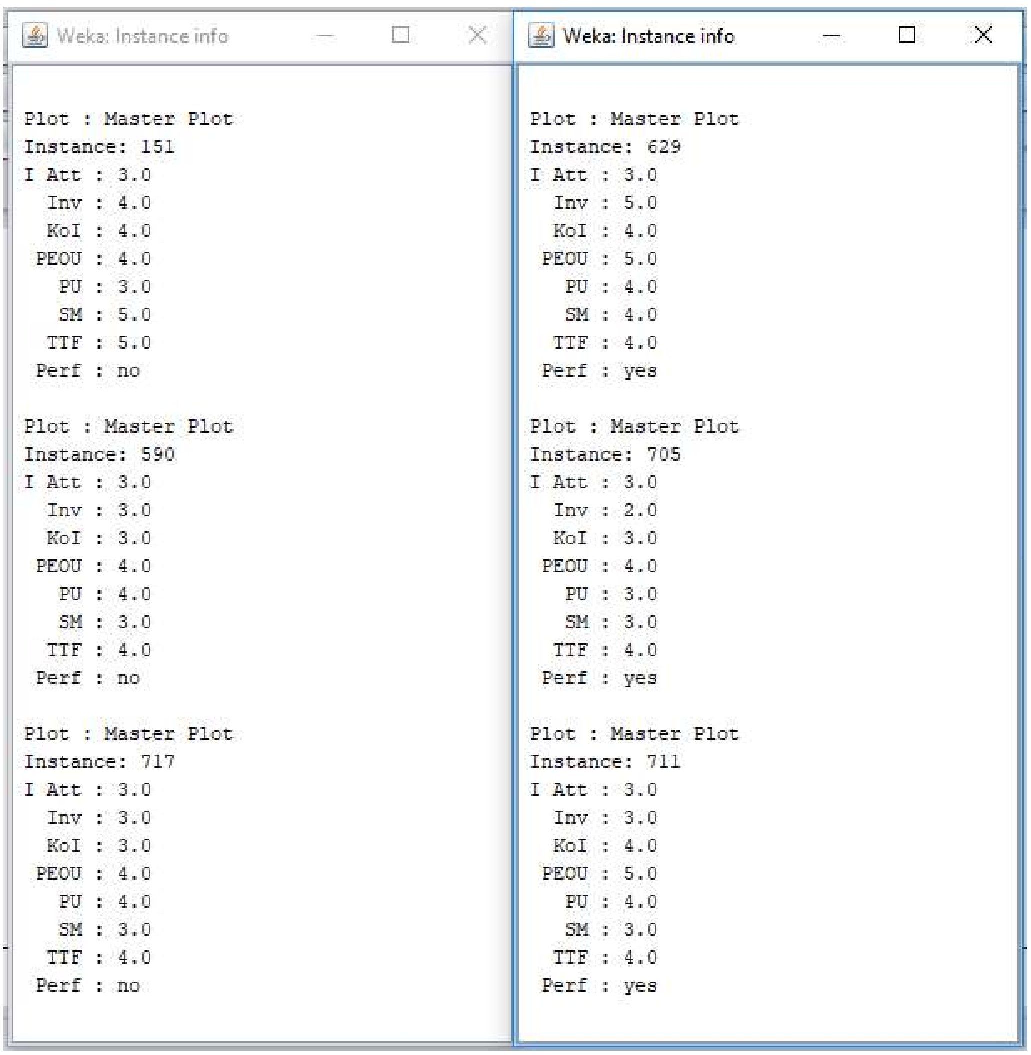

Figure 3.13 *Instances at x=3*

In this pattern, there existed a group of students who were neutral towards the use of internet technology in the learning process. The students were within universities that had invested considerably in the provision of the technology to its students and in other institutions the students were not sure about the investment made by their respective universities. Some students were not sure about the knowledge they had in the use of the technology while some of the students possessed a considerable degree of knowledge of the importance of the technology and they perceived the technology as easy to use. Some students were not sure about the usefulness of the technology while other students found the technology very useful in their learning process. The students received a lot of encouragement to use the technology while others were not sure about the influence of others in using the technology. However, all the students found the technology relevant in their studies. In this case, therefore, the students did not utilize the technology in the learning process and hence they did not perform well.

Another group of students that existed was indifferent to the use of the technology in the learning process and their universities had invested considerably and in other cases no investment was made for the provision of the technology. The students possessed the knowledge necessary for the use of the technology in the learning process while others were not sure about their knowledge levels. The students all perceived the technology as easy to use and they found the technology useful in their learning process. Some students received a lot of encouragement to use the technology in the learning process while others were not sure about the influence of others in using the technology in learning. All the students in this group found the internet a relevant resource in their learning process. As a result, the students achieved better performance in the use of the technology in the learning process.

At x=4, there existed two distinct groups of students that formed the patterns with features as shown in figure 3.14.

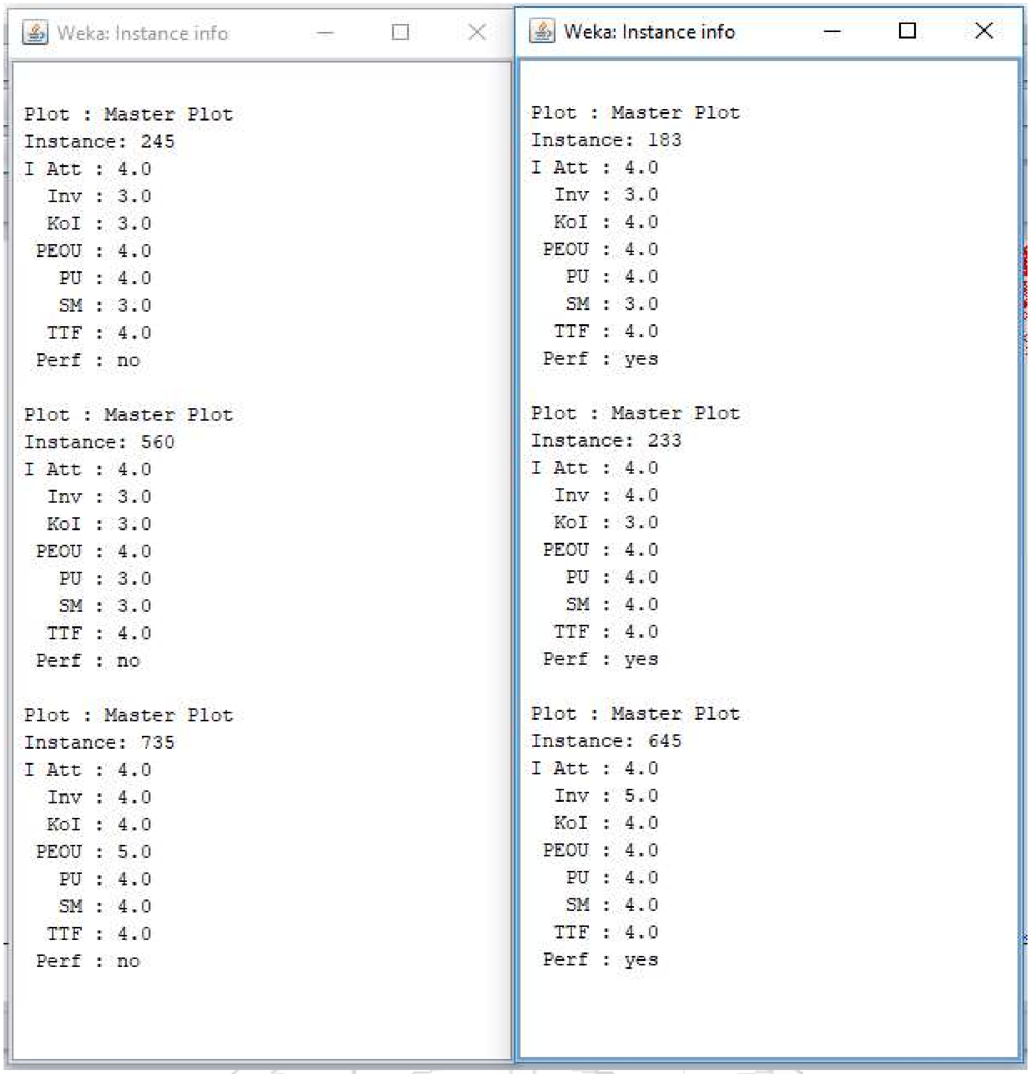

Figure 3.14 *Instances at x=4*

In the first group of students, the students possessed a positive attitude towards the use of the technology in the learning process. Although some of them were not sure about the investment done for the provision of the technology in their institutions, others affirmed that their institutions had invested in the provision of the technology. Some students were not sure about their level of knowledge in the use of the technology for the learning process while others were confident that they had the knowledge required to use the technology in the learning process. The students perceived the technology as easy to use, and they also perceived the technology as useful in their learning process. Some of the students were not sure about the influence of other people in the use of the technology in their studies while others received a lot of encouragement to use the technology in their learning process. All the students found the technology relevant in their studies. In all the above cases, the students' uncertainty regarding their knowledge or the influence of others in the use of the technology led them to perform poorly while using the technology in the learning process.

The second group comprised of students who possessed a positive attitude towards the use of internet technology in the learning process. The institutions of learning in this group had invested in the provision of the technology for learning purposes. Although some students were not sure about their knowledge levels in the use of the technology, other students affirmed that they possessed the knowledge required to use the technology in their learning activities. The students in this group perceived the technology as easy to use and useful in their learning process. The students affirmed that they received a lot of encouragement to use the technology in the learning process while others were not sure about the influence of others in the use of internet technology in the learning process. All students in this group affirmed the relevance of the technology in the learning process and as a result, they performed much better in their studies due to the use of the technology in the learning process.

At x=5, there existed two distinct groups of student features in the characteristics shown in figure 3.15.

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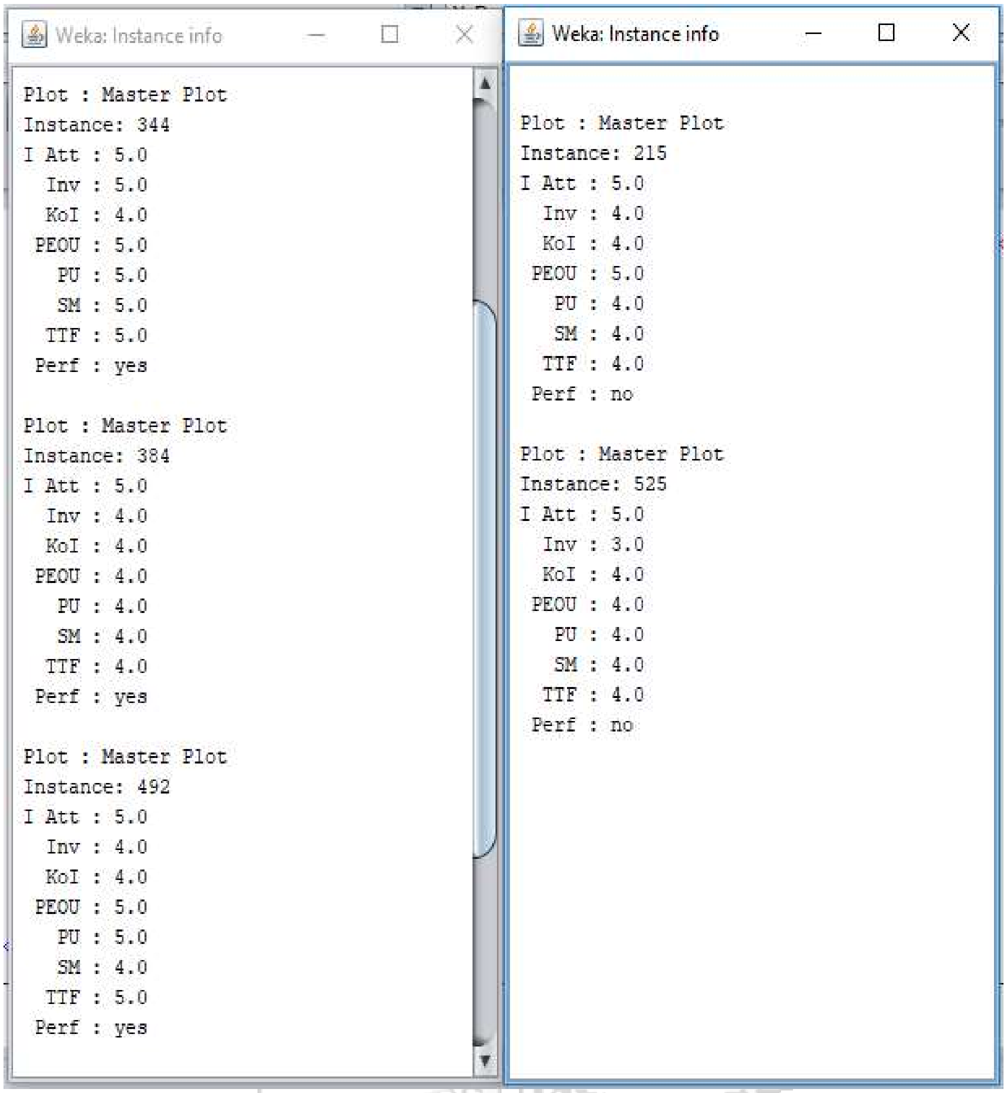

***Figure* 3.15** *Instances at x=5*

The first group of students comprised of students who had a positive attitude towards the use of internet technology in the learning process. In this case, their institutions had invested in the provision of internet technology in the learning process and the students possessed the knowledge necessary for the use of the technology in the learning process. They perceived the technology as easy to use and useful in their studies and they also received a lot of encouragement to use the technology in their learning process. The students considered the technology as a relevant resource in their learning process and as a result, the students ended up performing better in their studies while using the technology.

The other group of students possessed a positive attitude towards the use of the technology in the learning process. In some cases, the students were not sure about the investment made for the provision of the technology within their institutions while in other cases, students affirmed that their institutions had invested in the provision of the resource. The students possessed the knowledge required for the use of the technology in the learning process and they affirmed that the technology was both easy to use and useful in their studies. The students received encouragement to use the technology in the learning process and they found the technology relevant in their learning process. However, in this case, the students did not perform well in their studies.

This situation arises due to the fact that, the student always has two options in the use of a technology; either to use or not to use the technology in their learning process. For instance, if the student uses internet technology, then a nominal value *yes* is used and if the student does not use internet technology, then a nominal value *no* is used; that is,

$$U(x) = \begin{cases} yes & if\ student uses \\ no & otherwise \end{cases} \quad \ldots\ldots [3.28]$$

The student is thus in one of the two states, either in the state of using internet technology for better academic performance or not using the technology and hence poor performance. From the indicator variables given in equation 3.27, the probability of being in the using state or the non-using state is given by the Bernoulli distribution (since this distribution only gives possibility of two outcomes, either Yes/No or Success/Failure),

$$B(p,\ q) \quad \ldots\ldots [3.29]$$

where ***p*** represents a success in the utilization of internet, that is, being in the state of using the internet and ***q=1-p*** representing the state of not using the internet. The student who makes the decision not to use internet technology could be affected by attributes like time availability and risk attitude (lack of the ability to venture into a new technology with ease) (Neufville et al., 2011). This would therefore hinder the students' use of the technology resulting in poor performance.

Considering the other factors on the eight-dimensional instance space in figure 3.8, that is, PU, PEOU, TTF, KoI, SM, Inv, the student learning patterns generated are similar to figure 3.9 discussed earlier on. The patterns exhibited by the students have similar characteristics based on the other different attributes. These patterns are available on appendix I.

Subsequently, subjecting the dataset containing all variables (it was named as *Final8.arff)*, that is, the seven independent variables (PU, PEOU, IAtt, Inv, KoI, SM, and TTF) and the dependent variable (Perf) as shown in figure 3.10, to a further grouping process assisted in combining the variables further. The grouping criteria was based on ensuring that less factors were used in the prediction model. Therefore, PU and IAtt were combined together to represent student effort. This was because, effort is dependent on behavioural intention and a set of actions performed. Behavioural intention depends on individuals' attitude and their belief in the usefulness of the technology (PU).

The other set of factors that were combined together were SM, TTF, PEOU and KoI. These factors affect the effectiveness of student effort in the utilization of internet technology in the learning process. In order for a student to effectively use internet technology in learning, the subjective norm (SM) stresses that the student gets encouraged to use the technology within their specific environment, within their peer groups and within their families. Similarly, for a student to use the technology effectively, they have to understand that the technology fits in the learning process, is relevant and easy to use in their studies (TTF and PEOU). In the same way, it's difficult to interact with a technology whose knowledge is not sufficient. Hence, the knowledge of the internet (KoI) will assist the student in effectively using their effort in the learning process.

The final factor to be considered is investment (Inv). This factor is considered independent of any other factor since there are no other factors related to it.

The factors obtained after the grouping of the independent variables will therefore be student effort, investment and the effectiveness of student effort in the utilization of internet technology in learning. These three variables will then form the basis of the prediction model to be developed in Chapter 5.

3.6 Chapter Conclusion

The utilization of internet technology resembles the utilization of the different factors in the production process, aiming at having a final product for an output. This requires the use of an econometrics production function to assist in the generation of an output, in this case, the student performance. Utilization of internet technology in the learning process also specifically checks on ways in which the technology is utilized in the learning process, for instance, in classrooms and in online learning environments.

The utilization of internet technology in the learning process is also seen to be influenced by student behavioural patterns, as the TRA highlights. The attitude of the individual learner and the influence they receive from within their environments helps them acquire behavioural patterns methodically over a period of time or radically. The students end up becoming consistent, regular and persistent in the use of the technology in the learning process.

The student behavioural patterns have a direct influence on their learning patterns. Their behaviour contributes to their personal learning processes which influenced their perceptions of learning within their environment, their motivations to learn and the context of learning. Therefore, it is possible to deduce the learning patterns of students considering each of the mentioned factors, both within themselves and within the context of their environment.

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Chapter 4: Influence of Internet Technology on Student Learning Outcomes

4.1 Introduction

This chapter focuses on the influence of internet technology on the learning outcome of students in universities. In order to achieve this, the factors influencing learning in an internetworked higher learning environment are reviewed. An analysis of techniques that have been used to predict student performance in an internet mediated environment have also been presented. Finally, existing prediction models have been discussed.

4.2 Learning Outcome and Measures

The learning outcome of a student is defined as the statement or group of statements that describe what a specific student knows and understands at the end of a learning process. These outcomes are defined in terms of the knowledge, skills and competencies acquired by the learners (Pukelis, 2010). The knowledge levels of a learner are defined in terms of how extensive the learner's knowledge is and the nature and quality of knowledge the learner has acquired. The skill level of a student is defined in terms of the physical, intellectual and social skills demonstrated by the learner after the completion of the learning process. Skills are also assessed by considering how the learner is able to deal with complicated problems. Competence level is defined by considering the areas where the student is able to apply their knowledge and skills achieved so far. This considers the levels of responsibility that a learner can be able to take on both personally and in groups as they apply their knowledge and skills. The learner is expected to identify the gaps that do exist from their learning experience and be in a position to fill in these gaps with acquired knowledge. Finally, competence levels check the extent to which the learner has integrated the knowledge and skills acquired in their interactions with other people (Murray, 2016).

Learning outcomes greatly influence the end performance of a student since they are the basis for which a qualification is awarded. Student learning outcomes in this study are achieved when a student gets to know what is expected of them while using internet technology (knowledge), is in a position to perform tasks allocated to them using internet technology (skills) and understands the general value obtained from using the technology in their learning process (competence). Once the student learning outcome is achieved, the performance of the student is then predicted using different measures. This leads to the definition of the performance trend of a student.

Performance measurement refers to the methods used in gathering, evaluating and reporting the performance of a single person, groups of people, institutions or components. It also refers to the ordered measure of results and outcomes, aiming at producing trustworthy data that can be used to give possible inferences in a particular field. In the performance measurement process, there is need to consider different performance measures that work together in order to provide information about the required parameters. Hence, the different measures provide a guideline into what is required at a specific instance. The measurement of performance is a process that compares performance against the established standards and expectations. This involves checking the details involved in everyday activities and how they help in improving the overall performance of the individual. Therefore, it is a continuous and on-going day-to-day evaluation of different outcomes (Taylor & Taylor, 2014). Consequently, it becomes possible to check the performance trend of an individual over a period of time with the measures in mind. The trend obtained leads to a situation where past data can be used to predict the future using the aspect of trend analysis. As a result, the data obtained in performance measures helps in developing different patterns usable for prediction purposes.

The performance of the student in this study is based on a number of factors: the importance of internet technology, purpose and frequency of use of the technology, the belief that the technology is useful, the attitude of the student towards the internet, the investment incurred in provision of the technology, the learning resources available on the internet and the student performance while using the technology.

In considering the importance of internet technology, there is need to know the relevance of internet technology in the studies of a student. For instance, in the purpose of use, there is need to check the specific ways in which a student uses the technology in their learning process. In the frequency of use, this study establishes how often a student uses the internet for learning purposes on a daily basis. While considering the student's belief in the technology, this study tries to establish whether the student feels capable and confident in using the resource or otherwise. This is based on the Task Technology Fit (TTF) model where, if a user of the technology believes that the technology available can assist them in their tasks, then the technology is considered viable. The student's attitude towards the technology is also examined; individual attitude affects how a person behaves towards a technology.

The investment incurred in the provision of the technology considers the physical environment and the general internet technology infrastructure available to the student. This considers the situation at the specific university and within the student's environment outside the university. Performance is also based on the specific resources used by the students on the internet. This checks the different ways in which a student may find the use of the technology beneficial to their learning process due to what is available on the internet. The performance of the student while using internet technology checks on the benefits a student acquires while using the resource. This affects how the student accomplishes the set goals and feels confident about using the resource with greater ease.

A number of controlling and intervening factors are used in this study. The controlling factors examine the different stakeholders that influence a student to use internet technology. The major stakeholders considered are the university environment, the student's peers, the student's family and the student's personality. The intervening factors examine what affects the ability of a student from getting maximum benefits from internet technology. In this case, the knowledge of the technology is checked, as well as the speed of connection, the subject matter that needs to be accomplished using the internet, the costs incurred in using the technology, the time spent on the internet and the student effort needed to accomplish a task. Once the different measures are obtained, the data is used on the WEKA platform and the performance patterns are plotted to help appreciate the different learning patterns available.

4.3 Factors Influencing Learning in an Internetworking Environment

Learning in an internetworking environment is influenced by a number of factors specific to the institution and the students within the environment. Within the context of this study, an internetworking environment is defined as an environment where a range of daily activities and processes are conducted online by the people around the setting through the use of internet technologies (Brews & Tucci, 2015). The use of the internet technologies has superseded existing means of communication by overpowering the obstacles of distance, time and personal schedules. Consequently, ease of learning has been seen in the use of readily available communication channels, internet-aided learning and instruction, as well as availability of digital books along with other valuable resources essential for learning.

This section discusses the factors that influence how the learning process takes place in an internetworked environment. These factors include the knowledge and competence levels of the learners in using internet technology, their effort in using the technology, the physical learning environment, attitude and behaviour of the learners towards the technology, belief in the importance of the technology and the investment costs required to access internet technology.

4.3.1 Knowledge and Competence Levels

The knowledge and competence level of students in universities as they interact with internet technology improves over time. Though some students lack the simplest technological knowledge and skills to use the internet in the learning process, this is seen to gradually improve with their years in the university (Mills, 2016). Whereas some students find the use of internet in the learning process an enjoyable task, those with insufficient skill sets find the use of the technology a daunting task due to the large sea of information available to them within an instance. Students who do not possess the classical information-seeking behaviour do not benefit from the available modern information technologies. This situation can be combated by offering adequate training opportunities to the students in these learning institutions in order to ensure that they are equipped with the necessary skills they need to successfully use the internet in their learning process. Nwokedi (2010) posits that lack of searching skills among students is still an obstacle to the effective use of the internet in the learning process. Despite the challenges undergone by students in the use of internet facilities, it is obvious that the use of the resource enhances their academic performances in various fields. They therefore need to overlook these existing challenges and embrace the numerous benefits offered by the technological facility to enrich their intellects with the available knowledge.

Closely related to the knowledge level of a student are their intrinsic motivation, learning styles and learning strategies. Student motivation plays a critical role to their success in using internet technology in the learning process. Positive motivation enables the student to embrace the use of the technology from an early stage in their learning process, which leads to continuous improvements in their learning process (Azizi, 2014; Hughes & Dobbins, 2015). The use of the traditional means of learning is linked with poor motivation and poor performance, especially in technical courses within the university (Field, 2012). Student motivation is associated with intrinsic interest created by the student in the subject area. When a student is genuinely interested in a subject area, they tend to want to gain as much knowledge in the subject as possible. Engaging learners in immersive learning environments has been seen to positively support their motivation and interest in a subject area, for instance, in the use of game-based learning. Learning styles and learning strategies are equally essential in the acquisition of knowledge and skills in the learning process. Although there exist different learning styles and strategies, individuals define the way in which they learn best. They develop learning strategies that ensure that they make the most of the different learning materials presented to them in different forms (Muesser et al., 2011).

The process of acquiring knowledge and skills is also greatly influenced by metacognition in individuals. Metacognition refers to the ability of an individual to understand how they personally learn and this heavily relies on the learning strategies.

Having been taught in the traditional classrooms, many people have minimal knowledge about how to learn using internet technologies and hence have minimal experience with this learning strategy. With the great embrace of internetworking in universities, this trend has been changing rapidly as more and more people embrace learning with internet technology (MacKinnon & Bacon, 2015).

4.3.2 Students Effort

Student effort refers to the amount of time and energy expended by students in order to achieve a previously set objective. Effort targets a specific goal, leading to a situation where students could expend the same effort in attaining a goal while in some other cases they expend different levels of effort to accomplish the set goal. There exists different kinds of effort; rule-oriented, procedural and intellectual effort (Yair, 2000). Rule-oriented effort expects students to adhere to an already predefined set of rules and to keep away from misbehaviour. Procedural effort demands more from the students compared to rule-oriented effort. This kind of effort requires students to meet specific demands of their learning process, for instance, work on assignments and contribute during class sessions. Intellectual effort demands that the student applies their knowledge levels, capabilities and cognitive skills in order to understand the challenges presented in the learning process. Therefore, the focus of this study checks on the use of intellectual effort, specifically considering the knowledge and skill levels of students.

Student effort is a valuable predictor of success when considering cases of individual learners. It marks how motivated a student is in the subject area or how discouraged they are in the learning process (Skinner & Pitzer, 2012). Effort indicates how engaged the learners are in their academic work, whether they keep trying hard, continuously work hard or pay attention to their studies as indicated by consistency in their academic work (Reschly & Christenson, 2012). Effort can be easily controlled and changed by students voluntarily. Since individual effort affects the learning process and academic performance, effort influences the perceptions that individuals have about their capabilities (Richardson et al., 2012).

4.3.3 The Physical Learning Environments

In considering the learning environment of a student, Lizzio et al. (2002) noted that the student's achievement were greatly affected by the learning environment. The learning environment ought to inform the student about what is required of them, offer advice on the best way to achieve their learning outcome, collaborate with them in the achievement of their goals and help them manage their learning process effortlessly. Essentially, the learning environment refers to all the components and undertakings within which learning takes place. Hence, the learning environment has a role to play in affecting the learning process of a student.

Undeniably, the learning environment plays a crucial role in shaping the quality of achievements of the learner (Murugan & Rajoo, 2013). Researchers have concurred with this position by alluding to the fact that for a student to learn well, there is need to have an enabling environment that is free from possible intellectual disturbances. This therefore implies that the condition of the learner should be constantly checked to give conducive learning environs. When examining the student, there should exist an optimal balance in the body, soul and spirit; the environment should then have the right comfort levels, temperature, sufficient lighting and noise control, all enabling the learning process to take place with minimal interruptions (Ashby et al., 2011; Murugan & Rajoo, 2013; Shamaki, 2015).

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Internet technology has introduced a new model in the learning environments which requires a set of skills to navigate around. This requires the students to possess a set of critical thinking skills, assessment skills and exploration skills (Girasoli & Hannafin, 2008). There has been a great change in the learning environment due to the introduction of virtual learning environments that have provided immense learning opportunities to many students around the world. Hence, the technology has greatly revolutionised the learning spheres.

When considering any learning environments, internet technology has an effect on the present and it also has an effect on the future. The environments need to focus on providing information that leads to the mastery of a skill, and not passive information

(Fuchs, 2010). Additionally, the teachers in this environment need to assist the students by helping them stimulate their knowledge creation skills. This is achievable by providing the technology and ensuring that the learning environments are open-ended and they do not only focus on transmission of facts.

Authentic learning environments are achieved by the different perspectives in which the abundance of information is presented. The many multiple sources of information ensure that the information received is from authentic sources and therefore highly usable. Internet technology also assists in making learning environments authentic by simplifying even what are considered as complex learning processes (Jonnassen, 2010). The technology also introduces innovative learning processes, hence positively influencing what is regarded as complicated learning. With the use of the technology, the areas in which the technology is accessed have to be in such a way that they maximise the learning opportunities available. The learning environment has to enhance the student learning experience, thereby ensuring that the learners use their time intensively in order to obtain maximum results (Kennewell et al., 2013).

4.3.4 Attitude and Behaviour

As earlier discussed in section 3.4.1 under the Theory of Reasoned Action (TRA), the attitude of a student towards a technology is a characteristic of their individual behaviour. A person's attitude towards performing a specific behaviour refers to their individual views of personal desirability to perform the behaviour (Ajzen, 1991). Attitude depends on the prospects about effects of outcomes that result from their behaviour. Hence, the attitude of an individual is the result of the evaluation of their behaviour and the possible outcomes (Ajzen & Fishbein, 1980). Though Matheison (2000) defines attitude as the evaluation of a person's desire to use a system, this study defines attitude as the student's evaluation of the consequences related to the use of internet technology. Both the Theory of Planned Behaviour (TPB) and the Theory of Reasoned Action (TRA) have affirmed that individual attitude affects behaviour towards a stimulus (Trafimow & Lench, 2015).

The students' attitude towards the use of internet technology in the learning process is greatly fostered by having an internetworked learning institution (Bidin et al., 2011). The use of internet technology in the teaching and learning process automatically encourages students to use the technology since the students find themselves in an internet-enriched learning environment. This positively affects the attitude of the students in using the technology for learning purposes (Mitra & Steffensmeier, 2010). The learning approach adopted in many institutions presents a complex instructional system where learning is impacted on by a number of stakeholders, for example, lecturers, peers and computer hardware and software resources. Students who embrace the learning process with positive attitude end up using internet technology in their learning process with the same positive attitude (Hong et al., 2017).

The attitude of students towards internet technology can be assessed with ease due to its frequent usage in the field of education. Internet technology has enabled students to realise remarkable learning experiences while using the technology. Learning has become a constructive process where learners are not constrained to being receivers of information but they are actively involved in the generation of the information (Mahmud, 2011). In this learning experience, the students are required to adopt a conscious willingness in order to maximise the use of the technology in the learning process. Most importantly, in order to use internet technology productively, effectively and efficiently there is great need for correct and positive attitude in the students themselves.

According to Kaplan (2010), the attitude of students towards internet technology plays a pivotal role in the adoption of the technology in their learning process. A major challenge with the use of the technology in the learning process is the reluctance of the students to use the technology. Some students do not see its need and relevance in their studies. The major cause of this negative attitude towards internet technology are: lack of training in the usage and operations of the technology, discomfort with the enormous quantity of information available on this technological innovation and the perception that the internet breaks the learning process from the traditionally accepted learning approaches. Students in some universities regard the use of internet technology only with reference to social networking and not with reference to the learning process.

In order to combat the negative attitude in students, there is need for targeted educational activities that show the usefulness of the learning applications available on the internet. The provision of the resources that can assist with access to the technology can easily be a step forward in the use of internet technology in the learning environment. When considering attitude towards a technology, the Technology Acceptance Model (TAM) discussed in section 2.2.1 shows that perceived usefulness and perceived ease of use of a technology determine the attitude of an individual. Perceived usefulness of a technology defines the degree to which the technology will enable the user to perform better at work. When considering internet technology usefulness, this study therefore considers how important internet technology is to the performance of a student and the degree to which internet technology contributes to better performance of the student. Perceived ease of use defines the belief that the use of the technology will be effort free. In this study, perceived ease of use of internet technology is considered by examining the belief that the technology is useful and easily used in the learning process.

4.3.5 Belief in the Importance of the Technology

The belief in the importance of a technology aims at showing the technical developments that have so far been achieved over time and the general feel of the current users of the same technology. The development of the technology shows itself in the predictable and traceable path that can be seen so far in its use. This is also seen in the effects produced by the technology in solving current existing challenges and supporting further development of the work for which the technology engages in (Huesemann & Huesemann, 2011).

The belief in the significance of a technology does not segregate the users of a technology based on how much of the technology is available and how much of it can be used. Hence, technology exists as a part of human activity and is the basis for which humans act. This belief in the importance of technology identifies technology or technological advances as the cause of changes in social environments. As technologies become more and more available, they tend to stabilise and form a core part of the life of the individuals who use the technologies (Croteau & Hoynes, 2013). Consequently, the use of a technology is largely determined by the structure of the technology itself, specifically the functions for which the technology is used. Additionally, it is highly inevitable that the technology ends up introducing unavoidable developments in the environments where it is used (Morrison et al., 2010).

The belief in the importance of a technology can also be seen as discussed in the Technology Acceptance Model (TAM) in section 2.2.1. This belief is greatly influenced by the perceived usefulness and the perceived ease of use of a technology (Hussain et al., 2016). The perception of a user that a technology is useful originates from a belief that the technology assists them in accomplishing the task at hand. They are firmly convinced that using the technology will lead to better performance in their work. The perception that a technology is easy to use is also based on a firm belief that the technology is usable with minimal effort. The user of the technology is convinced that using the technology does not require a predefined set of knowledge or skills, but can actually use the technology with the least effort, if any.

4.3.6 Investment Costs

Investment costs have been incurred over the years in order to access internet technology as an essential requirement to unlock the doors of the future (Internet Society, 2017a). This is because technology improves the quality of education in a great way by opening the enormous repository of information, useful educational resources and ensuring that there are immense learning opportunities within and outside the classroom setup. Lecturers in institutions of learning have used the resource to prepare their lectures and the students have used the technology to extend their classroom acquired knowledge. Administrators within the institutions have also leveraged on using the technology in order to reduce operational costs and improve on the quality of service (Broadband Commission, 2013).

However, despite the many advantages associated with the use of internet technology in the learning process, a number of factors are known to inhibit the full realisation of its potential. Lack of access to the internet is a major challenge. Unavailability of sufficient connection bandwidth remains a major huddle in the use of the technology for provision of information services. In many developing nations, broadband connectivity is yet to be fully achieved in all parts of the country, hence hindering its use in education. This accounts for the technology costs where broadband connection requires a legal and regulatory environment that manages the investment and innovation in provision of broadband access. In order for internet access to be meaningful, there is need to ensure that the technology is provided at a reasonable cost to the institutions. The lecturers and students need to have the necessary digital literacy skills in order to make the best use of the technology (Kende & Rose, 2015).

According to the Internet Society (2017b) and UNESCO (2013), there has been a considerable improvement in the Internet for Learning in Africa Initiative. This can be seen in the improved broadband connectivity in specific countries, which has enhanced learners' and teachers' access to the internet. Internet access in universities has greatly improved due to the joint efforts from national research and education networks mainly due to funding from development partners like the European Commission and the World Bank. However, only specific universities in specific countries have attained acceptable degrees of connectivity compared to their counterparts in Asia and Latin America. Challenges that have been faced in the implementation of internet technology have been due to lack of a strategic vision and lack of capacity in drafting holistic policies that enable the implementation of learning powered by technology.

Although internet technology does not aim at sorting out all the problems associated with education, there is need to have national policies in place that will ensure that the contribution of the technology in the field of education is exhausted. Considerably, internet technology success in education is measured by improved student performance in different courses, accessibility to career opportunities for the students and cumulative contribution to national development. There are five key areas that need to be prioritised in order to ensure that investment costs are well addressed: infrastructure and access, vision and policy, content and devices, and inclusion and capacity (Internet Society, 2017c).

Physical investment costs in the provision of internet technology greatly revolve around infrastructure and access. As affirmed by the Internet Society Enabling Environment Framework (Internet Society, 2017b), setting up the technology for use requires infrastructural investment, expertise and support from the massive internet network. Broadband connectivity in many institutions is very unreliable due to poor infrastructure in many countries. There is need for governments to consider offering access and infrastructure models at more subsidised prices to ensure a certain level of connectivity in the universities. Accessibility to internet technology needs to be more affordable both to individuals and institutions in order to ensure effective use. With student financial resources being limited, access to internet technology is at times not possible from their home environment, hence the need to reduce considerably the cost of accessing the resource for universities. Within the institutions, there is need to have internet-enabled devices to assist in the learning process using internet technology. The devices need to be secured, upgraded and maintained if they are to remain useful over a long period of time. This calls for additional investment in the provision of the internet-enabled devices. As a result, the solution is to have both the capital costs and the operational costs provided for in the institutional annual budgets to avoid getting into financial constraints.

Investment costs also demand for development of a vision and policy for the future that is adopted to ensure that the technology not only benefit students of the future but also contributes to national development. The vision ought to be well safeguarded to ensure that the integration of the technology in the institution assists in ensuring that the students benefit from the technology (ITU, 2014). The policies adopted should assist all students to gain a level of competence in using the technology despite their choice of study discipline, hence improving digital literacy among all the students. The proposed policies should aim at providing access to internet technology within realistic financial resources. Improving educational management information systems assists in maximising the available resources, monitoring outcomes and targeting resource allocation.

The principle of inclusion in reviewing investment costs aims at ensuring that all individuals within an institution have access to the technology available and that this technology will ensure lifelong learning for all. Therefore, equitable access to internet technology is required. The technology should not discriminate students at different educational levels and at different stages in life. It should be open to all who need to learn. Inclusion also demands that all individuals are allowed equal access opportunities to this technology without discrimination, especially on gender basis. Consequently, the inclusion policy demands that all individuals have equal access to the technology regardless of their abilities, disabilities, ethnic groups or language spoken (Ogungbeni et al., 2016).

Investment costs also consider the fact that internet technology is instrumental in ensuring that people with different skillsets are available for job opportunities. By having sufficient access to valuable information on the internet, students are in a position to achieve better outcomes, with the skills required by the society. Since the current digital age requires digital skills, there is need to ensure that a certain level of digital literacy is achieved by those who will be required to pursue careers in ICT-demanding activities. This accounts for the psychic costs that need to be incurred by the learners. Therefore, students need to learn the basics of using online applications, searching for information online, determining whether the information is valuable, using the acquired information for decision making and staying safe while online (World Bank Development Report, 2016). For this investment cost to be fully realised, there is need to train the lecturers who will in turn transmit their knowledge to the students. Global experience affirms the need to invest in professional capacity building for the teachers who will introduce new learning paradigms in class with the learners. Similarly, educational administrators require similar capacity building levels in order to ensure that they can assist learners to make the most of their learning experience, and thereby maximise the value of internet technology in education (UNESCO, 2011; UNESCO, 2016).

While using internet technology in the learning process, there is an inevitable cost that demands that students access educational content from different authentic sources. The educational content needed by students can be availed as Massive Open Online Courses (MOOCs) or as Open Educational Resources (OER). This kind of content supplements locally available content by giving quality materials for the learners across the globe. Educators ought to encourage the students to use ideas from the already given content as a guideline in developing local content (Internet Society, 2017b). The advent of internet access using mobile devices has also introduced an individual cost to students who prefer to use their smart devices to access the internet. Impressively, Statista (2018) reveals that more than half of the total World Wide Web traffic originates from mobile gadgets with most internet traffic originating from Africa and Asia. With the growing content on the internet, the learning process ceases to be constrained within specific walls as learning can now take place wherever a student is most comfortable.

With the underlying investment costs for the provision of internet access, institutions are compelled to commit financial resources of a sizable amount in order to ensure that the technology is available to all the people within a learning institution. This therefore requires affordable accessibility to the technology, as well as the legal and regulatory structures that ensure that proper investment is done for connectivity purposes and assisting with capacity building in ensuring access to the technology.

4.3.7 Factors Influencing Learning on Internet Technology Mediated Platforms in Kenyan Universities

Based on the factors discussed in section 4.2, the data collected in this study was divided into a number of categories: importance of internet technology, purpose and regularity of usage, belief in usefulness of internet, attitude towards the internet, investment made in providing internet technology, useful resources on the internet and the degree in which internet technology enhances performance. Considering each of the measures one at a time assisted in revealing how each of the factors mentioned contributed towards the performance of students.

4.3.7.1 Importance of Internet Technology

In examining the importance of internet technology in the learning process, this study revealed that respondents considered the use of internet technology a vital component in their learning process. The respondents were required to choose one option indicated on a 5-point scale whether they considered the technology relevant to their studies or not. The 5-point scale included Irrelevant, Slightly Relevant, Not Sure, Relevant and Very Relevant. The results are shown on table 4.1.

Table 4.1 *Importance of Technology*

<table>
<tr><td colspan="5">How relevant has the internet been in your studies?</td></tr>
<tr><td>Irrelevant (n=8)</td><td>Slightly relevant (n=30)</td><td>Not sure (n=19)</td><td>Relevant (n=305)</td><td>Very relevant (n=382)</td></tr>
<tr><td>1.07%</td><td>4.02%</td><td>2.54%</td><td>40.83%</td><td>51.34%</td></tr>
<tr><td colspan="2">5.09%</td><td>2.54%</td><td colspan="2">92.17%</td></tr>
</table>

Source: Primary Data (2018)

Table 4.1 shows that 5.09% of the respondents did not consider the use of internet technology relevant in their learning process, suggesting that they did not use the technology in learning and they did not consider the technology a useful resource in the learning process. However, 92.17% of the respondents considered internet technology relevant in their learning process, meaning that, they used the technology in their learning process and they found the technology significantly important within their learning environment.

4.3.7.2 Purpose and Frequency of Use of Internet Technology

In considering the different purposes for which internet technology was used by students and how often it was used for learning purposes, the respondents were allowed to select the different ways in which they were using internet technology in their learning process. They were given six choices and they could choose more than one option. The choices were Research work, Assignments, Communication, Music/movies, Meeting people/friends/peers and Games. The results are shown on table 4.2.

Table 4.2 *Purpose of internet technology*

Please indicate for what purpose you use the internet					
Research work (n=605)	Assignments (n=575)	Communication (n=406)	Music/ movies (n=236)	Meeting people/friends/peers (n=143)	Games (n=108)
81%	77%	54%	32%	19%	14%

Source: Primary Data (2018)

Table 4.2 revealed that, indeed, respondents used internet technology for a number of tasks in their learning process. For instance, 81% of the respondents used internet technology for their research work; 77% of the respondents used the technology for their class assignments; 54% used the internet for communication purposes; 32% of the respondents used the internet for downloading music and movies; 19% used the resource for meeting people and 14% used the internet for gaming purposes. Hence, these statistics showed that the respondents were using the technology greatly for learning purposes as compared to other leisure related activities.

Additionally, the respondents were required to indicate how often they used the internet for their learning/ research work during the day. They were required to select a single option from the six options they were presented with. These options were Several times daily, Once per day, Once per month, Less than once a month, Never, and All the time. The results are shown on table 4.3.

Table 4.3 *Frequency of use of internet technology*

How regularly do you use the internet for learning/research work during the day?						
Several times daily (n=401)	Once per day (n=134)	Once per month (n=18)	Less than once a month (n=16)	Never (n=10)	All the time (n=147)	Not sure (n=21)
54%	18%	2%	2%	1%	20%	3%

Source: Primary Data (2018)

Table 4.3 revealed the regularity or frequency of use of internet technology in the learning process; 54% used the internet several times daily for learning purposes, 18% used the internet once a day, 2% used the internet for learning purposes once a month, another 2% used the internet less than once a month, 1% never used the internet for learning and 20% of the respondents used the internet all the time for learning purposes. This inferred that, the respondents were aware that they could use the technology for learning purposes and they therefore used internet technology in learning which was seen as an essential part in the learning process. At the same time, there was a set of respondents who were not sure about how often they used the technology in learning.

4.3.7.3 Belief in the Importance of Internet Technology

Another measure checked the belief held by the students as regards the importance of internet technology in the learning process. This measure was operationalized as the degree of the capability of the student in using the technology for learning purposes. The measure contained 10 items. The respondents were required to indicate the extent to which the items they were given were true regarding their self-confidence, approach to challenges and ease of use of the technology. Items were presented on a five point Likert-type scale ranging from 1 'Strongly Disagree' to 5 'Strongly Agree'. A higher score on the items, that is > 3 was associated with higher levels of belief while lower levels on the items given, that is, < 3, was associated with lower levels of belief in the importance of internet technology. As discussed in section 3.5.5, the mean values for the different parameters were obtained.

Consistent with previous studies, this measure checked the ease with which the students used the technology in learning, their approach towards the challenges presented to them in the learning process and the level of self-confidence exhibited by the students when they needed to handle a challenge in learning and the ease with which they tackled the challenge using the internet (Davis, 1989).

__Table 4.4__ Belief in the importance of technology

	n	Mean	Standard Deviation
Self-confidence with internet			
Internet does not scare me at all	747	4.06	1.05
I'm good with internet	747	4.30	0.79
I like learning using the internet	747	4.30	0.79
I look forward to using internet in my studies	747	4.19	0.79
I am confident that I can learn internet skills	747	4.31	0.73
Approach to challenges			
The challenge of learning about the internet is exciting	747	3.90	0.96
Anyone can learn to use internet if they are patient and motivated	747	4.35	0.71
Ease of use of technology			
I find the internet easy to use and enjoyable	747	4.25	0.82
Using the internet is a pleasant experience for me	747	4.15	0.83
Learning to operate internet is like learning any new skill – the more you practice, the better you become	747	4.43	0.76

Source: Primary Data (2018)

As shown in table 4.4, the respondents were required to rate their belief in the usefulness of internet technology in the learning process. When considering their self-confidence with internet technology in the learning process, the parameter highlighting confidence in learning internet skills obtained the highest mean of 4.31 (standard deviation = 0.73), implying that the respondents had been well exposed to use internet technology in their learning process and as a result, they felt that they were confident to continue learning internet skills. The same exposure also made the respondents feel that they were good with the internet and they liked learning with the internet as well. These parameters also obtained a high mean of 4.30 (standard deviation = 0.79).

The respondents also believed that they were confident enough to use the internet if they were patient and motivated. This parameter scored a mean value of 4.35 (standard deviation 0.71), implying that they could confidently approach a challenge and solve it to completion using internet technology.

The respondents also believed that internet technology was easy to use. They believed that, learning to operate the internet was like learning any new skill. This parameter scored the highest mean of 4.43 (standard deviation = 0.76), implying that the respondents believed that they could learn and use the technology confidently when they practiced its use regularly.

4.3.7.4 Student Attitude

Another measure that was considered was the student's attitude towards the use of internet technology in the learning process. This aspect tested the approach embraced by a student while using the technology in learning. Specifically, this measure was operationalized by examining student confidence in using the technology, whether the students were interested in what the technology offered for their studies and whether the student found the online resources necessary in their academics. This study checked whether the student used the materials available as the only source of updated information and whether they used learning systems in their studies.

The measure of student attitude contained 12 items. The respondents were required to indicate the extent to which the items given were true regarding their attitude towards internet technology. This measure presented its items on a 5-point Likert scale ranging from strongly agree (5) to strongly disagree (1). The results are shown on table 4.5.

Table 4.5 *Student Attitude*

Student Attitude	n	Mean	Standard Deviation
I am afraid that if I begin to use internet I will become dependent upon it and lose some of my reasoning skills	747	4.19	0.79
I am sure that with time and practice I will be as comfortable working with internet as I am in working with a library of books	747	3.90	0.96
I keep up with the advances happening in the internet field	747	4.31	0.73
I dislike working with internet since it appears like a machine that is smarter than I am	747	4.35	0.71
I have difficulty in understanding the technical aspects of internet	747	4.43	0.76
I hesitate to use internet for fear of getting too much information that requires a lot of sifting	747	2.87	1.29
I have avoided internet because it is unfamiliar and somewhat intimidating to me	747	4.03	0.93
I seek information from the internet for learning activities, for example, assignments and projects	747	3.87	0.96
I search for materials from the internet to complete my assignments and projects	747	2.27	1.29
I use the Internet as the main source of information for my studies	747	2.54	1.23
I use the internet to access the Learning Management System/E-learning portal as part of my learning activity	747	2.39	1.23
I seek the latest information online to enhance my knowledge related to the courses taken in the university	747	2.16	1.27

I use internet forums to exchange opinions on academic matters with my friends	747	3.73	1.05

Source: Primary Data (2018)

While considering student attitude towards the use of internet technology in the learning process, the parameter that scored the highest was, 'I have difficulty in understanding the technical aspects of internet'. This parameter scored the highest mean of 4.43 (standard deviation = 0.76), implying that majority of the respondents had a challenge with the technical aspects of the internet and they could not figure out its complex technical aspects, for instance, its infrastructure, terminology and its general structure.

Similarly, another parameter that scored a high mean was 'I dislike working with internet since it appears like a machine that is smarter than I am'. This parameter scored a mean of 4.35 (standard deviation = 0.71), denoting that many respondents found the internet smarter than they were and ended up not wanting to work with it.

On the other hand, the lowest mean was obtained from 'I seek the latest information online to enhance knowledge on courses taken at the university'. This parameter scored the lowest mean of 2.16 (standard deviation = 1.27), suggesting that the respondents were not fond of using internet technology to get the latest information about their fields of their study.

4.3.7.5 Investment in the Physical Environment

Another measure considered the investment made by institutions in providing internet technology for learning purposes - the students' perspective. This aspect checked the physical environment around the university and the general internet infrastructure available for accessing the technology. This parameter involved consideration of a number of measures, for instance, availability of internet connectivity within the university, availability of rooms where students could access the internet, accessibility to support services in case a student needed help in using the technology and availability of the technology within the institutions' library premises.

Focusing on the availability of internet connectivity within the specific institutions, the respondents were required to select between two options, Yes and No. The results are shown on table 4.6.

Table 4.6 *Availability of internet in universities*

Please indicate whether you have internet connectivity within your university	
Yes (n=719)	No (n=28)
96.25%	3.75%

Source: Primary Data (2018)

In this case, as shown in table 4.6 majority of the institutions had internet connectivity as confirmed by the respondents, 96.25% while only a few of the universities did not have any internet connectivity.

In order to establish whether the respondents' physical environment was suitable for accessing internet technology in the learning environment, there was need to check whether there were designated places where students accessed internet technology and whether the students were supported in using the resource within the university. Hence, the students were presented with a set of 15 items on a 5-point Likert scale that ranged between 1 for 'Never' to 5 for 'Always'. A higher score on the items, that is > 3 was associated with a better physical environment that supported access to internet technology while lower levels on the items given, that is, < 3, was associated with poor physical environment that did not support access to internet technology in the learning process. The results are shown on table 4.7.

Table 4.7 Physical environment and general internet infrastructure

Physical environment and general internet infrastructure	N	**Mean**	**Standard Deviation**
Spacious computer labs are available with adequate light, controlled temperatures and minimal noises.	747	3.62	1.22
There are many adequately equipped labs that are available with internet connectivity.	747	3.55	1.25
Internet connectivity is available all around the university.	747	3.25	1.38
I have a personal laptop for internet access.	747	3.61	1.39
I have a smart gadget(s) that I use for internet access in lecture halls.	747	3.93	1.24
Available study areas are comfortable (clean, well-organized) and with internet connectivity.	747	3.78	1.17
Lecturers have computers with internet connectivity.	747	3.63	1.24
I have access to consultation rooms with internet connection to enable me meet my lecturers.	747	3.04	1.41
I use the e-learning portal to get access to my learning materials.	747	3.59	1.35
The lecture theatres have internet connectivity and course work materials can be viewed in class using LCD projectors.	747	3.27	1.40
Adequate assistance is offered to students to ensure that they can access the internet in the university.	747	3.37	1.32
University hostels/student hostels around the university have adequate internet access.	747	2.81	1.40
Internet access is open and free to all within the university.	747	3.56	1.37
The university library has internet access for all library users.	747	4.04	1.16
Research materials are accessible from different online databases.	747	4.06	1.12

Source: Primary Data (2018)

As can be seen on table 4.7, the physical environment and general internet infrastructure within the universities occasionally met the needs of the learners within their institutions. It was also confirmed that many institutions often provided accessibility to internet technology within their library premise. This parameter scored a high mean of 4.04 (standard deviation = 1.16), implying that accessibility to internet technology was mainly confined to the library premises. At the same time, the respondents also affirmed that they could be in a position to access different online databases while within the library premise. This parameter scored the highest mean of 4.06 (standard deviation = 1.12).

On the other hand, it was evident that the university hostels rarely had accessibility to internet technology. This parameter scored the lowest mean of 2.81 (standard deviation = 1.40), inferring that the institutions had not yet invested in the provision of the resource for their students in their halls of residence. Similarly, the universities did not have consultation rooms with internet connectivity to enable respondents meet with their lecturers. This parameter scored a mean of 3.04 (standard deviation = 1.41), implying that access to such kind of facilities within the institutions was a rare occurrence.

In addition, after performing feature selection on the factors that affected institutional investment, further data analysis was done on the data obtained. This involved subjecting the factors obtained to factor analysis on the SPSS platform. In this case, using the correlation matrix, any factor that had a correlation value less than 0.5 to the output factor was further discarded and not used in the final computation of the factor means. The results obtained are shown on table 4.8.

Table 4.8 Correlation matrix for institutional investment

Correlation Matrix[a]

		C1	C2	C3	C4	C5	C6	C7	C8	C10	C11	C12	C13	C14	C15	Inv
Correlation	C1	1.000	.662	.496	.200	.232	.455	.407	.434	.420	.522	.327	.402	.428	.425	.699
	C2	.662	1.000	.592	.227	.244	.566	.437	.487	.525	.561	.372	.416	.434	.431	.762
	C3	.496	.592	1.000	.225	.221	.449	.376	.430	.475	.498	.392	.464	.374	.326	.700
	C4	.200	.227	.225	1.000	.285	.231	.234	.255	.222	.183	.242	.137	.106	.180	.419
	C5	.232	.244	.221	.285	1.000	.270	.245	.201	.232	.228	.150	.191	.171	.245	.427
	C6	.455	.566	.449	.231	.270	1.000	.555	.440	.438	.449	.311	.368	.405	.405	.689
	C7	.407	.437	.376	.234	.245	.555	1.000	.532	.502	.426	.360	.392	.355	.351	.677
	C8	.434	.487	.430	.255	.201	.440	.532	1.000	.584	.525	.499	.332	.267	.277	.699
	C10	.420	.525	.475	.222	.232	.438	.502	.584	1.000	.592	.517	.378	.315	.353	.730
	C11	.522	.561	.498	.183	.228	.449	.426	.525	.592	1.000	.475	.487	.460	.458	.757
	C12	.327	.372	.392	.242	.150	.311	.360	.499	.517	.475	1.000	.409	.270	.276	.629
	C13	.402	.416	.464	.137	.191	.368	.392	.332	.378	.487	.409	1.000	.565	.413	.656
	C14	.428	.434	.374	.106	.171	.405	.355	.267	.315	.460	.270	.565	1.000	.614	.621
	C15	.425	.431	.326	.180	.245	.405	.351	.277	.353	.458	.276	.413	.614	1.000	.618
	Inv	.699	.762	.700	.419	.427	.689	.677	.699	.730	.757	.629	.656	.621	.618	1.000

Source: Primary data

From table 4.8, it is clear that all the factors considered showed a high level of correlation to the final output of student attitude. As a result, the factors inputs used were highly reliable in the computation of the final output for this specific factor.

4.3.7.6 Useful online resources

Another measure involved investigating the utilization of online resources by students in their learning process. This factor was operationalized by considering the different ways in which the students used the technology in their learning process. The measure contained 14 items and it was expected that the respondents were to give the extent to which they benefited from the resources provided for them using internet technology. The respondents were required to indicate the relevance of the technology in their learning process, considering whether the technology was used as a source of updated information, a forum for exchanging ideas while learning, a way of communicating to different people who contributed to the learning process and a channel for getting updates on the recent happenings in various fields. The relevance of the technology was measured on a 5-point Likert scale ranging from 1 'Irrelevant' to 5 'Very Relevant'. A higher score on the items, that is, > 3 meant that there were high levels of usage of the available resources while lower levels on the items given, < 3, meant that less of the resources were accessed and used by the respondents. The results obtained are shown on table 4.9.

Table 4.9 *Relevance of internet resources*

Relevance of internet resources	**n**	**Mean**	**Standard Deviation**
Source of updated academic information	747	4.20	0.90
Access to learning materials through an e-learning portal/learning management system or to upload my assignment through the portal	747	4.18	0.95
Exchange of ideas through chats/instant messaging platforms	747	4.04	0.98
Email communication with lecturers	747	4.22	0.96
Use other online tools (Instant Messenger, Facebook, etc.) to contact lecturers about my studies	747	3.73	1.26
Email communication with classmates	747	4.01	1.06
Blogs/websites for sharing academic ideas with other students	747	3.97	1.03
Blogs/websites for sharing academic ideas with other internet users	747	3.80	1.11
Access to other learning materials for example, you tube videos	747	4.18	0.938
Avails news prompts on the recent happenings in academia and technology	747	4.09	0.92
Source of free online courses that have assisted me in a variety of disciplines	747	3.99	1.02
Search online for available part time job opportunities for students	747	4.03	1.04

VT OMNES VNVM SINT

Collection of a variety of online information good for my studies, then organizing it in files to be retrieved when I want	747	4.08	0.96
Check the university website for announcements, dates, updates etc.	747	4.21	0.95

Source: Primary data (2018)

In this case, the respondents confirmed the relevance of internet technology in their learning process. The results obtained indicated that most of the parameters scored above 4 in the survey. The parameter that scored the highest was 'Email communication with lecturers' which obtained a mean of 4.22 (standard deviation = 0.96). This inferred that the respondents used email communication often with their instructors in the learning process.

The parameter that scored the lowest mean 3.80 (standard deviation = 1.11) involved the use of blogs for sharing academic ideas with other internet users. This implied that the respondents were not at ease sharing academic ideas with other available internet users.

4.3.7.7 Student Performance while Using Internet Technology

The final measure was based on the performance of the students who used internet technology in their learning process. This aspect focused on the productivity of the students who used the technology in the learning process and whether or not the use of the technology assisted them to perform better. This aspect also considered whether the internet assisted the learners in enhancing the quality of the research output achieved by the student, whether the technology ensured that the student got better output in their research and whether they could comfortably work on a task that involved using internet technology.

In order to establish the effect of internet technology on student performance in the learning process, the factors considered were presented as a set of five items. These required the respondents to use a 5-point Likert scale where 1 represented 'Strongly

Disagree' and 5 represented 'Strongly Agree'. The results obtained are shown in table 4.10.

Table 4.10 Effect of internet technology on student performance

Effect of internet technology on student performance	n	Mean	Standard Deviation
Knowing how to research on the internet helps my studies and improves my grades	747	3.97	1.01
I score better grades whenever I use the internet to do research on my studies	747	3.63	1.09
The internet allows me to increase my productivity in my studies	747	4.24	0.86
The internet has enhanced the quality of the work I do in my studies	747	4.10	0.84
The internet has enhanced my performance in my studies	747	4.11	0.87

Source: Primary Data (2018)

The results obtained are shown on table 4.10 with the different parameters being considered when checking the influence of internet technology on the learning process of a respondent. The parameter that scored the highest mean of 4.24 (standard deviation = 0.86) was 'The internet allows me to increase my productivity in my studies'. This implied that, many respondents considered the use of the technology in the learning process as an essential part. This made the respondents use the technology and hence increased their productivity.

The parameter with the lowest mean of 3.63 (standard deviation = 1.09) was 'I score better grades whenever I use the internet to do research on my studies'. This implied that, majority of the respondents used the technology but they did not associate the usefulness of internet technology with attainment of better grades.

4.4 Techniques for Determining Student Performance on Internet Mediated Environments

Predicting the performance of students on internet mediated platforms has been greatly influenced by the enormous quantity of data that is available online, which spans hundreds of petabytes (Hughes & Dobbins, 2015). This is mainly attributed to the growth from Web 1.0 services to Web 2.0 services, where data is available on many platforms (social networks, online educational services, cloud services) all the time and for all sectors (Chen et al., 2014). In terms of learning on internet mediated platforms, it is clear that students have been engaging with online course materials and have been communicating with online communities by posting comments on forums, asking questions and receiving respective answers. The students also watch educational lectures and they take their quizzes all on the internet platform (Ramesh et al., 2013). As a result, this data about the different learning activities can be collected, profiled and used to predict the performance of the learners while they use internet mediated platforms in their learning process. As the online learning platforms become more and more popular, there is recurrent emergence of huge datasets regarding individuals and institutions. This leads to having massive data content that cannot be used for the benefit of the individuals and their institutions (Chen et al., 2014). Therefore, there is need to examine some of the existing ways of handling the large datasets being generated by considering different approaches such as data mining techniques, machine learning techniques, social media analytics techniques and prediction modelling techniques.

4.4.1 Data Mining Techniques

The application of data mining techniques can be used to help in extracting valuable information from the huge datasets available from the institutions and the individuals. This involves the field of statistics, pattern recognition and machine learning in order to extract valuable knowledge and detect patterns from complex datasets available (Duin & Pekalska, 2016). In this study, such approaches have been used to analyse the data collected from students in order to find patterns in their internet technology usage and their different behavioural patterns. This has assisted in the prediction of their performance levels with internet utilization.

Investigating student learning on internet mediated platforms and predicting their performance requires a series of algorithms and data analysis techniques. According to Hanna (2004), this can be done by applying data mining techniques that are able to turn large datasets into valuable facts and information. Since data is being created at fast rate, it can be permanently stored in many different databases with data warehousing technologies, for instance, data cleansing and data integration, coupled with online analytical processing (OLAP). This approach to data mining has become popular in mining educational data due to its universality in many applications and its high performance (Mansmann et al., 2014; Romero & Ventura, 2010; Angeline, 2013).

This data warehousing architecture consists of five main stages: raw data, ETL layer, data storage, analysis and visualisation. At the raw data stage, the data is obtained from all available relevant sources. During the ETL (extraction, transform and load) stage, the data undergoes a processing mechanism to ensure that its format is compatible to the warehouse. At the extraction level, data is pulled out from numerous sources and it comes in different formats. At the transform level, the data undergoes a series of processes such as categorization, grouping, integration and pivoting. This stage separates the text based data and numerical data, which forms the schemas that enable the loading of data onto the warehouse. The data held in the schemas comes from different sources in the general scope of education (Romero et al., 2013). Behavioural data about a student can also be obtained from social software and blogs, which can help determine some traits possessed by the learners (Kop & Fournier, 2011). The availability of the numerous data regarding students requires the use of advanced techniques that can be used to process the raw data available into knowledge and hence help in predicting the performance of the student on an internet mediated platform. Therefore, the process of predicting student performance requires that the data available gets divided into groups, extrapolated and combined into indices. The stored data can be subjected to a data mining technique so that the information obtained from it can be visually communicated for decision making purposes (Mansmann et al., 2014).

Data mining presents a common way of classifying available data by identifying the patterns formed by the data. This aspect employs the use of computer science and mathematical algorithms (Hughes & Dobbins, 2015). Data mining approaches are also used in other fields, for instance, in anomaly detection, dependency modelling, clustering and summarisation. In anomaly detection, data mining assists in isolation of erroneous cases in datasets for the purpose of establishing anomalies in research or correction of errors. For example, some students disregarded all presumptions about learning and still made it (Chandola et al., 2009). Dependency modelling can be seen in the creation of linked knowledge between different datasets. For example, do students spend the same amount of time studying regardless of whether they are on internet mediated platforms or studying using traditional hard copy text? In clustering, data mining ensures that the available large dataset is divided into smaller groups of the data that have some level of association with the dataset in which they belong. Summarization of the data refers to the conversion of the raw data into information, for instance, establishing the mean and standard deviation of a dataset (Maimon & Rokach, 2010).

4.4.2 Machine Learning Techniques

As discussed in section 4.3.1, data generation is becoming more and more phenomenal with time since data is being collected from a wide variety of sources. This data happens to be mainly unstructured or semi-structured and is therefore difficult to analyse. The increase in this nature of voluminous data of different kinds requires an advanced methodology that ensures that it can be understood, processed into information and summarised (Jain, 2010). This has led to the development of distributed databases, a recent phenomenon in the world of data storage. Unlike the older versions of databases that were tried and tested models, these databases are formulated on increase in hardware performance in order to run the operations of searching, sorting and filtering algorithms on data streams. These systems are mainly associated with big data analysis and they exist to complement and not replace the older databases.

In itself, the area of machine learning is a common research area that can be applied to a variety of heterogeneous datasets in order to establish patterns existing in the data that can be used in predictive modelling. A small portion of the data is first trained and the training data is used in the prediction of behaviour from previously unseen test data (Jain, 2010). In this type of learning, there are two main approaches: supervised or unsupervised learning. In supervised (classification) learning, the data is well labelled to establish how powerful the algorithm is at learning the solution to a problem while in unsupervised (clustering) learning, the data is unlabelled and the system forms natural groupings or clusters of patterns spontaneously (Duda et al., 2000).

Research done by Kloft et al. (2014) used support vector machines (SVMs) to predict when a student would leave a course. This research used clickstream data from millions of websites. The data used to train the classifier was in the form of comments and lecture video views. The resulting work achieved a reasonably good accuracy at the beginning of the course and this approach kept on improving over time. In another similar research, Ramesh et al. (2014) used probabilistic soft logic (PSL) to predict whether learners complete their class quizzes and assignments and also whether the same learners would eventually finish their course. This approach produced reasonably accurate rates and it illustrated the fact that some students were extremely engaged at the beginning, in the middle of the semester they became passive while at the end of the semester they became more active.

Another similar research was conducted by Jiang et al. (2014) using logistic regression to predict performance of students in their first assignment and social interaction in a MOOCs (Massive Open Online Courses) environment. This work achieved an accuracy of 92% in predicting whether a student achieved a distinction or a normal certificate and achieved 80% accuracy in predicting whether a student achieved a normal certificate or did not complete the course. In another research, Romero et al. (2013) developed a data mining tool for the Moodle platform for comparing the performance of data mining methods, statistical methods, decision trees and induction methods for predicting students' final marks. The data used in this research was obtained from assignments and class quizzes and this achieved moderate accuracy as well.

Another research done by Ezen-Can et al. (2015) used the unsupervised clustering approach to check on the content of posts in a MOOCs environment. The k-medoids algorithm is the algorithm that has been used to analyse and check the content posted by the learners in their discussion forums. The applications built using the k-medoids algorithm present significant development in the world of systems where the systems can automatically understand the topic of discussion in a collaborative forum and provide adaptive support to individual learners and to the collaborative group. While it is actually possible to predict student performance from their interaction with the course content in a learning period, more attributes and inputs are actually necessary in order to get a more accurate prediction (Romero et al., 2013).

4.4.3 Social Media Analytics Techniques

Existing social media sites offer an overabundance of information regarding its users, their behaviours and their preferences. All this information can be collected and analysed in order to assist with predictions. These sites have become inescapable with a high percentage of adults spending a considerable amount of time on them (Fan & Gordon, 2014). A closer examination of the social media platforms reveals that Twitter has 336 million monthly active users who collectively send 600 million tweets daily, and Facebook has 2.19 billion monthly active users who have created 60 million pages (Statista, 2018). In order to benefit from this growth, institutions have resorted to employing social media analytics who can assist with extracting useful patterns and intelligence from this voluminous dataset. A common approach in the analysis of this data involves the use of sentiment analysis. Sentiment analysis helps in uncovering existing behaviours, emotions, opinions and attitudes of learners using analytics on text, computational linguistics and natural language processing (Fan & Gordon, 2014; Wen et al., 2014).

A research carried out by Wen et al., (2014) used data from Twitter to study dropout behaviours on some online courses. The data collected in this study included the lecture topic and corresponding assignments. The results of the analysis revealed that there was a direct connection between the mood in the posts referring to the unit and the number of students who drop out of the course. Another similar work by Kop and Fournier (2011) used Moodle participation, blog posts and Twitter to identify the relationship between learners and a free online course over a period of time. This data revealed the number of blog posts and tweets generated in the online course. However, the study revealed that only a small percentage of members of the group made regular contributions on the online course. The greatest percentage of students on the course was mostly silent and did not contribute to the extensive discussions on the course. This research by Kop and Fournier (2011) provided clarity on the nature of the interactions between participants, resources and networks on internet mediated platforms while highlighting how analytics can be used in understanding the performance of learners in an open networked environment.

Similar work done by Koutropoulos et al. (2014) analysed the Twitter stream for of a short online course. In this course, positive emotions were displayed throughout the course and this content was mainly during the first few weeks after the commencement of the course. The twitter platform in this case was a major learning resource in the course since it was used by the participants to share relevant course links and resources; it was mainly a platform for reflecting on learning and for commenting on the live sessions of the course. As a result, the platform became very useful for dissemination of course concepts outside the classroom environment.

As can be seen from the above research, social media platforms provide an ideal and open forum for analysing the behaviour of learners outside the classroom environment and it also provides important behaviour and sentiments that can be used in the prediction of student performance. This is useful for predictive modelling where one can predict the student behaviour based on their interaction within different internet mediated environments.

4.4.4 Prediction Models

A prediction model applies a statistical model or a data mining algorithm to data for the sole purpose of predicting new or future observations from the data. The goal in prediction models is to predict the output values (Y) for new observations given their input values (X). In this case, all the observations until time t (the input) or at a specific time t are used to predict the future values at time $t + k, k > 0$ (the output) (Shmueli, 2010). Predictions include point or interval predictions, prediction regions, predictive distributions or rankings of new observations. Hence, a prediction model is any model that produces predictions, regardless of the underlying approach.

This section discusses the different ways in which prediction models are developed. Specifically, it examines the linear and non-linear prediction models, regression models and stochastic models.

4.4.4.1 Linear Prediction Models

Linear prediction models are models that are used to provide a robust, reliable and accurate way of estimating the parameters that characterise the linear time-varying systems. These predictive models are very important specifically in digital signal processing and in image processing. The models have been widely used in the estimation of basic speech parameters like the pitch, formants and spectra in sound. Linear predictive models are used in various other areas; for example, in speech and voice coding, model-based interpolation and spectral analysis, signal restoration and data forecasting. These prediction models are also referred to as autoregressive (AR) processes (Vaseghi, 2000). This kind of prediction has also been used in areas of adaptive filtering, system identification and spectral estimation (Benesty et al., 2010). The importance of linear prediction lies in its ability to provide extremely accurate estimates of speech parameters, as well as its relative speed of computation.

Linear prediction models (LPM) are most commonly used in speech applications that involve speech modelling, speech compression and speech recognition. This is mainly due to the fact that the speech production process is best modelled using LPM. Therefore, a well-recognised speech signal takes the form

$$x_k = \sum_{l=1}^{L} a_l \; x_{k-l} + Gu_k \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad [4.1]$$

where $\boldsymbol{k}$ is the time index, $\boldsymbol{L}$ represents the number of coefficients in the model (the order of the predictor), a_{l}, $l = 1, \ldots, L$ are defined as the linear prediction coefficients, $\boldsymbol{G}$ is the gain on the system and $\boldsymbol{u_k}$ is the excitation signal or a random noise source. The periodic source mainly produces voiced sounds like vowels and nasal sounds and the noise source produces unvoiced sounds, especially consonants. The parameters a_{l}, are mainly used in determining the different characteristics of a sound and these are therefore very useful in speech coding schemes and in automatic speech recognition systems.

The use of linear predictor models has mainly been in speech-related applications. These models help in modifying speech sounds in many ways, for instance, changing the pitch without altering the timing, changing the timing without changing pitch or blending the sounds of musical instruments and voices. Linear prediction provides a parametric modelling technique that's only useful in modelling the spectrum as an autoregressive process. The parametric models are mainly used in compression systems, systems identification problems in modern control systems, time series analysis for economic applications and spectral estimation in signal processing. The ideas proposed in linear prediction models are also used in system estimation and in system identification. Linear prediction models have been greatly useful in modelling the vocal tract which is useful for both theoretical and practical purposes.

Other areas where linear models have been applied include industrial engineering, actuarial science, in geometric distributions and in signal processing. In industrial engineering processes like drinking water treatment, linear models have been used in explaining the dose and concentration of the quantities required for the entire process. These variables in this case include sulphate and lime and the physical and chemical components of the raw water (Cepeda & Cepeda, 2015).

In the field of actuarial science, as shown by Siddig (2016), linear prediction models have been used in the rating application they use to determine the monthly premiums that should be charged to the policy holders. This requires accurately checking all parameters involved in the computation and the level of precision in the data in order to check on any probable losses. There is need to classify all observed losses according to the available risk factors; this will help to determine when the largest premiums should be charged (case of large losses) and when the smallest premiums should be charged (case of small losses).

Linear models are also widely used in the geometric distributions, where they assist in predicting the first occurrence of any given event. This approach has been used to predict and model all significant factors that could lead to the first instance of infant demise given a predefined birth order. Two approaches to linear predictive modelling are used in this case and the results from the two models are compared to show which approach is better (Jahan et al., 2016).

In many cases, linear prediction models have been widely used in a wide range of signal processing applications which range from low-bit-rate speech coding to model-based spectral analysis. This modelling approach also considers short-term and long-term correlations of signals where signals are processed with a quasi-periodic structure as is the case in voice signals.

Considering the nature of linear prediction models, the technique used in this case majorly focuses on time series analysis that only emerges from the examination of linear systems. Once all the inputs are determined, the linear predictive model obtains the cumulative sum in order to generate an output (Shumway & Stoffer, 2017). The inputs identified are a collection of random variables indexed according to the order in which they have been generated in time. This approach to prediction modelling does not fit in this study since the variables used were obtained at a specific instance and they were used as the input values.

4.4.4.2 Regression Prediction Models

A regression prediction model is a statistical model that is used to treat one variable as a function of another. Regression models result in an equation that is used in the prediction of an outcome from the value given in one or more predictor variables. This statistical methodology utilizes the relationships that exist between two or more variables in order to assist in predicting another variable. This approach is commonly used in the field of business, behavioural sciences and agriculture.

Regression predictive models are used mainly for descriptive purposes, control purposes and prediction purposes. The use of equations to describe a set of data is a common feature in data analytics. These models help in the formulation of the equations. They also ensure that the relationships that existed between the variables in the original data are still valid when the regression equations are introduced (control purposes). Besides prediction purposes, regression prediction models assist in control purposes (Besley et al., 2004). When being used for prediction purposes, regression models have no need for cause and effect relationships.

These prediction models are defined on the basis of functional relations. A functional relation existing between two variables can be expressed by a mathematical formula. If a variable named $\boldsymbol{T}$ denotes the independent variable (IV) and $\boldsymbol{G}$ denotes a dependent variable, the functional relation takes the form shown in equation 4.2.

$$G = f\ (T) \qquad [4.2]$$

This means that for a given value of $\boldsymbol{T}$, the function $\boldsymbol{f}$ gives the corresponding value of $\boldsymbol{G}$. A statistical relation, unlike a functional relation, is not a perfect one. Hence, statistical relations do not directly form curve relationships.

Depending on the nature of the relationship that exists between a variable or a set of variables and the outcome to be predicted, there can be the possibility of a linear regression model or a nonlinear regression model. This is because the outcome variable is always related to the set of input variables through a set of parameters. Linear models are models that are linear in the parameters while nonlinear models appear nonlinearly. Linear models present an adequate estimate for regression applications.

Linear regression modelling is a technique that is used to give numeric predictions in different fields, mainly in Psychology and medical research. A regression model is considered to be linear when the terms in the model are either constants or parameters multiplied by independent variables (IV). The model is then built by only adding the terms together (Frost, 2017). As a result, a linear regression model is defined as:

$$Dependent\ variable = constant + parameter * IV + \cdots + parameter * IV$$

Hence, this approach predicts the target value X from a series of attribute values $a_{1,} \dots \dots \dots, a_k$.

$$X = w_0 + w_1 a_1 + w_2 a_2 + \cdots + w_k a_k \quad \text{……………………………………………..} [4.3]$$

In equation 4.3, the regression coefficients are represented by $w_{1,\dots,} w_k$ and w_0. This forms the model parameters that are provided in the dataset (Witten & Frank, 2011).

Another consideration of equation 4.3 from the view of statisticians reveals that the equation is linear in the parameters provided. In case there is need to model a curvature with this type of regression model, there is need for a slight modification in the parameters involved. Since the function needs to be linear in the parameters, the independent variables can be raised by an exponent value in order to fit a curve; for instance, if an IV is squared, the model produces a U-shaped curve, as in equation 4.4

$$X = w_0 + w_1 a_1 + w_2 a_1^2 \quad \text{………………………………………………………………..} [4.4]$$

While one of the independent variables is squared, the model is still linear in its parameters. These linear regression prediction models also contain log terms and inverse terms and they all represent different kinds of curvatures and yet still continue being linear in nature (Field, 2013). When using log terms, equation 4.4 can be written as shown in equation 4.5.

$$\log(X) = w_0 + w_1 \log a_1 + w_2 \log a_2 \text{………………………………………………………} [4.5]$$

Representing equation 4.6 using inverse terms can be done as follows,

$$X = w_0 + w_1 a_1 + w_2 a_2 \text{…………………………………………………..……………} [4.6]$$

Suppose the value of $a_1$is required in the prediction model and the values of the other parameters are known. The value of a_1 would be given using inverse terms as shown in equation 4.7.

$$a_1 = \frac{X - w_0 - w_2 a_2}{w_1} \quad \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . \dots \dots \dots [4.7]$$

A non-linear regression prediction model does not follow the rules of a linear model. In this model, at least one of the parameters appears nonlinearly;

for example, the Weibull growth curve, which gives an s-shaped curve as represented in equation 4.8.

$$Weibull\ growth = K = \theta_1 + (\theta_2 - \theta_1) * \exp\left(-\theta_3 * X^{\theta_4}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [4.8]$$

Another example is the Michaelis-Menten model, one of the best models that is used to model enzyme kinetics. The model has two parameters and one independent variable as shown in equation 4.9.

$$f\ (x, \beta) = \frac{\beta_1\, x}{\beta_2 + x} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [4.9]$$

This kind of a model takes a variety of possible forms fitting a numerous set of curves. As a result, any other predictive model that does not conform to the features and characteristics of linear regression predictive models qualifies to be a non-linear regression predictive model. The differentiating characteristic in both kinds of models are the functional forms used in the models. The functional forms that define the linear models being specific therefore mean that all other functional forms are non-linear in nature (Frost, 2017).

In general, when determining whether to use a linear or a non-linear regression prediction model, the decision involves using linear regression to determine whether the model fits the particular curve in the already generated data. If the desired curve is not obtained, then there is need to consider using a non-linear regression predictive modelling curve. Linear regressions are easier to use, simpler to interpret and thus obtain more statistics that help in assessing the model at hand. Although linear regression is used in modelling different forms of curves, it is relatively restricted in the kinds of curves that it can be in a position to fit, depending upon the nature of the data given. Non-linear regression prediction models are used to fit more forms of curves, though they require more effort to determine the best fit of the curves and to interpret the function of each of the independent variables (Frost, 2017).

Applications of regression predictive models exist when establishing the relationship between different interacting wave models at specific points, each containing a different frequency. The same approach is used when determining and predicting existing anomalies when rain water flowing in a given direction exhibits a time series in an opposite direction (Roundy & Frank, 2004).

These models have also been used in the field of economics to predict the expected sales in a game event. In this case, the major parameters considered are the game attendance records. Regression prediction in this case provides a powerful tool that can assist in the modelling of specific cases in litigation processes (Mills, 2011).

A research by Ra et al. (2012) applies regression prediction models in modelling to predict the area that happens to have the highest risk of producing disease maps. This involves studying the exact regions where the disease is most prevalent within specific locations. The dependent and independent variables are formulated and these variables are examined to check on the relationships that do exist between them. Data collected from the different factors is used to give the predictions of the specific disease infested zones.

4.4.4.3 Stochastic Prediction Models

The use of stochastic prediction models is essentially important in the field of business, education, science and economics. Stochastic prediction modelling is also instrumental in modelling of user behaviour in varied circumstances. Stochastic predictive models have also been implemented in the prediction of financial trends that define individual behavior, company behaviors and country behaviors. Stochastic models assist in predicting the state of the economy and defining how banking institutions can plan their appropriate monetary policies (Sasikumar & Abdullah, 2015).

By definition, a stochastic process is a family of random variables $\{X_\theta\}$ indexed by a parameter θ, where θ belongs to an index set Θ. When Θ represents a set of values of integer type, signifying specific time points, there is a possibility of a stochastic process existing in discrete time or in continuous time. A stochastic process in discrete time occurs when the index set Θ is a set of integers representing specific time points. If the index set Θ is a set of integers occurring on the real line or within some intervals on the real line, then the stochastic process occurs in continuous time.

From a general perspective, a discrete time process with a random variable X_n will depend on earlier pre-existing values of the process, $X_{n-1}, X_{n-2}, \ldots$. Likewise, a continuous time process with a random variable $X(t)$ will equally depend on the values $X(u)$ for $u < t$.

Therefore, of major interest are conditional distributions which are represented to satisfy the Markov property in the form

$$\Pr\left(X_{t_k} \middle| X_{t_{k-1}}, X_{t_{k-2}}, \ldots, X_{t_1}\right) \qquad [4.10]$$

for some time $t_k > t_{k-1} > \cdots > t_1$, which depends on the values of $X_{t_{k-1}}, X_{t_{k-2}}, \ldots, X_{t_1}$.

The Markov property, named after Andrei Markov (1856-1922), states that given the present (X_{k-1}), the future X_k is independent of the past $X_{k-2}, X_{k-3}, \ldots, X_1$. The Markov property in equation 4.6 can also be rewritten as

$$\Pr\left(X_{t_k} \middle| X_{t_{k-1}}, X_{t_{k-2}}, \ldots, X_{t_1}\right) = \Pr\left(X_{t_k} \middle| X_{t_{k-1}}\right) \qquad [4.11]$$

It is referred to as the lack of memory property.

In considering human behavior, as in the case of this study, researchers have developed and used a variety of probabilistic methods trying to learn user behaviors from social data (Purushotham et al., 2012). These models consider a user and their interest in a given topic and how the user responds to the topic in a discussion forum. The assumption made in these models is that the more a user responds in a topic of discussion, the more they are interested in the topic. On the other hand, the probabilistic models do not account for user's behavior in relation to the responses given in the topic, for instance, how often a user visits the website with the topic, how many messages the user receives on the topic and how many times the user responds to the messages received. As a result, failing to consider these areas from the perspective of users leads to insufficient explanation of the developed probabilistic models. These models therefore need large amounts of data in order to accurately predict human behavior, which this may not be available.

Stochastic predictive modelling has been applied widely in the modelling of user behavior (Chua et al., 2012; Kang, et al., 2013; Wang & Blei, 2011; Hogg, et al., 2014). The method in this case uses a probabilistic technique, and this considers each user as a stochastic process that transitions between states with some probability. The probabilistic approach captures the uncertainty of actions by users while using internet technology. When modelling a website, the user states and therefore the behavioral outcomes are constrained to the user interfaces provided, for instance, visiting a website, seeing some valuable content on it and using it in accomplishing a given task. Transitions are represented as dependencies between different states, for example, using the content on a website depends on seeing the value in the content and being interested in it (Hogg et al., 2014). This modelling approach uses parameters that govern the frequency of usage of a technology or a resource and these are the parameters that capture the significant mechanisms that influence human behavior. The model parameters used are always user-specific, but to reduce the required data and improve generalizations, the parameters are associated with populations of similarly-behaving users.

Another application of the stochastic modelling approach is implemented in the stochastic modelling framework to describe dynamics of popularity of content on social media (Hogg & Lerman, 2011; Lerman & Hogg, 2012). In the stochastic modelling framework, the specific behavior of users online depends on their history of interacting with other users online and the content provided by the website, which varies considerably among user populations. The stochastic models summarize the behavior by representing an individual entity, whether a user or the available content, as a stochastic process with a few states (Hogg & Lerman, 2009). The models embrace the use of the Markov property, where the future state of a user or the available content depends only on the present state; the input from the available content and the users at that time. The Markov process is then captured by a state diagram showing the possible states and transitions between those states. Each of the states given represents the probability that a user will perform an action. Consequently, using the probabilistic interpretation of the model, the user behavior allows for the computation of the likelihood that the user will perform a given observed action. This can be represented as shown in equation 4.12.

$$A(t) = \sum_{t=1}^{n} (a_t * b_t * r_t) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.\dots\dots\dots\dots [4.12]$$

where $A\,(t)$ represents the specific action observed, a_t denotes the student attitudes towards the action at hand, b_t denotes the student belief in carrying out the action and r_t is the expected outcome from the action. This equation is discussed in detail in section 5.4.2.

4.5 Chapter Conclusion

Internet technology greatly influences the learning outcome of students within universities. There is need to ensure that all the factors are well taken care of by the universities or by the individual students in order for them to achieve maximum benefits from the use of the technology and thereby improve their performance levels.

The determination of the performance of students, according to literature, involved a number of techniques and prediction models. Similar techniques are used in this study to assist in the prediction of student performance as they utilize internet technology in their learning process. Specifically, this study uses data mining techniques together with stochastic prediction modelling techniques.

VT OMNES VNVM SINT

Chapter 5: A Model for Predicting Student Performance in an Internetworked Environment

5.1 Introduction

This chapter discusses the model development approach that was used together with the model conceptual framework that has been incorporated in the study. With the conceptual framework, the predictive model structure and the Cobb-Douglas utility function and the different parameters used in the study have also been highlighted. Finally, the process of predicting student performance has been described with the help of the dataset and model system equations.

5.2 Development of the Student Performance Prediction Model

Internet Technology usage by students is dependent on behavioural intention as has been explained by the Technology Acceptance Model (TAM). According to the Theory of Reasoned Action (TRA), the behavioural intention of a student, like any other technology user, is influenced by students attitude and behaviour (Amirah et al., 2015). Therefore, a student behaves (uses the internet) based on their attitude and their intentions towards the activity to be conducted using internet technology. The intention to use a technology depended on the perceived usefulness of the technology. According to TAM, the intention to use a technology is based on the perceived usefulness of the technology and the perceived ease of use of the technology. On the other hand, the perceived usefulness of the technology defines the degree to which the technology will enable its users to enrich their performance at work and hence influence their attitude and behaviour towards the technology. The degree of acceptance of the technology is also seen to be influenced by the context in which the technology will be used (Omwenga, 2016). For students, the context in which internet technology is found significantly influences their attitudes and actions.

Student performance has been analysed using many methods. Some of these methods include data mining techniques (Anjali & Ankita, 2017), decision tree techniques (Nguyen et al., 2011) and Factorization Techniques (Anderson et al., 2014). These approaches presume existence of databases with student attributes that influence performance. A new domain of knowledge in predicting student performance is developing around behavioural pattern analysis. This is considered to be richer in cognitive aspects of the students that largely influence the learning outcome of a student. Behavioural patterns have also been considered in the analysis of the student performance by Verhallen and Pieters (1984). In a study by Ajzen (1991) to analyse student performance on a MOOCs platform, the data used was described by four Vs; that is, velocity, volume, variety and veracity. By considering these characteristics of data, they were pointing to the trend of moving away from static databases to more dynamic databases that handle student data. Moreover, this implied existence of unstructured databases whose data was generally non-linear in nature. In this research, a non-linear approach was considered by modelling of student behavioural patterns as stochastic processes with a number of random disturbances.

In this research, the model development approach that has been used is the stochastic modelling approach. A stochastic model is a mathematical explanation of a process that take into consideration the use of random variables. This modelling approach provides a prediction index that is based on a set of assumptions predefined by the user. The index provided after considering the assumptions could represent an average expected outcome, a strained environment or another outcome that leads the user into other different scenarios.

According to the International Actuarial Association (2010), stochastic models have become more widespread and have therefore been used in different scenarios to generate output. This has mainly been due to the fact that computing power has become inexpensive and more readily available. Stochastic models have been used following procedures and ideals that have been issued by governments, professional bodies as well as regulatory bodies. Stochastic methods are also sometimes used to indicate the likelihood of very rare occurrence scenarios which may or may not take place at a future date. For instance, the models can help to infer useful suggestions that can help in dealing with an outbreak of a pandemic or in the cases of economic development, the models can help in the prediction of the likelihood of a particular event.

A stochastic model also defines the change that takes place on a random variable through time and according to probabilistic laws. The time series observed is considered to be a realization of the stochastic process, just as a single instance of a random variable is a possible value that the variable may assume. A stochastic model involves a set of random variables ordered within a discrete time variable. The features that define a stochastic model are defined by a single time series. In order to achieve this, several assumptions are put into consideration. In the first place, the process is assumed to be stationary, hence the process does not change over time. Therefore, if a process is strictly stationary, then the joint distribution of random variables $X(t_1), \ldots, X(t_n)$ is similar and identical to the joint distribution of $X(t_{1-t}), \ldots, X(t_{n-t})$ for any t.

For a stationary stochastic process, the mean and the variance can be written as $\mu_x = E\, X(t)$ and $\sigma^2 = Var\,[X(t)]$ both being independent of time.

Herzog (2013) defines a situation where there is a differential equation in which one or more terms is a stochastic process. In this case, a stochastic differential equation (SDE) is formulated to give a solution which also happens to be a stochastic process. In order to define a stochastic differential equation, there is need to examine an ordinary differential equation (ODE) first.

Suppose an ODE is defined as

$$\frac{dx\,(t)}{dt} = f(t, x), \qquad dx(t) = f\,(t, x)dt \quad \ldots\ldots \quad [5.1]$$

with initial conditions $x(0) = x_0$ can be written in integral form

$$x(t) = x_0 + \int_0^t f\big(s, x, (s)\big)\, ds \quad \ldots\ldots \quad [5.2]$$

where $x(t) = x(t, x_0, t_0)$ is the solution with initial conditions $x(t_0 = x_0)$. An example is given as

$$\frac{dx(t)}{dt} = a\,(t)x(t), \qquad x(0) = x_0 \quad \ldots\ldots \quad [5.3]$$

Taking the ODE 5.3 and assuming that $a(t)$ is a stochastic parameter, the equation becomes a stochastic differential equation (SDE). The stochastic parameter $a(t)$ is given by

$a(t) = f(t) + h(t)\,\xi\,(t)$ …………………….……………………………………….. [5.4]

where $\xi\,(t)$ denotes a "white noise" process.

Equation 5.3 then becomes

$\frac{dX(t)}{dt} = f\,(t)X(t) + h(t)\,X\,(t)\xi\,(t)$…………………………..………………………… [5.5]

When 5.5 is written in differential form, and $dW(t) = \xi\,(t)dt$ where $dW(t)$denotes differential form of Brownian motion, then we obtain

$dX(t) = f(t)X(t)dt + h(t)\,X\,(t)\,dW(t)$ ……………..…………………………....……. [5.6]

In general, a SDE is given as

$dX(t,\omega) = f\big(t, X(t,\omega)\big)dt + g\big(t, X(t,\omega)\big)dW(t,\omega)$ …………………………………… [5.7]

where ω denotes that $X = X(t,\omega)$is a random variable that possesses the initial condition $X\,(0,\omega) = X_0$with probability one.

The general model structure used in the CTSM-R package to develop the required equations is shown in appendix C.

5.3 Model Conceptual Framework

The conceptual framework used in this research highlights the different variables found in the study and how they relate to each other. In this case, student performance in an internetworked university environment is influenced at an instance in time by a number of factors. These factors are grouped as endogenous and exogenous factors. Endogenous factors are the factors that are determined by other factors in the environment. These factors are directly influenced by other independent variables. The exogenous factors are factors that are not affected by other factors in the environment at hand. Exogenous variables are fixed when they enter the model, they are taken as they are in the model and they influence endogenous factors in the model. They are neither explained nor determined by the model.

In this study, the exogenous factors considered are the institutional investment based on the behavioural costs over a period of time and the performance level of a student. The endogenous factors considered here are the student effort at an instance in time and the effectiveness of student effort at an instance in time.

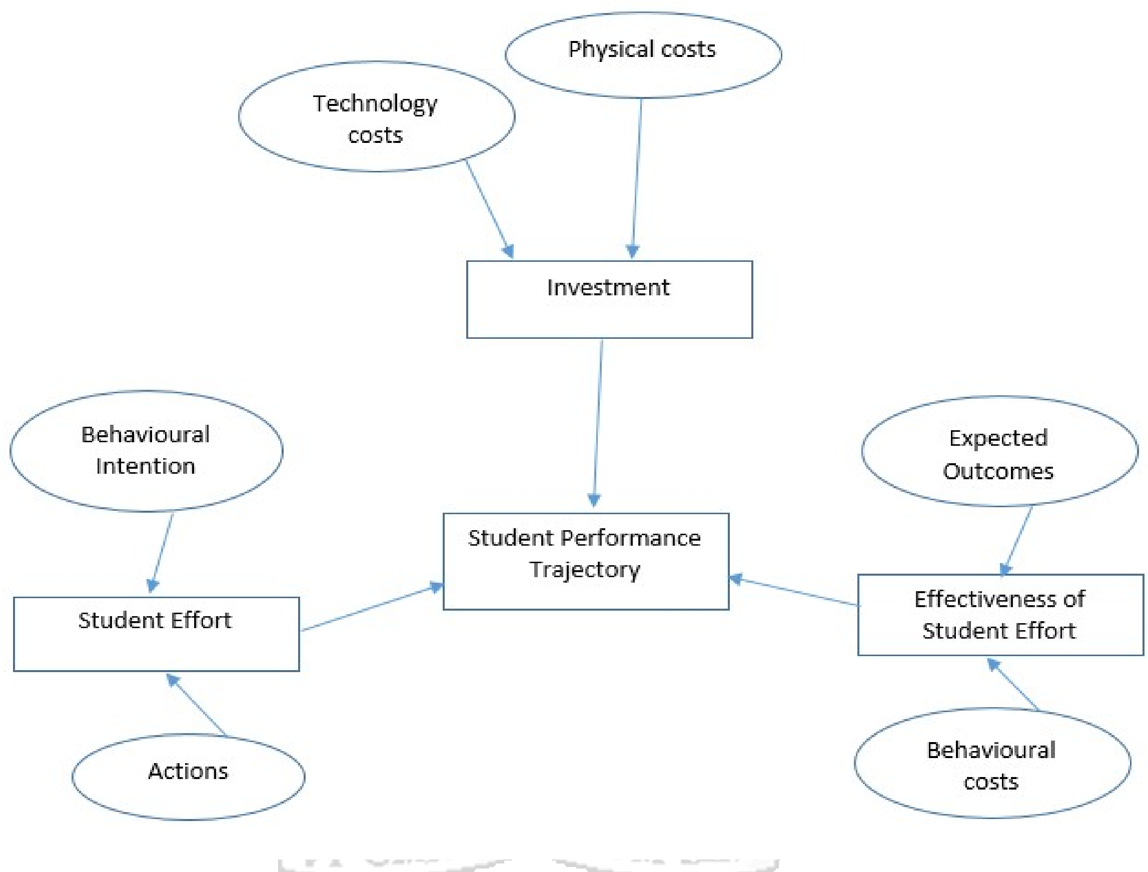

Figure 5.1 *Conceptual Framework*

In this research, institutional investment took into consideration the shared costs in the physical costs and technology costs within the institutions, specifically, the availability and accessibility to internet technology. In terms of internet availability, the students were required to confirm whether there was internet connectivity within their institution. In terms of accessibility, the students were required to check whether they were in a position to access the resource around the university, in their lecture rooms, the university library, their halls of residence or in the university labs. The data obtained from these parameters was used in the student performance prediction model to represent an input value I_t. In the classification algorithm, institutional investment was represented using the value Inv.

Student effort in this research considered the behavioural intention of a student together with their set of actions in performing a task. Student behavioural intention to use a technology is directly affected by the student's attitude towards the use of the technology. The attitude of the student specifically considered whether the student found the technology favourable for them to use or unfavourable for them to use. These aspects were considered for individual students and their attitude was determined. This was represented as $IAtt$. The actions of the students was based on whether they perceived the technology as useful or not. Specifically, this checked on whether the students considered the technology as a useful resource in their learning process. This was measured and represented as PU. The $IAtt$ and PU were both used as the factors that represented the value of student effort (e_t) in the prediction model. In the classification algorithm, student effort was represented using the value $Effort$.

Effectiveness of student effort in the utilization of internet technology in this research was examined by considering the behavioural costs and the expected outcomes in the use of internet technology in the learning process. The expected outcomes in the use of the technology was based on the influence of the environment in the use of the technology and the fit existing between the technology and the tasks to be accomplished. The influence from the environment checked on the different groups who influenced the students to use the technology, specifically, their peers, family and the university environment. These were measured and used as SM. The students were also expected to check how the technology fitted into their learning activities and how they used the technology in the learning process. This was measured and presented as TTF. These two, SM and TTF represented the expected outcomes in the use of the technology. Additionally, the behavioural costs were examined by checking the level of knowledge of internet technology and the perceived ease of use of the technology in the learning process. The knowledge level assessed how the students interacted with the technology in learning. This was presented as KoI. The perceived ease of use of the technology examined the ease with which the students used the technology in their learning process. This was represented as $PEOU$. Hence, KoI and $PEOU$ both represented the student behavioural costs. As a result, effectiveness of student effort (k_t) was presented using SM, TTF, KoI and $PEOU$ in the student performance trajectory prediction model. In the classification algorithm, it was presented as $Effe$.

Institutional investment (I_t), student effort (e_t) and effectiveness of student effort in the utilization of internet technology (k_t) were used as the input parameters in the prediction of the student performance trajectory. The same inputs were used in the classification algorithm to obtain the decision tree that assisted in establishing the student performance perceptions.

5.4 Stochastic Differential Equation (SDE) Student Performance Predictive Model

Stochastic differential equations were formulated to represent an individual student whose actions possess the features of a stochastic process that changes with probability. The stochastic model developed reflects a set of random variables all of them considered within a specific time for each particular student. In this case, therefore, the variables that affect the performance of a student are considered at an instance in time (Sasikumar & Abdullah, 2015).

As a result, the performance of a student in a university is influenced by a number of factors which can be grouped as earlier seen in section 5.3 as endogenous and exogenous factors. This study puts into consideration the investment costs ($I(t)$) as exogenous factors, while the student effort $\left(E(t)\right)$ in the utilization of internet technology resources and effectiveness of the student effort (K) in utilizing of the internet resources are considered as endogenous factors.

5.4.1 Investment Costs

The investment involved in this study is framed around the concept of behavioural costs. Behavioural costs capture two important elements that can be used to measure individual student investments in a learning process. These elements include: behavioural resources (also referred to as sacrifice) and opportunity costs. For a student to behave (act) in a particular way, they must make use of behavioural resources. This is confirmed by Shugan (1980) when he affirms that human behaviour conforms to a set of behavioural costs. It is also important to note that for every outcome there is a comparable alternative outcome which the student must make a decision based on the expected relative costs. Verhallen and Pieters (1984) have identified these costs to be time costs (time budget), psychic costs (mental budget) and physical costs (physical budget). Time costs refer to the expected time needed to perform the action required, commonly referred to as the time budget. Psychic costs express the perceived task requirements and any opportunity costs; the costs not to behave otherwise. This is also referred to as the mental budget. The time budget and the mental budget were both considered under the student effort. The physical costs express perceived task requirements as well as the physical effort required in fulfilling a required task. This expressly refers to the physical budget required.

In this research, a fourth cost is introduced and it is identified as technology costs. This cost touches on aspects to do with technology proficiency or technical attributes of the technology itself inherent on the student environment and the institutional technology utilization policies.

Therefore, the measure of investment is defined as shown in equation 5.8

$I(t) = \sum f(t_c, M_c, P_c, T_c)$ …………………………………………………………………… [5.8]

where $t_c$are time costs as measured by time demanded by an activity, $M_c$are psychic costs as measured by the perceived mental demands of the activity, $P_c$are physical costs as expressed by the physical budget needed for the activity and $T_c$are the technology costs as expressed by the technological needs, resources or policies for the activity to be done. All these costs are relative except the time costs.

In a learning environment, the behavioural costs tend to exhibit unique characteristics due to the social nature of the environment and the interactions that take place. Due to the likelihood of individual students borrowing a resource from one another and even seeking assistance from one another, the individual costs tend to be shared out. Moreover, some costs are generally shared, for instance, the physical costs and the technology costs. In order to ensure that these costs are well shared out, the concept of consumption ratios in the computations of the investment costs for individual students is introduced.

Thus, equation 5.8 can be written as:

$$I(t) = \sum f\left(\frac{t_c}{t_b}, \frac{M_c}{M_b}, \frac{P_c}{P_b}, \frac{T_c}{T_b}\right) = \frac{Action\ price}{Action\ budget} \quad \text{[5.9]}$$

where $t_b$is budgeted time costs to undertake an activity, $M_b$is perceived mental demand/psychic costs to completion of an activity, $P_b$is budgeted resources to undertake an activity and $T_b$is the budgeted/planned technology costs as expressed by the technological needs, resources or policies completion of an activity.

It is important noting that the action price is influenced by attractiveness of a set goal. Less important goals tend to attract less budget and vice-versa. Therefore, student invests more of their resources on what they consider important and the action price will not be significant due to the commitment and motivation.

5.4.2 Students Effort

Ajzen and Fishbein (1980) demonstrated the relationship between attitude and actions. They considered that in a single act there is a corresponding attitude and context. They proposed a model for predicting behaviour outcome that considered attitude, beliefs, expected consequences and subjective norms. Subjective norms are important in a strictly controlled environment, but in loosely bound environment like internet mediated learning environment, this factor may not play a significant role. This means that a behavioural outcome is dependent on attitudes, beliefs and expected consequences. Therefore, borrowing this analogy, it is possible to proxy the behavioural outcomes as a consequence of the actions of students in the utilization of internet technology in the context of learning.

Verhallen and Pieters (1984) noted that attitude about an activity heralds the level of performance of an activity expressed as a behavioural intention, which is stochastic in nature. As a result, a model is developed to measure student effort in the utilization of internet technology by considering the behavioural intentions and the student actions.

Allowing the student's behavioural intention to be denoted by $BI(t)$ and the actions that follows the intention be $A(t)$, then relating the two aspects gives:

$BI(t) = e_t(A(t)) \qquad t \geq 0$ ……………………………………...…………… [5.10]

where e_t is the relative effort put by the student to carry out a specific action.

Equation 5.10 can be written as:

$e_t = \frac{BI(t)}{A(t)}$ …………………………………………………………….……….. [5.11]

with, $A(t) = \sum_{t=1}^{n}(a_t * b_t * r_t)$ where a_t denotes the student's attitudes towards an activity, b_t denotes the student's belief in carrying out the activity and $r_t$is the expected outcome from the activity.

Therefore, equation 5.11 becomes:

$e_t = \frac{BI(t)}{\sum_{t=1}^{n}(a_t * b_t * r_t)}$ …………………………………………..………….……..... [5.12]

Equation 5.12 gives a relative measure of the effort e_t used by the student to achieve a particular behavioural outcome, considering the actions taken at time t. It is assumed that the student's behavioural intention will shift depending on a number of other controlling factors.

5.4.3 Effectiveness of Student Effort

Effectiveness in this case was measured as the difference between two possible action strategies by the student. This is based on the law of preferences where students generally prefer to perform one action as compared to another. Hence, effectiveness in this case was measured by:

$K = A_1 - A_2 = w_1(EO_1 - EO_2) - w_2(BC_1 - BC_2)$ …………………………..……... [5.13]

where $A_1 - A_2$ is the relative student preference of action 1 to action 2, which measures the effectiveness of the actions selected; $EO_1$and EO_2 represent the expected outcome from action 1 and 2 respectively; while BC_1 and BC_2 represent the behavioural costs associated with action 1 and 2 respectively.

5.4.4 Student Performance

Assuming performance of student to be a continuous stochastic process, it can therefore be represented as a nonlinear stochastic system given by

$d(p(t) = f((p(t), i(t))dt + \sigma(t)d\omega(t),\ p(0) = p_0$ ……………………………………… [5.14]

where the performance state $p\epsilon\mathbb{R}^m$, the input $i\epsilon\mathbb{R}^m$, therefore drift term $f: \mathbb{R}^m \times \mathbb{R}^n \to \mathbb{R}^m$ and the diffusion $\sigma: \mathbb{R}^n \to \mathbb{R}^m$.

The Weiner process ω in the system equation models the randomness of the student performance due to unknown errors.

Now, let the student performance outcome be denoted by

$Y(t) = f(I(t), k(t), e(t)) \quad Y_t \geq 0$ ………………………………………………………. [5.15]

Taking student performance at time t to be denoted byP_t; using the production $\mathbb{R}$ function of the Cobb-Douglas type, student performance outcome in 5.15 is modelled as

$P_t(t, Y(t)) = I_t^a(k_t e_t)^b$ …………………………………………………………………… [5.16]

For some arbitrary but fixed student investment costs, $a \epsilon (0,1)$ and $b = 1 - a$.

The student effort e_t in the utilization of the internet technology is characterised by random dynamics due to the levels of competences on the internet technology and total productivity factor (Pukelis, 2010; Murray, 2016; Mills, 2016). It can therefore change over time following a geometric form of the Brownian motion represented by the stochastic differential equation (SDE) as

$de_t = \mu_e e_t dt + \sigma_e e_t dw_t^e \ , \quad e_0 > 0$ ……………………………………………………. [5.17]

Given the average improvement in performance $\mu_e \geq 0$ and constant unpredictability change in technological innovation, $\sigma_e > 0$, $\mu_e e_t dt$ term represents the drift part and $\sigma_e e_t dw_t^e$represents the diffusion term with dw_t^e ,denoting the Weiner process which has a Gaussian distribution characteristics.

The measures of the effectiveness of student effort in the utilization of internet of internet technology in the learning process can also be captured as geometric Brownian motion given by

$dk_t = \mu_k k_t dt + \sigma_k k_t dw_t^k \ , \ k_0 > 0$ ……………………………………………………… [5.18] for an average rate of change $\mu_k \epsilon \mathbb{R}$ and constant unpredictability of the effectiveness of student effort in the utilization of internet technology in the learning process, $\sigma_k > 0$.

In this study, it is considered that the investment level in technology by a higher learning institution is directly affected by the student demand for the technology and the perceived student performance due to the utilization of the technology. Further, the demand for internet technology in learning environment can be inferred by the effort put by the student on its usage (ITU, 2014; Ogungbeni et al., 2016). Therefore, considering that universities are more likely to make policies on investment on the internet technology considering the effort put by the students to use the internet and expected performance. These dynamics are captured as

$$dI_t = [P_t - \rho I_t - e_t c_t]dt + \sigma_I I_t dw_t^I\ ,\quad I_0 > 0 \ldots\ldots [5.19]$$

where σ_I denotes the constant unpredictability change in investment, c_t is the random institutional utilization policies rate on internet technology (e.g., broadband sharing ratios, domain separation, platform accessibilities, etc.) at time t and $\sigma_I > 0$.

Therefore, without loss of generality, c_t is dependent on $(I_m)_m \geq 0, (k_m)_m \geq 0, (e_m)_m \geq 0$ only and follows a Markovian property of memory less time-homogeneous.

Hence, $c_t = c(I_t, k_t, e_t)\ \forall\ institutional\ utilization\ policies$

Thus, equation 5.19 can be written as

$$dI_t = [P_t - \rho I_t - e_t c(Y_t)]dt + \sigma_I I_t dw_t^I\ ,\quad I_0 > 0 \ldots\ldots [5.20]$$

From the above equations, the values of I_t, k_t, e_t are all influenced by inherent random errors captured as uncertainties which are modelled as independent standard Brownian motions dw_t^I, dw_t^k and dw_t^e respectively.

Equation 5.20 can be rewritten as

$$dI_t = [I_t^a (k_t e_t)^b - \rho I_t - e_t c(Y_t)]dt + \sigma_I I_t dw_t^I\ ,\quad I_0 > 0 \ldots\ldots [5.21]$$

Assuming a student as a consumer of the internet technology is supposed to have a constant rate $\varphi \geq 0$ of the time-preference and Constant Relative Risk Aversion (CRRA) utility function given by

$$u(c_t) = \frac{c_t^{1-\theta} - 1}{1-\theta} \ldots\ldots [5.22]$$

By considering work by Feicht and Stummer (2010), assume $\theta = a$ under circumstances where there is uniformity in the applicability of intervening factors like resources accessibility policies.

Previous research shows that internet technology utilization by students in a higher learning institutions is dependent on a collection of institutional policies and internet consumption strategies (Verhallen & Pieters, 1984; Farrel, 2007; UNESCO, 2013; ITU, 2014), which we denote by $C(t, y)$ with t representing time point and y is the observable value of Y_t.

The desire of many learning institutions is to optimise consumption rate of internet technology as a resource by its students (Loan, 2011; Teo et al., 1999). They thus set utilization strategies and policies as estimated by the utility function given by equation 5.22 aimed at aiding students to achieve best performance outcomes. A study by Acemoglu and Guerrieri (2008) estimates the optimal consumption utility value by

$$c(Y_t) = h\frac{I_t}{e_t} \qquad h \geq 0 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [5.23]$$

and by the principle of marginal rate of technical substitution (MRTS)$h = \frac{b}{a}$. It can be noticed that the optimal consumption rate of the internet technology is dependent on investment costs and the effort.

Substituting equation 5.23 in equation 5.21 gives

$$dI_t = [I_t^a (k_t e_t)^b - \rho I_t - hI_t]dt + \sigma_I I_t dw_t^I, \qquad I_0 > 0 \quad \ldots\ldots\ldots\ldots\ldots\ldots [5.24]$$

which simplifies to

$$dI_t = [I_t^a (k_t e_t)^b - (\rho + h)I_t]dt + \sigma_I I_t dw_t^I, \qquad I_0 > 0 \quad \ldots\ldots\ldots\ldots\ldots\ldots [5.25]$$

Considering equation 5.16 and applying Ito's formula, we get

$$dP_t = \mu_P P_t dt + \sigma_P P_t dw_t^P, \qquad P_0 > 0 \quad \ldots\ldots\ldots\ldots\ldots\ldots [5.26]$$

$$dP_t = \mu_P I_t^a (k_t e_t)^b dt + \sigma_P I_t^a (k_t e_t)^b dw_t^P, \qquad P_0 > 0 \quad \ldots\ldots\ldots\ldots\ldots\ldots [5.27]$$

$$dP_t = \left[a I_t^{a-1} (k_t e_t)^{1-a} + (1-a) I_t^a (k_t e_t)^{-a}\right]dt + \sigma_P I_t^a (k_t e_t)^b dw_t^P \ldots\ldots\ldots\ldots\ldots [5.28]$$

which is the stochastic differential equation (SDE) with initial condition $P_0 = x$. Equation 5.28 gives the student performance at time t.

5.4.5 SDE Student Performance Predictive Model Parameters

By considering the dynamics surrounding the student learning environment to be of continuous nature, it is therefore necessary to use continuous-time stochastic differential equations. Therefore, a Maximum Likelihood Estimation (MLE) method is used to estimate the parameters. Table 5.1 gives parameters that have been used in some growth studies as presented by Feicht and Stummer (2010).

Table 5.1 *SDE student performance estimated model parameters*

Parameter	True Value	Estimated Value	Reference
A	0.1-0.77	0.76905	Acemoglu and Guerrieri (2008)
σ_K	0.0148	0.0148	Bucci et al. (2008)
σ_I	0.012	0.012	Palacios (2010)
σ_E	0.01	0.01	Jensen and Richter (2007)
μ_K	0.0176	0.0176	Williams (2004)
μ_E	0.01-0.02	0.014142	Jensen and Richter (2007)
P	0.05-0.08	0.063246	Jensen and Richter (2007)

5.5 Chapter Conclusion

The prediction of students' performance forms an essential part in the learning process, both for the students and the educational practitioners. This is attributed to the fact that the predictions assist the practitioners to understand the implications of the resources, strategies and policies they embrace and use within their institutions.

This chapter has assisted in analysing the implications caused by the students' behaviour patterns by specifically examining the students' effort, investment costs and the effectiveness of student effort in the utilization of internet technology as they employ in achieving good performance in the learning process.

This chapter has also presented a stochastic differential equation student performance predictive model that considers students' performance as a stochastic process characterized by random noises. This approach towards the prediction of student performance therefore assists educational practitioners to focus on the performance of a student as seen at an instance in time rather than as a longitudinal process that spans a period of time.

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Chapter 6: Applicability and Implication of the Proposed Model

6.1 Introduction

This chapter presents a summary of the theoretical foundations behind the developed model and an overview on how the model works in an internetworked environment with a focus on the universities in Kenya. An analysis through the use of classification algorithms of the factors that influence learning in Kenyan universities to ascertain the applausabiliy of the factors considered in the developed performance prediction model is presented. The validation of the model using the data collected is then highlighted.

6.2 An Overview of the Developed Model

Based on the belief, attitude and performance chain, internet usage behavioural patterns were analysed from the perspective of self-reported perceptions and student performance. The student's behavioural intention in the use of the technology as explained by Davis (1989) and Choo's (1991) in the technology acceptance model (TAM) were adopted to empirically assess the use of the internet for the goal-directed tasks by learners. The theory of reasoned action (TRA) was used to show how a student uses a technology mainly due to their attitude towards it or their behaviour towards it (Amirah et al., 2015). Predictive algorithmic modelling techniques were used for the analysis of internet utility among the learners. The technology utilization theory in a learning environment was used to focus the modelling process by considering the student's effort, the technological investment and the effectiveness of student effort in the utilization of the internet technology as predictor variables. Since, the learning environment in an internet technology mediated platform is characterized by highly dynamic data (Hughes & Dobbins, 2015), stochastic differential models were used as the underlying mathematical models. The behaviour pattern of a student was then analysed as a stochastic process with a number of random variables each contributing to the learning outcome and performance of a student.

6.3 Application of the Model to Predict Student Performance

The developed model was tested in an internetworked environment in the context of higher learning institutions in Kenya. The data used in testing the model was collected using survey methodologies. In particular, self-administered questionnaires as shown in appendix A were used. The focus of the survey was to collect data on the factors that influenced learning on internet mediated platforms by analysing the student performance perceptions.

In the determination of factors that contribute significantly to performance in an educational environment, Kabra and Bichkar (2011) noted that data mining techniques had already been used. Specifically, classification techniques were used to analyse the structures of data so as to make decisions on the factors to be used (Han & Kamber, 2011). Table 6.1 shows attributes identified by different researchers using decision trees to be predictors of student performance.

***Table 6.1** Attributes that predict student performance*

Attributes considered	**Reference**
Final grades	Bidgoli et al., 2003
Final cumulative grade point average (CGPA)	Ibrahim & Rusli, 2007; Natek & Zwilling, 2014; Mayilvaganan & Kapalnadevi, 2014; Jishan et al., 2015
Marks obtained from the particular courses	Romero et al. 2008
Internal assessments	Romero et al. 2008; Elakia et al., 2014; Mayilvaganan & Kapalnadevi, 2014;
Psychometric factors	Mishra et al., 2014; Gray et al. 2014
External assessments	Bunkar et al., 2012; Natek & Zwilling, 2014
Student demographics	Ramesh et al., 2013; Natek & Zwilling, 2014; Elakia & Aarthi, 2014; Osmanbegovi´c, & Sulji´c, 2015
High school background	Ramesh et al., 2013; Osmanbegovi´c, & Sulji´c, 2015

Scholarship and social network interaction	Osmanbegovi´c, & Sulji´c, 2015
Extra-curricular activities	Mishra et al., 2014; Elakia et al., 2014; Natek & Zwilling, 2014; Mayilvaganan & Kapalnadevi, 2014
Soft skills	Mishra et al., 2014

There exists a number of algorithms under the classification approach. Among these algorithms are the decision tree, artificial neural networks, naives bayes, k-nearest neighbour and support vector machine.

The decision tree algorithm was used to analyse the factors in this study. It was adopted due to its simplicity and comprehensibility in uncovering both small and large datasets and predicting a value out of the data provided (Osmanbegovi´c, & Sulji´c, 2015; Natek & Zwilling, 2014; Shahiria, et al. 2015). Decision tree models are also easily understood because of their reasoning process and can be easily converted into IF-THEN statements (Romero et al., 2008).

The task of constructing a tree from the training dataset is known as the tree induction process or the tree building process. Most existing tree induction systems adopt a greedy (non-backtracking) top-down divide-and-conquer manner. Starting with an empty tree and the entire dataset, a tree induction algorithm as shown in appendix H is applied on the training data (where each tuple is associated with a class label) until no more splits are possible (Han & Kamber, 2011). In this study, a training dataset named *Final8-1 Training set.arff* was used. The run information for the training set is shown in appendix F.

In the context of this study, determination of how the various factors in an internetworked learning environment in the Kenyan universities influences the substantive model variables was examined, that is, student effort, institutional investment and the effectiveness of student effort in the utilization of the internet technology; classification technique was conducted using WEKA version 3.8.3. The classification algorithm used in the analysis was J48 classifier. Before the classification algorithm was executed, feature selection was conducted using *CorrelationAttributeEval* technique that required the use of a *Ranker search method,* to eliminate outliers and factors that did not contribute significantly to the model variables.

Figure 6.1 shows the decision tree obtained after executing the classification algorithm by considering the factors that influence student performance. The classification accuracy that was obtained from the dataset used in this study was 84.6051% as shown in appendix G. This means that out of 747 instances of data collected, 632 instances were correctly classified and therefore could be used to reliably predict student performance perceptions on internet mediated platforms. The nodes on the decision tree represent the investment made on internet technology (Inv), student effort (Effort) and the effectiveness of student effort in the utilization of internet technology in the learning process (Effe). Student performance perceptions are denoted by the leaf nodes.

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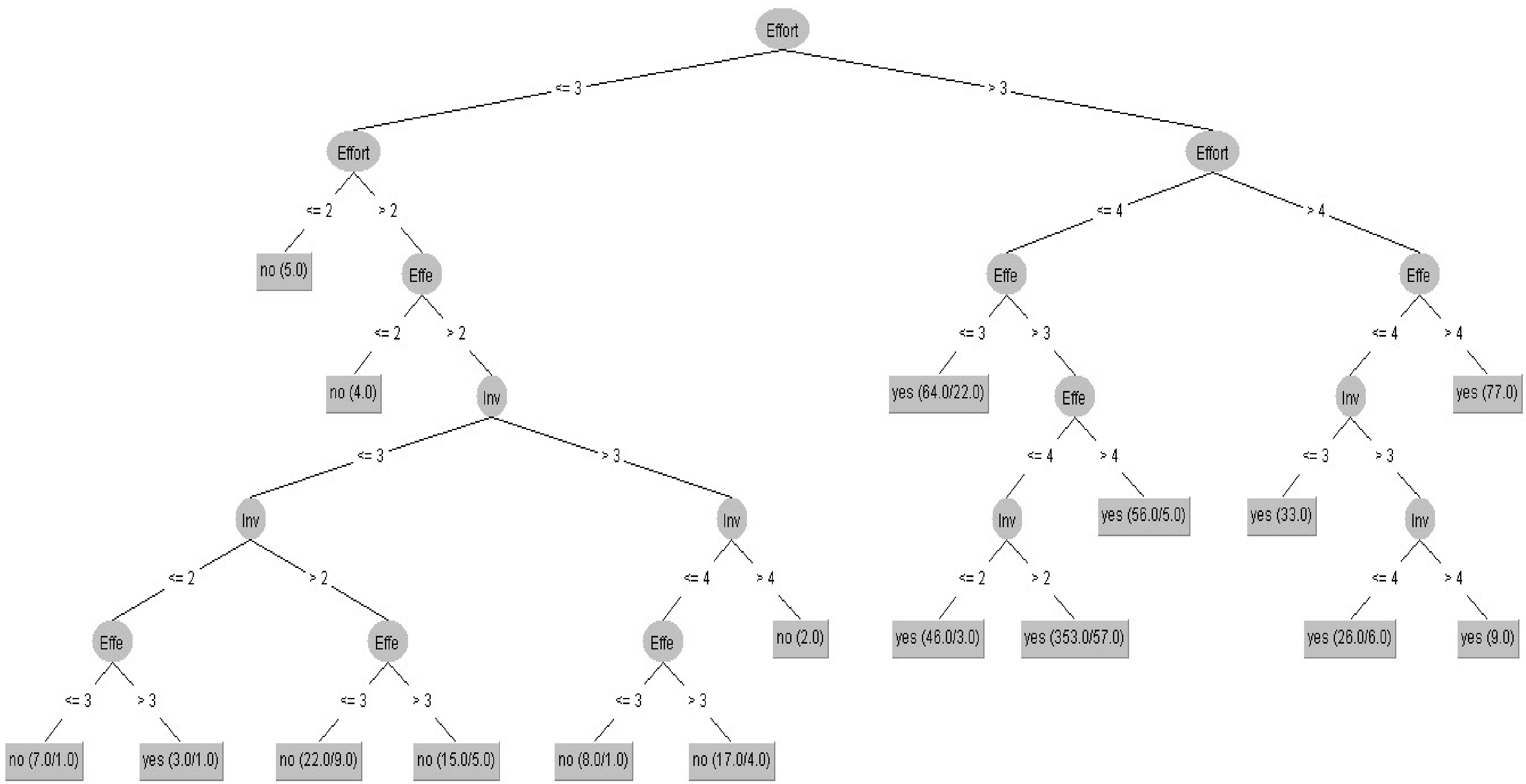

Figure 6.1 *Decision tree on the factors that influence student performance on an internet mediated environment*

From figure 6.1 it can be inferred that data on student effort, institutional investment and effectiveness of student effort in the utilization of the internet technology was used in the determination of the perceptions of student performance in an internetworked environment. The numeric values 1-5 were used to give the values representing the main variables in this study (effort (Effort), investment (Inv) and effectiveness (Effe) of student effort in the utilization of internet technology). That is, a factor with a value given as <=3 was considered to be a low value while a factor with a value >3 was considered to be a high value. Student performance (Perf) was presented using two Boolean values: yes and no. The value 'yes' meant that the student performance was affected positively leading to an improvement in the students studies while the value 'no' meant that student performance was affected negatively meaning low performance and with no improvement.

The decision tree in figure 6.1 can be divided into two major parts based on the root node, that is, the left side of the root node and the right side of the root node. The left side of the root node mainly focuses on the 'no' perception of student performance while the right side focuses on the 'yes' perception of student performance. For instance, on the left side of the root node, it can be observed that a low value of student effort contributed to poor performance of the students; where,

If Effort <=2 then Perf = 'no'.

This means that, for students effort to be <=2, the students perceived usefulness of internet technology was low (<=2) and the student attitude towards internet technology tended towards the negative (<=2) as well. Therefore, the student did not find internet technology useful in their learning process and they did not have the positive urge to use the technology. Hence, the student did not perceive the technology as important in improving their performance.

It can also be observed that when student effort is low and effectiveness of student effort in the utilization of the internet technology is low, the performance is low. That is,

If Effort <=3 and Effe <=2 then Perf ='no'

This means that, for students effort to be low (<=3), students perceived usefulness of internet technology was low (<=3) and students attitude towards internet technology was low (<=3). Moreover, for the effectiveness of student effort to be low (<= 2), then, the influence from the people important to them (for example, family, friends and peers) in the use of internet in learning was low (<=2), the students' knowledge about internet technology was low (<=2) and the perceived ease of use of the technology in the learning process was also low (<= 2). Therefore, the student did not expend any effort while using internet technology in the learning process and as a result their perception about using the technology to improve their performance was low.

Similarly, when student effort was low and effectiveness of student effort in the utilization of the internet technology is high, then performance of the student is also dependent on investment. That is,

If Effort <=3 and Effe > 2 else if Inv <=3 and Effe <=3 then Perf = 'no'

This means that, when student effort was low (<=3), then students' attitude and perceived usefulness of the technology were low (<=3). When the effectiveness of student effort in the utilization of internet technology was low (>2) then, this meant that, the subjective norm to use the technology, the task-technology fit, the knowledge about the technology and the perceived ease of use of the technology were also low (>2). However, when the investment was low (<=3), this meant that availability and accessibility to the technology was also low (<=3). Hence, with a low value of the effectiveness of student effort in the utilization of internet technology in learning, the student perception about using the technology to improve their performance was low.

Moreover, on the right side of the root node on the decision tree, several perceptions can be formulated. For instance, when student effort is high (>3) and the effectiveness of student effort in the utilization of internet technology is high (>4), then, the students perceived performance as high. That is,

If Effort >4 and Effe >4 then Perf = 'yes'

This means that, when student effort was high (>4) then, student attitude and their perceived usefulness of internet technology were high (>4). When the effectiveness of student effort in the utilization of internet technology was high (>4), the subjective norm, the task-technology fit, the knowledge about the technology and the perceived ease of use of the technology were also high (>4). This meant that the students were influenced by different parties to use internet technology in learning and they found the technology relevant in their studies. They also perceived the technology as easy to use in their learning. As a result, the student perception about using the technology to improve their performance was high.

Likewise, when student effort was high and effectiveness of student effort in the utilization of internet technology was high, then performance of the student was also dependent on investment. That is,

If Effort >3 and Effe >3 else if Effe <=4 and Inv >2 then Perf = 'yes'

This means that, when student effort was high (>3), the students attitude and perceived usefulness of the technology were also high (>3). When the effectiveness of student effort in the utilization of internet technology was high ($3 < \text{Effe} \leq 4$), the subjective norm to use the technology, the task-technology fit, the knowledge about the technology and the perceived ease of use of the technology were also high, that is, between >3 and <=4. In addition, when the investment was low but with a potential to grow (>2), this meant that availability and accessibility to the technology were low but with a potential to grow. Therefore, with a high value of investment in the technology, a high value in the effectiveness of student effort in the utilization of internet technology in learning and a high value of student effort, the student perception about using the technology to improve their performance was high.

In the same way, when student effort was high, the effectiveness of student effort in the utilization of internet technology was high and investment was high, then student performance was perceived to be high. That is,

If Effort >4 and Effe <=4 else if Inv >4 then Perf = 'yes'

This means that, when student effort was high (>4), the student attitude and perceived usefulness of the technology were also high (>4). When the effectiveness of student effort in the utilization of internet technology was high <=4, the subjective norm, the task-technology fit, the knowledge about the technology and the perceived ease of use of the technology were also high (<=4). When investment was high (>4), this meant that availability and accessibility to the technology was at a high value. Therefore, with a high value of investment in the technology, a high value in the effectiveness of student effort in the utilization of internet technology in learning and a high value of student effort, the student perception about using the technology to improve their performance was high.

Generally, from the decision tree, it can be seen that the values of student effort and the effectiveness of student effort in the utilization of internet technology can be used to determine the student performance perceptions. However, when the value of effectiveness is greater than 2 (>2), then there is need to consider the investment made for the utilization of internet technology. Largely, it can also be seen that when student effort, institutional investment and the effectiveness of student effort in the utilization of internet technology values are high, it follows that the perceptions about student performance are also high. Conversely, when the values of student effort, institutional investment and effectiveness of student effort in the utilization of internet technology are low, the perceptions about student performance are also low.

Further analysis on the prediction capability of the classification model was done using the confusion matrix as proposed by Brownlee (2016). Figure 6.2 shows the results of the confusion matrix obtained. The confusion matrix gives the number of the correct and incorrect classifications that were obtained from the class Perf.

```
=== Confusion Matrix ===

  a   b   <-- classified as
 61  93 |   a = no
 22 571 |   b = yes
```

Figure 6.2 *Confusion matrix*

In figure 6.2, the total number of actual negative responses (no) in the dataset considered, is the sum of the values on the '***a***' column (61+22=83). The total number of actual positive responses (yes) in the dataset is the sum of the values on the **'b'** column (93+571= 664). The total number of correct values are organized in a diagonal line from the top-left to the bottom-right on the matrix (61+571=632). The total number of incorrect values is organized as the remaining values on the matrix (93+22=115). Hence, this means that more errors were made in predicting the positive responses than the negative responses.

In describing the accuracy of the model based on the Perf class that was used in the classification model, other computations were required. These include, TP Rate, FP Rate, Precision, Recall and F-Measure. TP Rate refers to the true positives in the dataset. This was the number of instances in the dataset that had been positively predicted and they were actually positive. In this Perf class, 84.6% were classified as TP, meaning that the majority of the students involved in the survey were actually classified as using the internet in their studies to aid their performance.

FP Rate refers to the false positives in the dataset. This was the number of instances in the dataset that had been positively predicted and they were actually negative. In this class, 48.7% were classified as FP, meaning that in the context of this research, there existed a group of student who used the technology in the learning process, though they indicated that the technology did not assist in ensuring that they performed better.

Precision refers to the fraction in the dataset of the values that had been predicted as positive and they were actually positive. It was computed as $Precision = \frac{TP}{predicted\ Positive}$. In this case, 83.4% level of precision was obtained in the Perf class. This meant that the prediction model had managed to properly predict the positive values that had been used in checking the students' performance perceptions.

Recall refers to the sensitivity of the predicted model. It is the fraction of the values in the dataset that were actually positive and they were predicted as positive. It was computed as $Recall = \frac{TP}{actual\ Positive}$. In this case, 84.6% level of sensitivity was obtained in the Perf class. This model was highly sensitive since it could be in a position to classify corrected predicted instances as positive.

The F-Measure combines the recall and precision of the model into a harmonic mean, because the recall and precision are evenly weighted. It was computed as $F = 2 . \frac{precision\ .\ recall}{precision + r}$. In this case, 82.7% was obtained as the harmonic mean of precision and recall. This meant that the model was very reliable due to the high value of the F-Measure obtained based on the precision and recall values obtained by the model.

The WEKA Classifier was also used in the visualization of the margin curve associated with the dataset. The margin curve is used to illustrate the prediction margin of the classification model. This margin is defined as the difference between the actual class probability and the highest probability predicted for other classes. The margin curve obtained using the Perf class is shown in figure 6.3.

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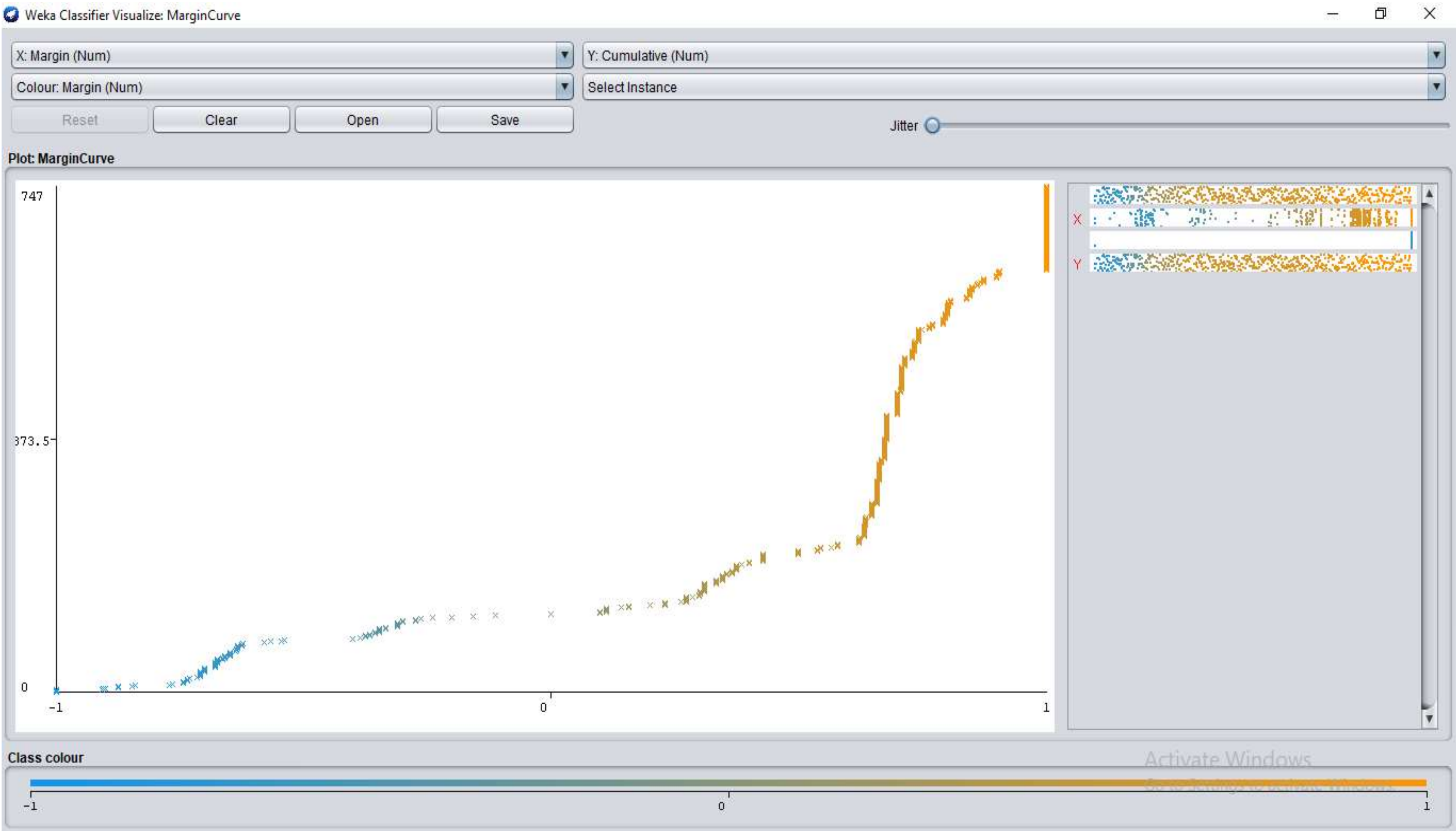

__Figure 6.3__ Perf class margin curve for the consideration of investment, effort and effectiveness

In cases where there exists only a single class to be classified, the class can either be predicted as positive or as negative. Figure 6.3 represents such a case. Positive predictions with probability p imply that the margin is given as $p - (1 - p) = 2p - 1$. Negative values on the prediction scale imply the presence of classification errors with a few existing incorrectly classified instances. The margin value containing the positive and negative prediction values were plotted on the x-axis while the cumulative number of available instances on the dataset which are either less than, equal or greater than the margin, were plotted on the y-axis.

In the context of this research, the margin curve represents an upward trend exhibited by students in terms of their perceived improvement in performance with the use of internet technology in the learning process. At the initial stages where $Perf = (-1 \; to \; 0)$, some of the students in the survey were slowly adopting the use of the technology in the learning process. Over a period of time as can be seen in another group of students, some of the students acquire momentum in using the technology, which leads to an increase in the use of the technology in the learning process until they finally get acquainted with the technology. This is similar to the curve presented as the s-shaped diffusion curve in figure 2.5.

6.4 Model Validation

Data used in the validation of the developed model for predicting student performance trajectory was obtained from the survey questionnaires after conducting the feature selection as discussed in section 6.3. The student performance prediction model given by equation 5.26, that is,

$$dP_t = \left[a\, I_t^{a-1}(k_t e_t)^{1-a} + (1-a)\, I_t^{a}(k_t e_t)^{-a}\right]dt + \sigma_P I_t^{a}(k_t e_t)^{b} dw_t^{P} \quad \ldots\ldots\ldots\ldots\ldots\ldots \; [6.1]$$

was used to predict student performance trajectory. The student performance trajectory refers to a curve or a path of a projectile that cuts all of a given family of variables under the influence of a series of conditions.

Since the data in this study was time-dependent and continuous, a continuous time stochastic modelling R package (CTSM-R) version 3.4.3 was used in the analysis. The package was adopted since it has the capability of handling non-linear stochastic processes. In order to fit the model given by equation 6.1 into the package, there was need to formulate a set of system of equations that formed the performance analysis algorithm in R. These system equations were categorized as system equations, observation equations and output equations. The student performance trajectory prediction model system equations, observation equations and the output equations used in this study are shown in appendix D.

As discussed in section 5.4.5, the model parameters were estimated using the MLE method. Table 6.2 gives the estimated model parameter values as compared to the expected parameter values. The estimated parameter values were generally within the expected range and were therefore adopted into the developed student performance trajectory prediction model given by equation 6.1.

Table 6.2 *SDE student performance estimated model parameters*

Parameter	True Value	Estimated Value	Reference
A	0.1-0.77	0.76905	Acemoglu and Guerrieri (2008)
σ_K	0.0148	0.0148	Bucci et al. (2008)
σ_I	0.012	0.012	Palacios (2010)
σ_E	0.01	0.01	Jensen and Richter (2007)
μ_K	0.0176	0.0176	Williams (2004)
μ_E	0.01-0.02	0.014142	Jensen and Richter (2007)
P	0.05-0.08	0.063246	Jensen and Richter (2007)

Figure 6.4 gives the predicted student performance trajectory after fitting the model and running it in R-Software. The figure was generated after considering three predictor variables (investment costs, student effort and effectiveness of student effort) based on the classification conducted as discussed in section 6.3. In the graph, x-axis represents input variables (effort, effectiveness and investment) observed together at instance in time. It is assumed that the inputs or dependent variables exist jointly and therefore influence each other in a simultaneous manner. The y-axis represents the generic performance trajectory generated representing the expected rate of improvement at different input variable combinations. From the graph, increase in the cumulative values of investment costs, student effort and effectiveness of student effort is seen to contribute to a positive change in performance.

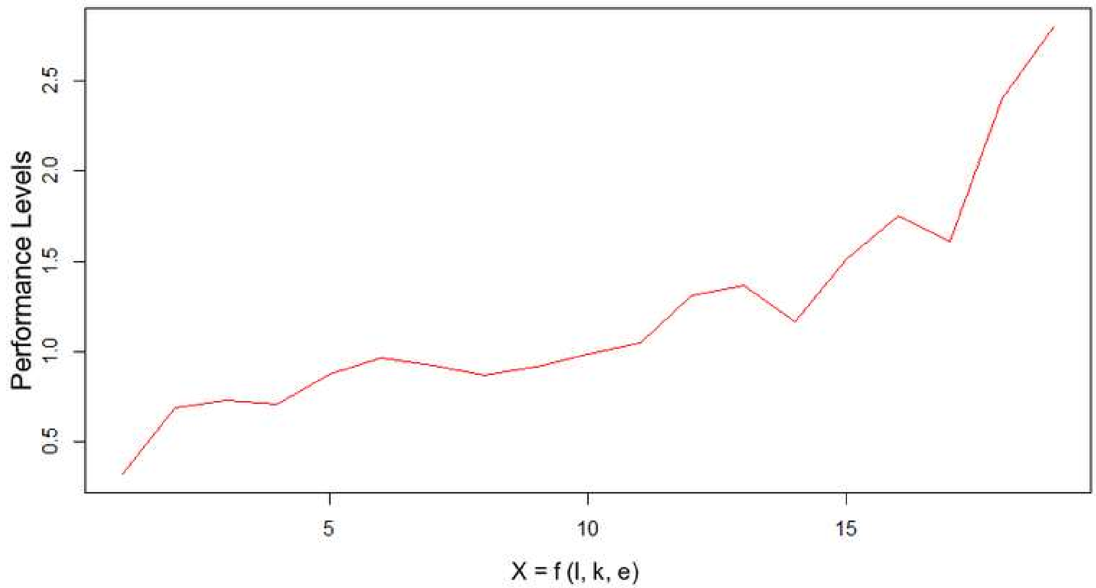

Figure 6.4 Student performance trajectory

Consequently, it is worth noting that, when the input variables were considered together at an instance in time, the student learning patterns that were discussed in section 3.5.6 could also be generated. These patterns were useful in the prediction of student performance within the context of their learning based on their attitude, investment made, the knowledge of the internet, perceived ease of use, perceived usefulness, subjective norm and the task technology fit at an instance in time. The student performance trajectory is also similar to the margin curve shown in figure 6.3 after consideration of both the dependent and independent variables in the classification approach.

6.5 Chapter Conclusion

The classification algorithm was used to confirm the factors that were required in the modelling of student performance perceptions within internetworked environments. These were student effort, investment and effectiveness of student effort in the utilization of internet technology in learning.

As a result, the factors were used to generate the decision tree which gives student performance perceptions based on the values obtained from the survey already carried out with university students. From the classification accuracy level obtained in this study, it is clear that the model can be used to successfully predict students' performance perceptions as they use internet technology in the learning process.

Chapter 7: Conclusions, Recommendations and Future Works

7.1 Introduction

This chapter highlights the conclusions drawn from this research. It gives recommendations from the general study findings and areas where there is possibility of models applications in future. Highlight about the academic contributions brought in by the study are given. Finally, a proposal of the different future works is given in light of the uses of the modelling approach.

7.2 Conclusions

The main aim of this research was to develop a model that could be used in the prediction of student performance trajectory by analysing the internet technology behavioural patterns. Specifically, the research objectives addressed the adoption of internet technology, the internet technology utilization behaviour patterns, the different ways in which internet technology influenced the learning outcome of students and the development and validation of the student performance prediction model in an internetworked environment.

The first research objective required an analysis of the current ways in which internet technology had been adopted in the learning process of students in universities. This objective was addressed by examining how internet technology had been adopted in the learning process. Precisely, this involved a deeper look at evolution of the learning environment with the invention of internet technology. It also involved examining the technology adoption theories and models that aimed at explaining how individuals accepted and used the technology as shown in the Technology Acceptance Model (TAM), the Task Technology Fit model (TTF), the Diffusion Of Innovation theory (DOI) and the Technology, Organization and Environment (TOE) framework. Finally, the objective discussed the general concept of utilization, how internet technology had been adopted in higher learning institutions and how internet technology utilization influenced student learning.

The second research objective examined internet technology utilization behaviour patterns that existed among university students. This objective was addressed by focusing on student behavioural patterns in learning converging with pattern analysis techniques. This involved an explicit discussion around student learning patterns, the learning patterns on technology mediated platforms and the learning patterns on internet mediated platforms in Kenya. This objective was achieved by the generation of the different student learning patterns based on the relationship between the seven independent variables (PU, PEOU, IAtt, Inv, KoI, SM and TTF) and the one dependent variable (Perf) considered in this research.

The third objective required an analysis of the ways in which internet technology influenced the learning outcome of students in universities. This objective was addressed by examining the learning outcome (performance of student) and the different ways that its measured in this research. This focused on determining the factors that influenced learning in an internetworked environment. These factors included student knowledge and competence levels, student's effort, physical learning environments, student attitude and behaviour, belief in the importance of the technology and investment costs. This was achieved by showing how each of the factors influenced learning on internet technology mediated platforms in Kenyan universities. Additionally, several techniques for determining student performance on internet mediated environments were highlighted with different prediction models being highlighted as well.

The fourth objective in this research required the development and validation of a model for predicting student performance trajectory in an internetworked environment. This objective required the development of the stochastic differential equations (SDEs) student performance prediction model. The equations focused on the exogenous factor (investment cost) and the endogenous factors (student effort and effectiveness of student effort) used in this research. The estimated model parameter values were also given based on the data collected in the questionnaire survey. The prediction model was validated using the same data collected from the university students and this achieved the student performance trajectory expected at an instance in time. Likewise, student performance perceptions were predicted in an internetworked environment using a decision tree algorithm which assisted in predicting the performance perceptions in these of students in these environments based on a number of attributes.

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7.3 Recommendations

From the research findings, the need for the provision of internet technology for learning purposes is evident. There is need to ensure that the universities invest adequately in the provision of internet technology for the students, for use in learning. This will enable the students to have access to the technology within the university environment and there will be no need for the students to invest any extra amounts in the provision of the technology. Widespread internet connectivity around their institutions will enable the students have unlimited access to the resource for their learning needs. Once there is adequate access to the technology, there is need to ensure that there are minimal downtime sessions. Regular downtime periods discourage students from using internet technology since they are never sure about the availability of the technology for their learning needs.

Concerning areas where predictive models can be applied, there exists different areas where the use of stochastic prediction models are emerging. Governments and professional bodies may embrace the use of this predictive approach in determining the likelihood of rare occurrences of events in an unknown date in future. This can be seen when these models assist in the prediction of economic growth for a number of future years to come based on a set of input variables that affect economic growth. In other cases, the models can also be used in the prediction of pandemics where a set of parameters are measured in relation to the pandemic and this is used in the prediction of a future occurrence.

7.4 Contributions of the Research

This research provides a general view about the use and influence of internet technology in the learning process. It also provides a clear description of the models and theories that have been used in the adoption of technology in general and has synthesised the use of these theories in the adoption of internet technology. In particular, internet adoption in the Kenyan universities has been described.

This research provides a general overview of the behavioural patterns exhibited by students in the learning process. It is anticipated that this study contributed to a broader understanding of the student learning patterns on internet mediated platforms in the Kenyan universities based on how investment in the technology, perceived usefulness and ease of use of the technology, the subjective norm, knowledge of the internet and the relevance of the technology, affect the performance of a student.

It also illustrates how different factors are capable of influencing the learning outcome of students as they use internet technology mediated platforms in the learning process.

This research applies the Cobb-Douglas production theorem in measuring the utility of internet technology in the learning process. This was done by considering predictor variables as the factor inputs and students' performance as the output expected from the prediction model.

A major contribution to the existing knowledge and literature is the development of a model that is time dependent. The time dependent model assumes the dynamic nature of the factors that affect learning on an internet mediated platform. It further assumes that the dynamics surrounding the student learning environment are continuous in nature. Therefore, continuous-time stochastic differential equations were developed to predict and infer the student performance trajectory. The model considered the current state and apriori data points unlike other longitudinal approaches which adopt cumulative nature data points.

This study contributes significantly in understanding the factors that influence the use of internet technology in the learning process of students. This research presents the use of a classification algorithm, specifically, a decision tree that defines the factors that assist with the prediction of student performance perceptions in an internetworked environment. This outcome is expected to be useful from an academic or scholarly standpoint and enables other researchers in Kenya and also around the world.

7.5 Future Work

This research considered the effectiveness of student effort as one of the predictor variables. In order for a student to effectively use internet technology in the learning process, they require a certain level of initial knowledge about the technology. This study focused on the intrinsic knowledge of a student at a specific instance in time. However, as students continue using the technology, they acquire a certain level of knowledge from their environment, their instructors or their peers. Therefore, future work could consider this externally acquired knowledge in terms of how it affects the effectiveness of student effort.

Additionally, this research considered that the input variables used in generating the student performance trajectory, that is, student effort, effectiveness of student effort in the utilization of internet technology and institutional investment, existed jointly and as a result, the variables influenced each other in a simultaneous manner. Thus, future work could consider examining each of the variables independently and analysing the effect of the variables on the expected outcome of the student trajectory.

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VT OMNES VNVM SINT

Appendices

Appendix A: Research Questionnaire

Research questionnaire

Dear Respondent,

RE: DATA COLLECTION

My name is Esther Khakata, a student at Strathmore University pursuing a Doctorate in Information Technology. As a requirement, I am undertaking a study on 'Algorithmic Prediction of Internet Technology Utilization in Learning' in Kenyan institutions of higher learning.

The purpose of this study is to establish the indicators that can be used to assess the level of usage of the internet resource and whether or not the internet contributes to the learning process of a student. The results of this study will be used by universities to gauge the utilization of the internet resource in assisting the students at different education levels in their learning process.

I humbly request you to participate in this study by filling this questionnaire to enable me obtain data for the research. The information obtained will be treated with utmost confidentiality and will only be used for academic purposes.

Your cooperation will be highly appreciated.

Thanks in advance.

May God bless you abundantly.

<u>Section A: Background Information</u>

Please select the most suitable option for you (*single selection only*).

A1. Category of University:	Private	[ ]	Public	[ ]
A2. Education level:	Undergraduate	[ ]	Postgraduate	[ ]
A3. Gender:	Male	[ ]	Female	[ ]

<u>Section B: Knowledge on Internet Usage</u>

Kindly select the most suitable option for you.

B1. Please indicate whether you have internet connectivity within your university (*single selection only*).

Yes [ ]   No [ ]

B2. How often do you experience internet downtime/unavailability in the university? (*Single selection only*).

Very regularly [ ]   Regularly [ ]   Not regularly [ ]

B3. Please indicate for what purpose you use the internet: ***(multiple selection allowed)***

Research work [ ]   Assignments [ ]   Communication [ ]
Music/movies [ ]   Meeting people/friends/peers [ ]
Games [ ]

B4. Please indicate how you access the internet to carry out the activities in B3 above ***(multiple selection allowed).***

From university network (wireless/labs/LAN) [ ]
From a cybercafé around campus [ ]
From mobile phone/smart gadget [ ]
From home, through a paid connection [ ]

B5. How regularly do you use the internet for learning/research work during the day? (*Single selection only*).

Several times daily [ ]   Once per day [ ]   Once per month [ ]
Less than once a month [ ]   Never [ ]   All the time [ ]

Please indicate by ticking in the appropriate box the extent to which you agree or disagree with each of the statements. (Single *selection only*).

	Self-Efficacy / Capability of the student	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
		1	**2**	**3**	**4**	**5**
B6	Internet does not scare me at all					
B7	I'm good with internet					
B8	I like learning using the internet					
B9	I use the internet in my studies					
B10	Generally, I feel OK about trying new problems on the internet					
B11	The challenge of solving course work problems with internet appeals to me					
B12	I do not feel threatened when others talk about internet and learning					

B13	I think learning using the internet is enjoyable and stimulating					
B14	I am sure I can do school work with internet with ease					
B15	I'll need a firm mastery of internet for my future academic pursuits					
B16	I do well with internet					
B17	I use the internet greatly in my daily life especially in the university					
B18	I appreciate and understand how some people can spend so much time researching on the internet and seem to enjoy it					
B19	I use the internet in many ways in my studies					
B20	I feel at ease in a class that requires the use of internet in learning					
B21	I think using internet is very hard for me					
B22	Once I start learning using the internet, I find it hard to stop					
B23	Knowing how to research on the internet helps my studies and improves my grades					
B24	I get a sinking feeling when I think of trying to use internet for my assignments					
B25	I score better grades whenever I use the internet to do research on my studies					
B26	I do as little research with internet as possible					
B27	The internet has taught me to do things in many varied ways					
B28	If a problem is left unsolved in class, I continue to think about it afterward and use the internet to read more about it					
B29	Internet makes me feel uneasy and confused especially when I get too much text to read					

B30	I have a lot of self-confidence when it comes to working with internet					

	Attitude of the student	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
		1	2	3	4	5
B31	I look forward to using internet in my studies					
B32	The challenge of learning about the internet is exciting					
B33	I am confident that I can learn internet skills					
B34	Anyone can learn to use internet if they are patient and motivated					
B35	Learning to operate internet is like learning any new skill – the more you practice, the better you become					
B36	I am afraid that if I begin to use internet I will become dependent upon it and lose some of my reasoning skills					
B37	I am sure that with time and practice I will be as comfortable working with internet as I am in working with a library of books					
B38	I keep up with the advances happening in the internet field					
B39	I dislike working with internet since it appears like a machine that is smarter than I am					
B40	I have difficulty in understanding the technical aspects of internet					
B41	I hesitate to use internet for fear of getting too much information that requires a lot of sifting					
B42	I have avoided internet because it is unfamiliar and somewhat intimidating to me					
B43	The internet is a necessary tool in my academics					

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B44	I seek information from the internet for learning activities e.g. assignments and projects					
B45	I search for materials from the internet to complete my assignments and projects					
B46	I use the Internet as the main source of information for my studies					
B47	I use the internet to access the Learning Management System/E-learning portal as part of my learning activity					
B48	I seek the latest information online to enhance my knowledge related to the courses taken in the university					
B49	I use internet forums to exchange opinions on academic matters with my friends					

Section C: Other Factors that Enhance Learning with the Internet

Kindly indicate by ticking in the appropriate box the most suitable response based on your individual circumstances in the university environment (*single selection*).

	Physical environment and general internet infrastructure	Never	Rarely	Occasionally	Often	Always
		1	2	3	4	5
C1	Spacious computer labs are available with adequate light, controlled temperatures and minimal noises.					
C2	There are many adequately equipped labs that are available with internet connectivity.					
C3	Internet connectivity is available all around the university.					
C4	I have a personal laptop for internet access.					
C5	I have a smart gadget(s) that I use for internet access in lecture halls.					
C6	Available study areas are comfortable (clean, well-organized) and with internet connectivity.					
C7	Lecturers have computers with internet connectivity.					

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C8	I have access to consultation rooms with internet connection to enable me meet my lecturers.					
C9	I use the e-learning portal to get access to my learning materials.					
C10	The lecture theatres have internet connectivity and course work materials can be viewed in class using LCD projectors.					
C11	Adequate assistance is offered to students to ensure that they can access the internet in the university.					
C12	University hostels/student hostels around the university have adequate internet access.					
C13	Internet access is open and free to all within the university.					
C14	The university library has internet access for all library users.					
C15	Research materials are accessible from different online databases.					
	Influence to use internet (University, Peers, Family and Personality)					
		Never	**Rarely**	**Occasionally**	**Often**	**Always**
	University	**1**	**2**	**3**	**4**	**5**
C16	Internet is available in the university all the time.					
C17	The connection speed is always very good.					
C18	There are many places from where internet can be accessed in the university.					
C19	Internet connection is reliable all throughout the semester.					
C20	The ICT department has put in place policies that govern the use of internet.					
C21	There is available software and hardware that assist with internet access in the university.					
C22	There exists no access limitations as far as access and use of the internet are concerned.					

C23	The university is committed to offering overall support in using the internet.					
		Never	**Rarely**	**Occasionally**	**Often**	**Always**
	Peers	**1**	**2**	**3**	**4**	**5**
C24	A lot of teamwork in campus allows me to learn with the internet.					
C25	Availability of many types of shareware from my peers has made me learn more about the internet.					
C26	Sharing of resources with my peers using the internet has made me learn a lot.					
C27	My peers have influenced me to positively use the internet especially for learning.					
C28	My peers are a great source of assistance in overcoming the difficulties involved in learning using the internet.					
		Never	**Rarely**	**Occasionally**	**Often**	**Always**
	Family	**1**	**2**	**3**	**4**	**5**
C29	I get a lot of encouragement from my family members to use the internet for learning purposes.					
C30	I have a personal laptop at home.					
C31	I have a smartphone/iPad/tablet at home.					
C32	I have access to various software applications at home.					
C33	I have unlimited internet access at home.					
		Never	**Rarely**	**Occasionally**	**Often**	**Always**
	Student Personality	**1**	**2**	**3**	**4**	**5**
C34	I enjoy forming new relationships with fellow internet users.					
C35	I treat other internet users with respect.					
C36	I like spending a lot of time on the internet studying.					
C37	I concentrate very well on my studies whenever am using the internet for learning.					

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C38	I have developed a dependency on using the internet whenever I need anything for my studies.					
C39	The internet has made me prefer to work alone without interference from my peers.					
C40	I have a lot of internet browsing discipline where I only access learning resources when studying.					
C41	I have a lot of self-drive in matters regarding my studies especially when concepts require further research.					
C42	The idea of looking for new knowledge excites me and motivates me to continue using the internet.					
C43	I appreciate and participate a lot in academic/learning websites/blogs.					
C44	I use social media sites (for example, face book and twitter) for learning purposes.					

Section D: Utility of internet technology

Kindly select the most suitable option for you

D1. How relevant has the internet been in your studies? **(*Single selection*)**

Irrelevant [ ] slightly relevant [ ] Not sure [ ] Relevant [ ] Very relevant [ ]

D2. How would you rate your proficiency/abilities in using the internet for learning purposes? **(*Single selection*)**

Beginner [ ]

Basic [ ]

Average [ ]

Advanced [ ]

Very advanced [ ]

D3. What do you consider in rating internet availability in the university? (***Multiple selection allowed***)

Access speeds [ ]

Nature of connectivity (Wireless/Local Area Network) [ ]

Number of locations that can help access the internet [ ]

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D4. What would you consider to be the factors that affect your ability to use the internet effectively in learning? (***Multiple selection allowed***)

Knowledge of the internet [ ]

Internet speeds [ ]

Subject matter [ ]

Costs incurred to access internet [ ]

Time spent on internet [ ]

Effort needed [ ]

On a scale of 1-5, please rate the following factors, in order of preference, on how they affect your ability to get maximum benefits from the internet (single selection).

		Irrelevant	Slightly relevant	Not sure	Relevant	Very relevant
		1	2	3	4	5
D5	Knowledge of internet					
D6	Speed of the internet					
D7	Subject matter					
D8	Costs incurred to access internet					
D9	Time spent on internet					
D10	Effort needed					

Please indicate the relevance of the internet in the following aspects of the internet in your academic work (*single selection*).

		Irrelevant	Slightly relevant	Not sure	Relevant	Very relevant
		1	2	3	4	5
D11	Source of updated academic information					
D12	Access to learning materials through an e-learning portal/learning management system or to upload my assignment through the portal					
D13	Exchange of ideas through chats/instant messaging platforms					
D14	Email communication with lecturers					

D15	Use other online tools (Instant Messenger, Facebook, etc.) to contact lecturers about my studies					
D16	Email communication with classmates					
D17	Blogs/websites for sharing academic ideas with other students					
D18	Blogs/websites for sharing academic ideas with other internet users					
D19	Access to other learning materials for example, you tube videos					
D20	Avails news prompts on the recent happenings in academia and technology					
D21	Source of free online courses that have assisted me in a variety of disciplines					
D22	Search online for available part time job opportunities for students					
D23	Collection of a variety of online information good for my studies, then organizing it in files to be retrieved when I want					
D24	Check the university website for announcements, dates, updates etc.					

Please rate the extent to which you think the internet has enabled you to achieve the below aspects in learning (*single selection*).

		Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
		1	2	3	4	5
D25	The internet allows me to increase my productivity in my studies					
D26	The internet has led me to rely less on hard copy text for my studies					
D27	The internet has enhanced the quality of the work I do in my studies					
D28	The internet gives me a great sense of accomplishment after using it for learning purposes					

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D29	The internet has enhanced my performance in my studies					
D30	I find internet useful in my studies					
D31	Using the internet enables me to accomplish tasks more quickly					
D32	I believe I can communicate with other people about the pros and cons of using internet					
D33	I feel that using internet resources gives me a great deal of opportunity for my studies					
D34	I find the internet easy to use and enjoyable					
D35	People who influence my behaviour (e.g. course mates, friends) think that I should use internet					
D36	People who are important to me (e.g. family members) think that I should use internet					
D37	Lecturers in the university have been encouraging the use of internet					
D38	The university has supported the use of internet					
D39	I find that I have fewer challenges with my studies than my course mates/friends due to use of the internet					
D40	I have the knowledge necessary to use internet					
D41	Using the internet is a pleasant experience for me					
D42	A specific person (or group) is available for assistance should I encounter difficulties with the internet					
D43	I can competently complete any assigned task using internet					

………………………………..**Thanks for your time**…………………………………….

Appendix B: Refined Data Classification on Questionnaire

Table B-1 *Refined data classification*

Attribute	**Values used**
Perceived usefulness (PU)	B5, B43, D26, D28, D30, D31, D32, D33, D39,D43
Perceived Ease of Use (PEOU)	B6, B7, B8, B31, B32, B33, B34, B35, D34, D41
Task Technology Fit (TTF)	D11, D12, D13, D14, D15, D16, D17,D18, D19, D20, D21, D22,D23
Attitude (IAtt)	B36, B37,B39,B40,B41, B42, B44, B45,B46,B47,B48,B49
Subjective Norm (SM)	C16, C17,C18, C19, C20,C21,C22, C23, C24, C25, C26,C27,C28,C29, C30,C31,C32, C33,C34,C35, C36,C37,C38, C39, C40,C41,C42, C43, C44,D24, D35, D36,D37, D38, D42
Knowledge of Internet (KoI)	B9,B10,B11,B12,B13.B14,B15,B16,B17,B18,B19,B20, B21,B22, B24, B26, B27,B28,B29,B30,D40
Investment (Inv)	B4A, B4C,C1, C2, C3,C4, C5, C6, C7, C8,C9,C10, C11, C12, C13, C14,C15
Relevance and Ability (R&A)	D1, D2
Performance (Perf)	B23, B25, D25, D27, D29

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Appendix C: Formulation of System and Observation Equations on CTSM-R Package

The general model structure used in CTSM-R is a state space model defined as

$dx_t = f(x_t, u_t, t, \theta)dt + \sigma(u_t, t, \theta)d\omega_t$ [C.1]

$y_k = h(x_k, u_k, t_k, \theta) + e_k$ [C.2]

Where C.1 is a continuous time stochastic differential equation which is a physical description of a system and C.2 is the discrete time observation of the original physical system (CTSM-R Development Team, 2015).

The CTSM-R model structure assumes the nature of object oriented programming. In this case the mathematical equations are added one at a time. The process begins by initializing the model where an empty model is created and the corresponding mathematical models are added to the object.

This is done as

$model2 < -ctsm()$ ……………………………………………………………….. [C.3]

where model2 is the model name and ctsm () is the generator function which defines the reference library needed for computations in the model. The object returned is an instance of the class ctsm and the methods help in defining the model structure and the parameter limits.

CTSM-R requires a number of equations to be added in order to assist in generating the desired output. These equations are mainly the system equations, observation equations, the inputs, variance and parameters.

In order to add a system equation, the continuous time stochastic differential equations are added into the model by defining them as

$model2\$addSystem(formula)$ …………………………………………..…… [C.4]

the formula is written as a SDE which is valid in R. For instance:

$dP \sim (a * TC^{-a})) * (Es * Ls)^{1-a} * dt + Tc^{a} * \Sigma p * d\omega p$ ……………………. [C.5]

While adding an observation equation, the equation used takes the form

$model2\$addObs(formula)$ ………………………………………………………... [C.6]

the formula becomes a measurement equation which can take the form:

$Y \sim P(h, x, t)$ ……………………………………………………………………..……... [C.7]

Another important component that needs to be defined is the variance. The variance of the measurement noise is added for the output with the function

$model2\$setVariance(Y \sim s)$ ………………………………………………...……. [C.8]

Equally important are the input values that will be used in the model. The inputs are the values computed from the collected data and are available for use in the model already defined. This is done by defining the inputs that will be used in the function using the below structure

$model2\$addInput(symbol)$ ………………………………………………………… [C.9]

where the symbol defines which variables are external inputs to the system. For example,

$model2\$addInput(Tc, Es, Ls)$ ……………………………………………..……. [C.10]

where *Tc*, *Es*, and *Ls* are all inputs which must be columns in the collected data.

As the model equations are being defined, it is important to consider that there will be values that will be used in the equations and these value could be constants, or values that assume a certain range. Therefore, parameter estimation in CTSM-R is considered by maximizing the likelihood function with an optimization scheme. The scheme is defined by giving the lower limit, the upper limit and the initial values for the parameters. For instance, to define the limits of a variable, the equation is set as

$model2\$setParameter(a = c(init = 0.45, lower = 0.1, upper = 0.77))$ ……… [C.11]

In order to define a specific constant value of a parameter, the function is defined without the limits, for instance,

$model2\$setParameter(a = c(init = 0.45))$ …………………………………... [C.12]

Model equations are defined by a number of rules, for instance, the characters accepted by the interpreter include letters A-Z or a-z, integers 0-9, operators + - * / ^, parentheses () and the decimal separator. The interpreter is case sensitive with respect to the input names, parameter names and algebraic equations. By default, t is considered the equations time variable. The interpreter only works with specific number formats, for instance, scientific (e.g. 1.2E+3), standard (1.26) or integers (12). Each equation that is input is checked whether it corresponds to any of the inputs, outputs, system equations or observation equations. In case it does not correspond to any, it is treated as a parameter. The common mathematical functions accepted by the interpreter are: abs(), sign(), sqrt(), exp(), log(), sin(), cos(), tan(), arcsin(), arctan(), sinh() and cosh().

Appendix D: System Equations, Observation Equations and Output Equations used in the study

```
library(ctsmr)

modelc3<-ctsm()

modelc3$addSystem(dp~(((a*It^(a-1))*(et*kt)^(1-a))+((1-a)*It^a*(et*kt)^(-
a))*dt+It^a*(et*kt)^(1-a)*sigmap*dwp))

modelc3$addSystem(dI~((It^a*(et*kt)^(1-a)-(rho-((1-a)/a))*It)*dt+It*sigmat*dwt))

modelc3$addSystem(dk~((muk*kt)*dt+kt*sigmak*dwk))

modelc3$addSystem(de~((mue*et)*dt+et*sigmae*dwe))

modelc3$addObs(Y~p)

modelc3$setVariance(Y~s)

modelc3$addInput(It,kt,et)

modelc3$setParameter(a=c(init=0.45,lower=0.1,upper=0.77))

modelc3$setParameter(mue=c(init=0.0176))

modelc3$setParameter(muk=c(init=0.011,lower=0.01,upper=0.02))

modelc3$setParameter((rho=c(init=0.06,lower=0.05,upper=0.08)))

modelc3$setParameter(sigmae=c(init=0.0148))

modelc3$setParameter(sigmat=c(init=0.012))

modelc3$setParameter(sigmaI=c(init=0.012))

modelc3$setParameter(sigmak=c(init=0.01))

modelc3$setParameter(sigmap=c(init=0.1,lower=0.01,upper=1))

modelc3$setParameter(s=c(init=0.1))

modelc3$setParameter(p=c(init=0.4,lower=0,upper=1))
```

```
modelc3$setParameter(I=c(init=0.8))

modelc3$setParameter(k=c(init=0.5))

modelc3$setParameter(e=c(init=0.3))

modelc3$setParameter(rho=c(init=0.06))

fitc3<-modelc3$estimate(data2q)

tempc3<-predict(fitc3)[[1]]

data2q$YHat<-tempc3$output$pred$Y

plot(data2q$t, data2q$YHat, geom= 'smooth', span =0.7, color='red', type='l', ylab =
'Performance Levels', xlab='X=f(I,k,e)')
```

Appendix E: Run Information for Feature Selection of the Model Attributes

E-1: IAtt

=== Run information ===

Evaluator: weka.attributeSelection.CorrelationAttributeEval

Search: weka.attributeSelection.Ranker -T -1.7976931348623157E308 -N -1

Relation: IAtt

Instances: 747

Attributes: 18

B31
B32
B33
B34
B35
B36
B37
B38
B39
B40
B41
B42
B44
B45
B46
B47
B48
B49

Evaluation mode: evaluate on all training data

=== Attribute Selection on all input data ===

Search Method:

Attribute ranking.

Attribute Evaluator (supervised, Class (numeric): 18 B49):

Correlation Ranking Filter

Ranked attributes:

0.29277 17 B48
0.26911 4 B34
0.26035 7 B37
0.25029 14 B45
0.24801 16 B47
0.23881 8 B38

0.22814 5 B35
0.22323 3 B33
0.22153 1 B31
0.17565 13 B44
0.16818 15 B46
0.14296 2 B32
0.02544 12 B42
0.01246 11 B41
0.00483 9 B39
0.00188 6 B36
-0.01716 10 B40
Selected attributes: 17,4,7,14,16,8,5,3,1,13,15,2,12,11,9,6,10 : 17

E-2: Inv

=== Run information ===
Evaluator: weka.attributeSelection.CorrelationAttributeEval
Search: weka.attributeSelection.Ranker -T -1.7976931348623157E308 -N -1
Relation: Inv
Instances: 747
Attributes: 17
B4A
B4C
C1
C2
C3
C4
C5
C6
C7
C8
C9
C10
C11
C12
C13
C14
C15
Evaluation mode: evaluate on all training data
=== Attribute Selection on all input data ===
Search Method:

Attribute ranking.
Attribute Evaluator (supervised, Class (numeric): 17 C15):
Correlation Ranking Filter
Ranked attributes:
0.6137 16 C14
0.4579 13 C11
0.4308 4 C2
0.425 3 C1
0.4128 15 C13
0.4051 8 C6
0.3527 12 C10
0.351 9 C7
0.326 5 C3
0.2766 10 C8
0.2763 14 C12
0.245 7 C5
0.1947 1 B4A
0.1802 6 C4
0.0731 2 B4C
-0.0179 11 C9
Selected attributes: 16,13,4,3,15,8,12,9,5,10,14,7,1,6,2,11: 16

E-3: KoI
=== Run information ===
Evaluator: weka.attributeSelection.CorrelationAttributeEval
Search: weka.attributeSelection.Ranker -T -1.7976931348623157E308 -N -1
Relation: KoI
Instances: 747
Attributes: 26
B6
B7
B8
B9
B10
B11
B12
B13
B14
B15
B16

B17
B18
B19
B20
B21
B22
B23
B24
B25
B26
B27
B28
B29
B30
D40

Evaluation mode: evaluate on all training data

=== Attribute Selection on all input data ===

Search Method:

Attribute ranking.

Attribute Evaluator (supervised, Class (numeric): 26 D40):

Correlation Ranking Filter

Ranked attributes:

```
 0.2906   11 B16
 0.2733   22 B27
 0.2623    2 B7
 0.2593   25 B30
 0.2468   14 B19
 0.2395   23 B28
 0.2386   12 B17
 0.2352    8 B13
 0.2351   15 B20
 0.2292    9 B14
 0.2126    3 B8
 0.1978    6 B11
 0.1929   18 B23
 0.1912    7 B12
 0.1885   20 B25
 0.1232    5 B10
 0.1163    1 B6
 0.1059    4 B9
```

0.0646 10 B15
0.0524 13 B18
0.0367 17 B22
0.0314 19 B24
-0.0903 16 B21
-0.1157 21 B26
-0.1393 24 B29
Selected attributes: 11,22,2,25,14,23,12,8,15,9,3,6,18,7,20,5,1,4,10,13,17,19,16,21,24: 25

E-4: PEOU

=== Run information ===
Evaluator: weka.attributeSelection.CorrelationAttributeEval
Search: weka.attributeSelection.Ranker -T -1.7976931348623157E308 -N -1
Relation: PEOU
Instances: 747
Attributes: 2
D34
D41
Evaluation mode: evaluate on all training data
=== Attribute Selection on all input data ===
Search Method:
Attribute ranking.

Attribute Evaluator (supervised, Class (numeric): 2 D41):
Correlation Ranking Filter
Ranked attributes:
0.494 1 D34
Selected attributes: 1: 1

E-5: PU

=== Run information ===
Evaluator: weka.attributeSelection.CorrelationAttributeEval
Search: weka.attributeSelection.Ranker -T -1.7976931348623157E308 -N -1
Relation: PU
Instances: 747
Attributes: 13
B5
B43
D25
D26

D27
D28
D29
D30
D31
D32
D33
D39
D43
Evaluation mode: evaluate on all training data
=== Attribute Selection on all input data ===
Search Method:
Attribute ranking.
Attribute Evaluator (supervised, Class (numeric): 13 D43):
Correlation Ranking Filter
Ranked attributes:
0.4261 10 D32
0.4208 6 D28
0.4086 8 D30
0.3933 12 D39
0.3872 3 D25
0.3603 9 D31
0.3499 11 D33
0.3283 5 D27
0.3206 7 D29
0.3075 4 D26
0.3066 2 B43
0.0468 1 B5
Selected attributes: 10,6,8,12,3,9,11,5,7,4,2,1 : 12

E-6: R&A

=== Run information ===
Evaluator: weka.attributeSelection.CorrelationAttributeEval
Search: weka.attributeSelection.Ranker -T -1.7976931348623157E308 -N -1
Relation: R&A
Instances: 747
Attributes: 2
D1
D2
Evaluation mode: evaluate on all training data

=== Attribute Selection on all input data ===
Search Method:
    Attribute ranking.
Attribute Evaluator (supervised, Class (numeric): 2 D2):
    Correlation Ranking Filter
Ranked attributes:
0.0193 1 D1
Selected attributes: 1: 1

E-7: SM
=== Run information ===
Evaluator: weka.attributeSelection.CorrelationAttributeEval
Search: weka.attributeSelection.Ranker -T -1.7976931348623157E308 -N -1
Relation: SM
Instances: 747
Attributes: 35
    C16
    C17
    C18
    C19
    C20
    C21
    C22
    C23
    C24
    C25
    C26
    C27
    C28
    C29
    C30
    C31
    C32
    C33
    C34
    C35
    C36
    C37
    C38
    C39

C40
C41
C42
C43
C44
D24
D35
D36
D37
D38
D42

Evaluation mode: evaluate on all training data

=== Attribute Selection on all input data ===

Search Method:

Attribute ranking.

Attribute Evaluator (supervised, Class (numeric): 35 D42):

Correlation Ranking Filter

Ranked attributes:

0.365	34 D38
0.3619	32 D36
0.3031	31 D35
0.297	33 D37
0.2521	30 D24
0.2464	13 C28
0.2388	11 C26
0.2374	7 C22
0.2295	1 C16
0.2257	2 C17
0.2241	10 C25
0.2209	4 C19
0.2152	8 C23
0.2075	3 C18
0.206	14 C29
0.1946	28 C43
0.1905	6 C21
0.1889	26 C41
0.1873	12 C27
0.1818	9 C24
0.1791	25 C40
0.1779	22 C37

0.1717   21 C36
0.1694   29 C44
0.1676   23 C38
0.1644   19 C34
0.156   20 C35
0.1518   27 C42
0.1514   24 C39
0.1145   17 C32
0.11   5 C20
0.0934   18 C33
0.0829   15 C30
0.0819   16 C31
Selected attributes:
34,32,31,33,30,13,11,7,1,2,10,4,8,3,14,28,6,26,12,9,25,22,21,29,23,19,20,27,24,17,5,18,15,16: 34

E-8: TTF

=== Run information ===
Evaluator: weka.attributeSelection.CorrelationAttributeEval
Search: weka.attributeSelection.Ranker -T -1.7976931348623157E308 -N -1
Relation: TTF
Instances: 747
Attributes: 13
D11
D12
D13
D14
D15
D16
D17
D18
D19
D20
D21
D22
D23
Evaluation mode: evaluate on all training data
=== Attribute Selection on all input data ===
Search Method:
Attribute ranking.

Attribute Evaluator (supervised, Class (numeric): 13 D23):
Correlation Ranking Filter
Ranked attributes:

```
 0.515 11 D21
 0.511 12 D22
 0.422 10 D20
 0.388  9 D19
 0.358  7 D17
 0.347  4 D14
 0.341  3 D13
 0.339  1 D11
 0.335  2 D12
 0.331  5 D15
 0.329  8 D18
 0.316  6 D16
```

Selected attributes: 11,12,10,9,7,4,3,1,2,5,8,6 : 12

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Appendix F: Run Information for the Training Dataset (Final8-1 Training set.arff)

=== Run information ===

Scheme: weka.classifiers.trees.J48 -C 0.25 -M 2

Relation: Final 8-1 Training set

Instances: 29

Attributes: 4

Inv

Effort

Effe

Perf

Test mode: 10-fold cross-validation

=== Classifier model (full training set) ===

J48 pruned tree

: yes (29.0/4.0)

Number of Leaves: 1

Size of the tree: 1

Time taken to build model: 0 seconds

=== Stratified cross-validation ===

=== Summary ===

Correctly Classified Instances	25	86.2069 %
Incorrectly Classified Instances	4	13.7931 %
Kappa statistic	0	
Mean absolute error	0.2436	
Root mean squared error	0.3541	
Relative absolute error	93.0308 %	

Root relative squared error 99.9423 %

Total Number of Instances 29

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.000	0.000	?	0.000	?	?	0.160	0.138	no
	1.000	1.000	0.862	1.000	0.926	?	0.160	0.788	yes
Weighted Avg.	0.862	0.862	?	0.862	?	?	0.160	0.698	

=== Confusion Matrix ===

a b <-- classified as

0 4 | a = no

0 25 | b = yes

Appendix G: Run Information for the Final Dataset (*Final8-1.arff*)

```
=== Run information ===
Scheme:      weka.classifiers.trees.J48 -O -U -M 2
Relation:    Final8 - 1
Instances:   747
Attributes:  4
             Inv
             Effort
             Effe
             Perf
Test mode:   10-fold cross-validation
=== Classifier model (full training set) ===
J48 unpruned tree
------------------
Effort <= 3
|   Effort <= 2: no (5.0)
|   Effort > 2
|   |   Effe <= 2: no (4.0)
|   |   Effe > 2
|   |   |   Inv <= 3
|   |   |   |   Inv <= 2
|   |   |   |   |   Effe <= 3: no (7.0/1.0)
|   |   |   |   |   Effe > 3: yes (3.0/1.0)
|   |   |   |   Inv > 2
|   |   |   |   |   Effe <= 3: no (22.0/9.0)
|   |   |   |   |   Effe > 3: no (15.0/5.0)
|   |   |   Inv > 3
|   |   |   |   Inv <= 4
|   |   |   |   |   Effe <= 3: no (8.0/1.0)
```

| | | | | Effe > 3: no (17.0/4.0)

| | | | Inv > 4: no (2.0)

Effort > 3

| Effort <= 4

| | Effe <= 3: yes (64.0/22.0)

| | Effe > 3

| | | Effe <= 4

| | | | Inv <= 2: yes (46.0/3.0)

| | | | Inv > 2: yes (353.0/57.0)

| | | Effe > 4: yes (56.0/5.0)

| Effort > 4

| | Effe <= 4

| | | Inv <= 3: yes (33.0)

| | | Inv > 3

| | | | Inv <= 4: yes (26.0/6.0)

| | | | Inv > 4: yes (9.0)

| | Effe > 4: yes (77.0)

Number of Leaves: 17

Size of the tree: 33

Time taken to build model: 0.05 seconds

=== Stratified cross-validation ===

=== Summary ===

Correctly Classified Instances 632 84.6051 %

Incorrectly Classified Instances 115 15.3949 %

Kappa statistic 0.4329

Mean absolute error 0.2427

Root mean squared error 0.3503

Relative absolute error 74.0218 %

Root relative squared error 86.5808 %

Total Number of Instances 747

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.396	0.037	0.735	0.396	0.515	0.462	0.783	0.569	no
	0.963	0.604	0.860	0.963	0.909	0.462	0.783	0.923	yes
Weighted Avg.	0.846	0.487	0.834	0.846	0.827	0.462	0.783	0.850	

=== Confusion Matrix ===

```
  a   b   <-- classified as
 61  93 |   a = no
 22 571 |   b = yes
```

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Appendix H: Tree Induction Algorithm

Algorithm:

1) Create a node N.

2) If all the tuples in the partition are of the same class then return N as a leaf node labelled with that class.

3) If attributes list is empty then return N as a leaf node labelled with the most common class in samples.

4) identify the splitting attribute so that resulting partitions at each branch are as pure as possible.

5) Label node N with splitting criterion which serves as test at that node.

6) If splitting attribute is discrete valued then remove splitting attribute from attribute list.

7) Let *Pi* be the partitions created based on the *i* outcomes on splitting criterion.

8) If any *Pi* is empty then attach a leaf with the majority class in the partition to node N.

9) Else recursively apply the complete process on each partition.

10) Return N.

Appendix I: Other Student Learning Patterns

Examining the pattern generated when considering task technology fit (TTF) versus performance (Perf) gives figure I-1 which has characteristics similar to those in figure 3.9.

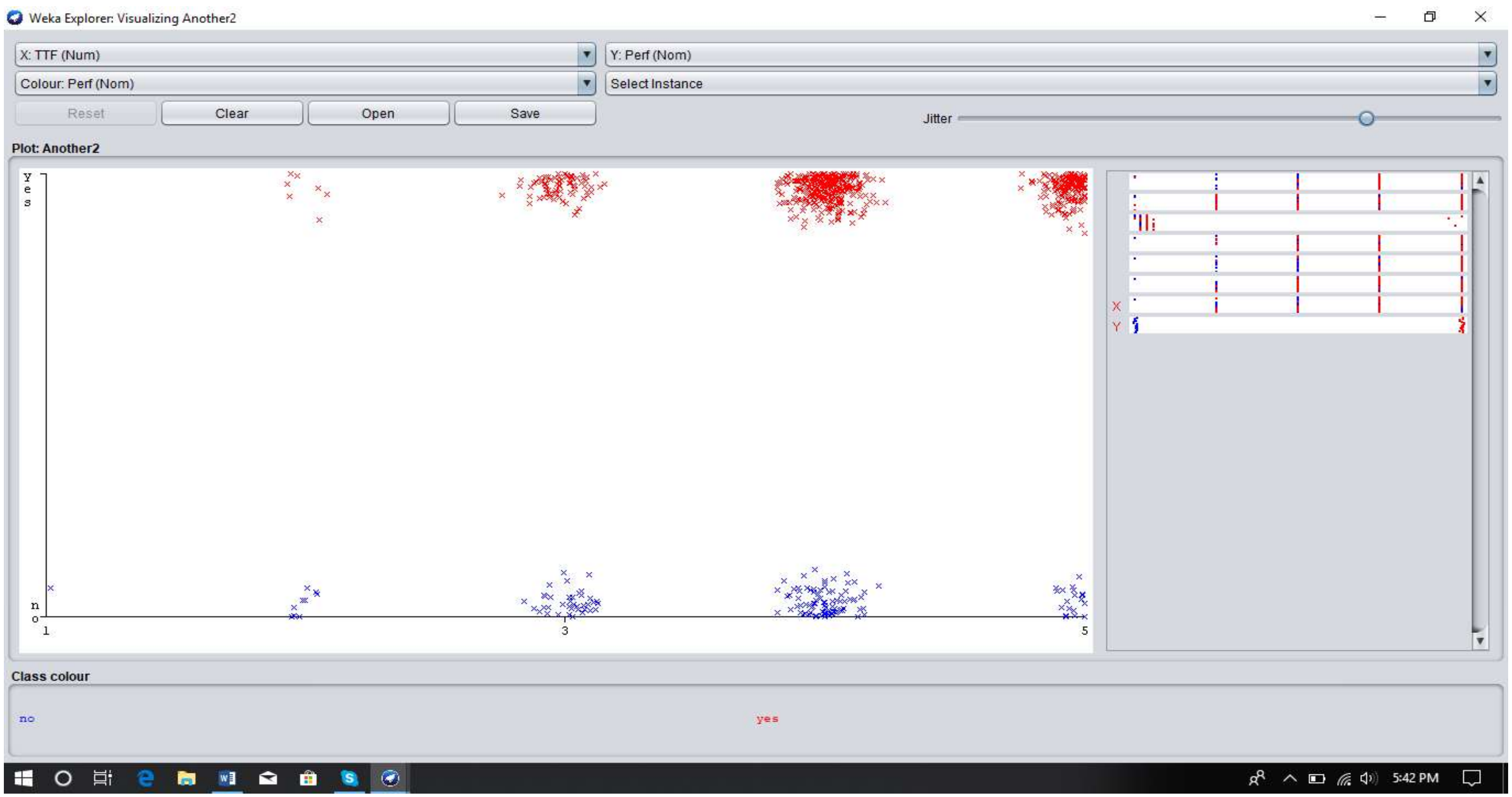

Figure I-1 *Learning pattern with task technology fit (TTF) versus performance (Perf)*

The pattern generated when considering subjective norm (SM) versus performance (Perf) is shown in figure I-2. This pattern is similar to the pattern generated on figure 3.9.

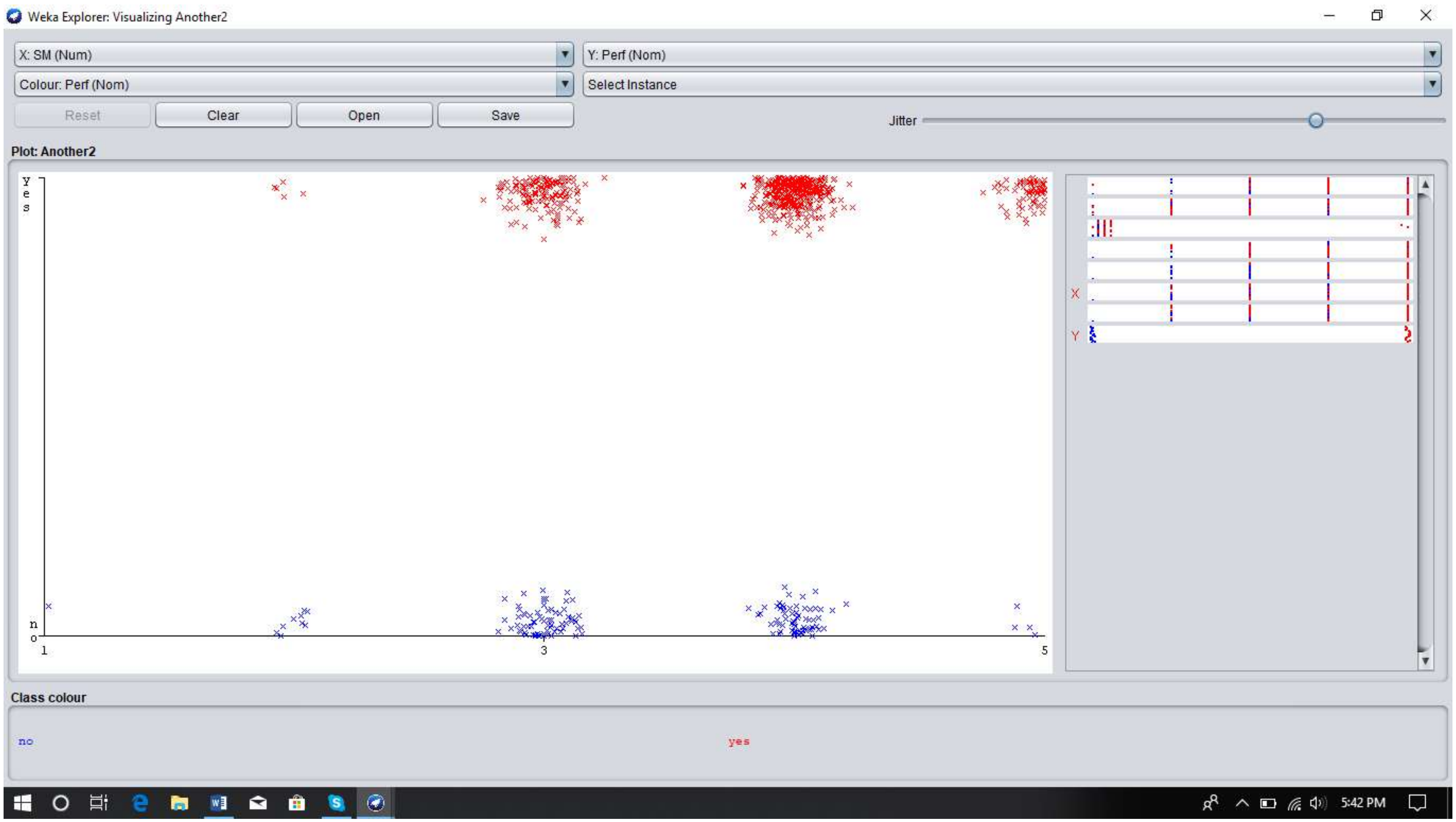

Figure I-2 *Learning pattern with subjective norm (SM) versus performance (Perf)*

Another similar pattern is generated when examining perceived usefulness (PU) versus performance (Perf) as shown in figure I-3. This pattern is also similar to what is generated in figure 3.9.

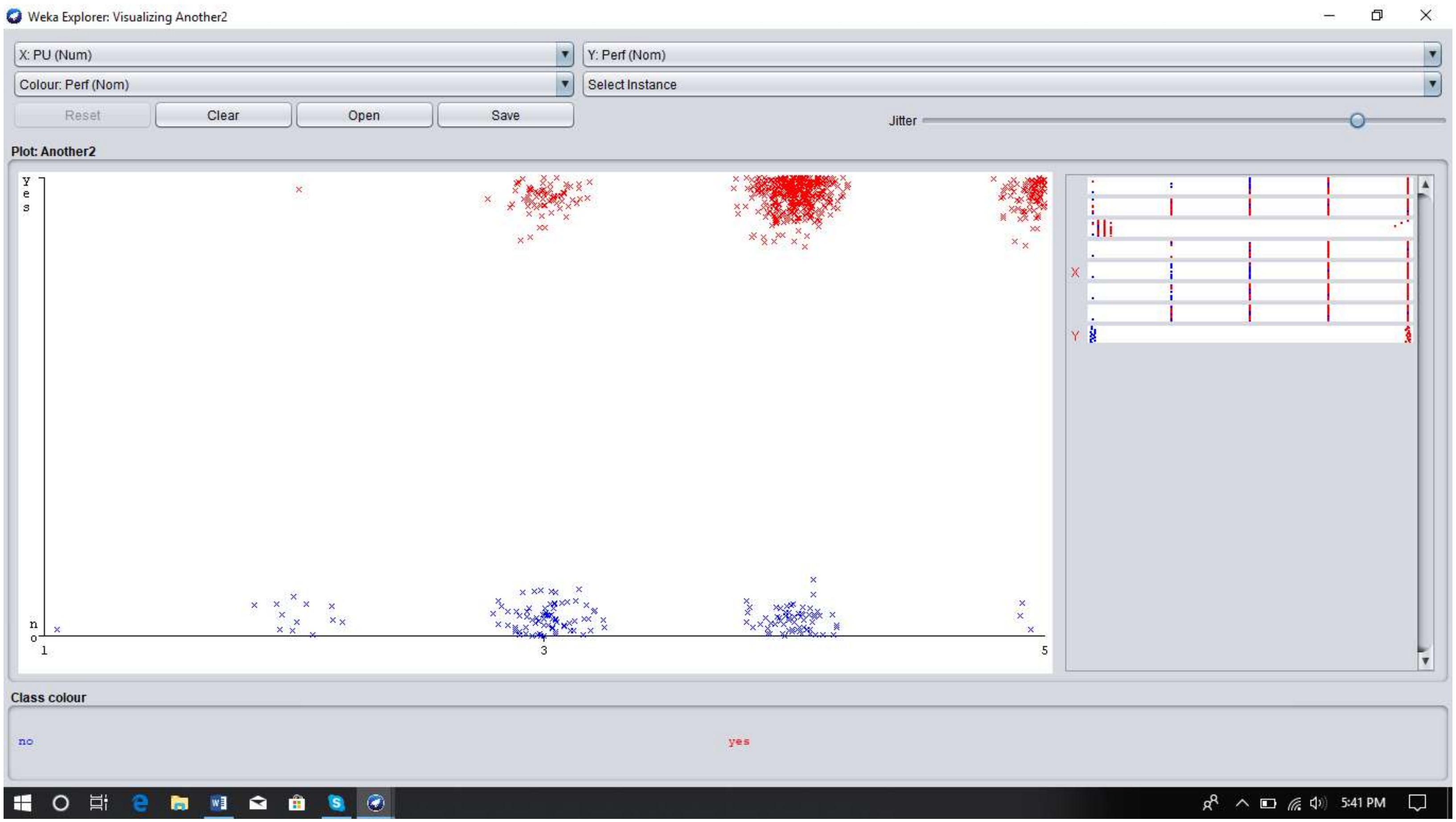

Figure I-3 *Learning pattern with perceived usefulness (PU) versus performance (Perf)*

There also exists another pattern generated when considering perceived ease of use (PEOU) versus performance (Perf) as shown in figure I-4. This pattern is also similar to the pattern generated on figure 3.9.

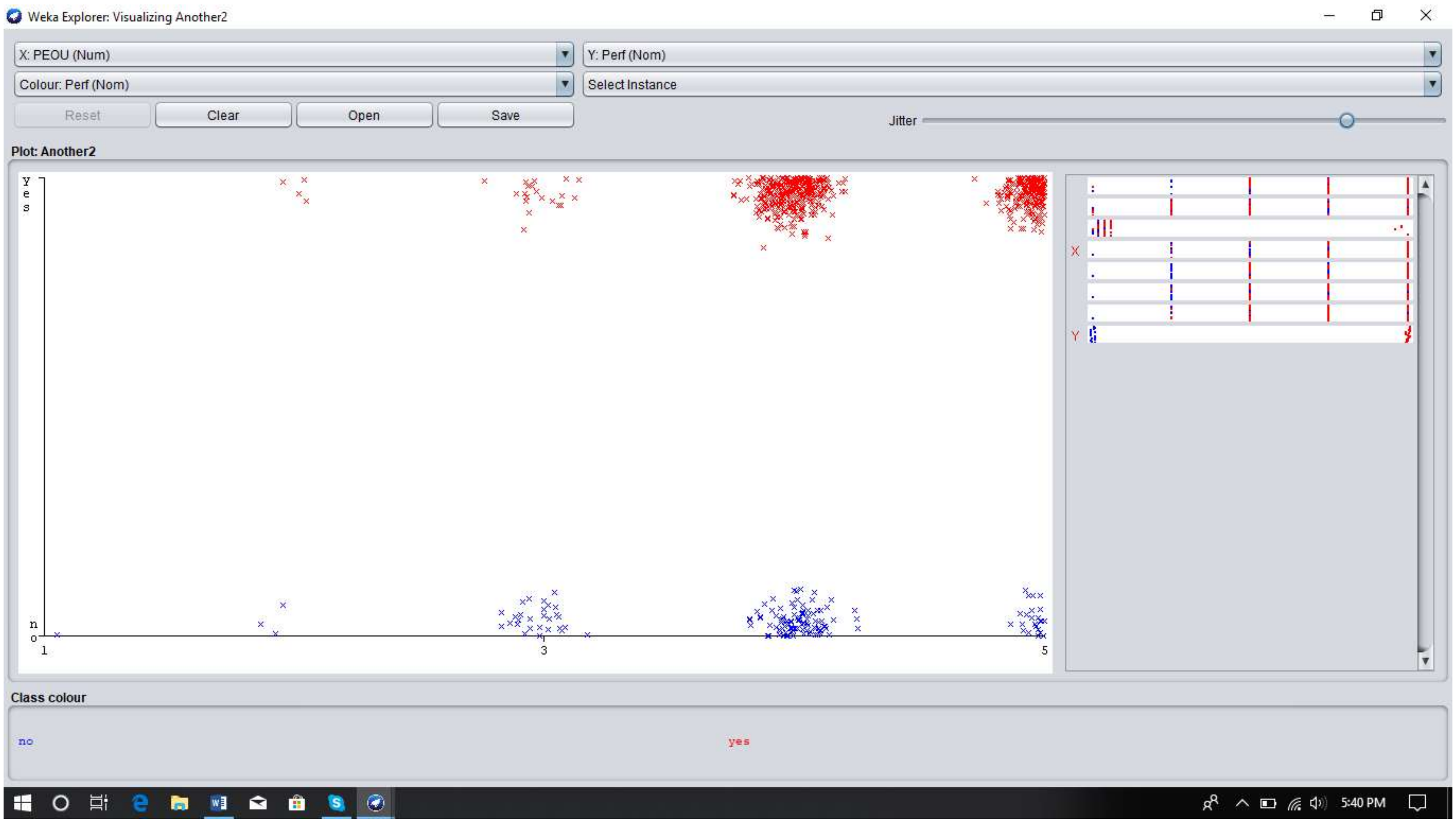

Figure I-4 *Learning pattern with perceived ease of use (PEOU) versus performance (Perf)*

The learning pattern generated when considering investment (Inv) versus performance (Perf) is shown in figure I-5. In this case, a pattern similar to the one in figure 3.9 is generated.

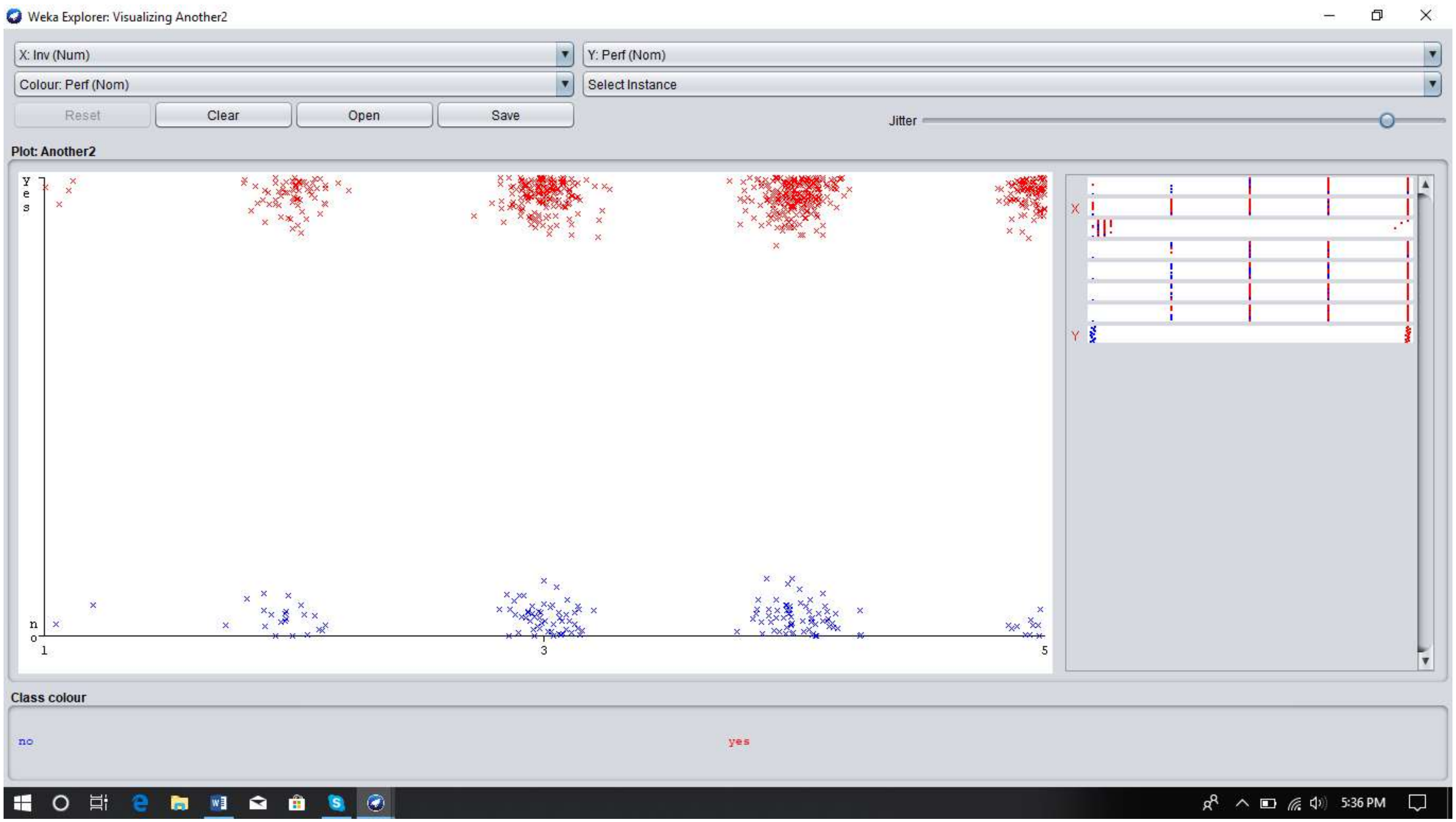

Figure I-5 *Learning pattern with investment (Inv) versus performance (Perf)*

Within figure 3.8, the pattern generated when considering knowledge of the internet (KoI) versus performance (Perf) is shown in figure I-6.

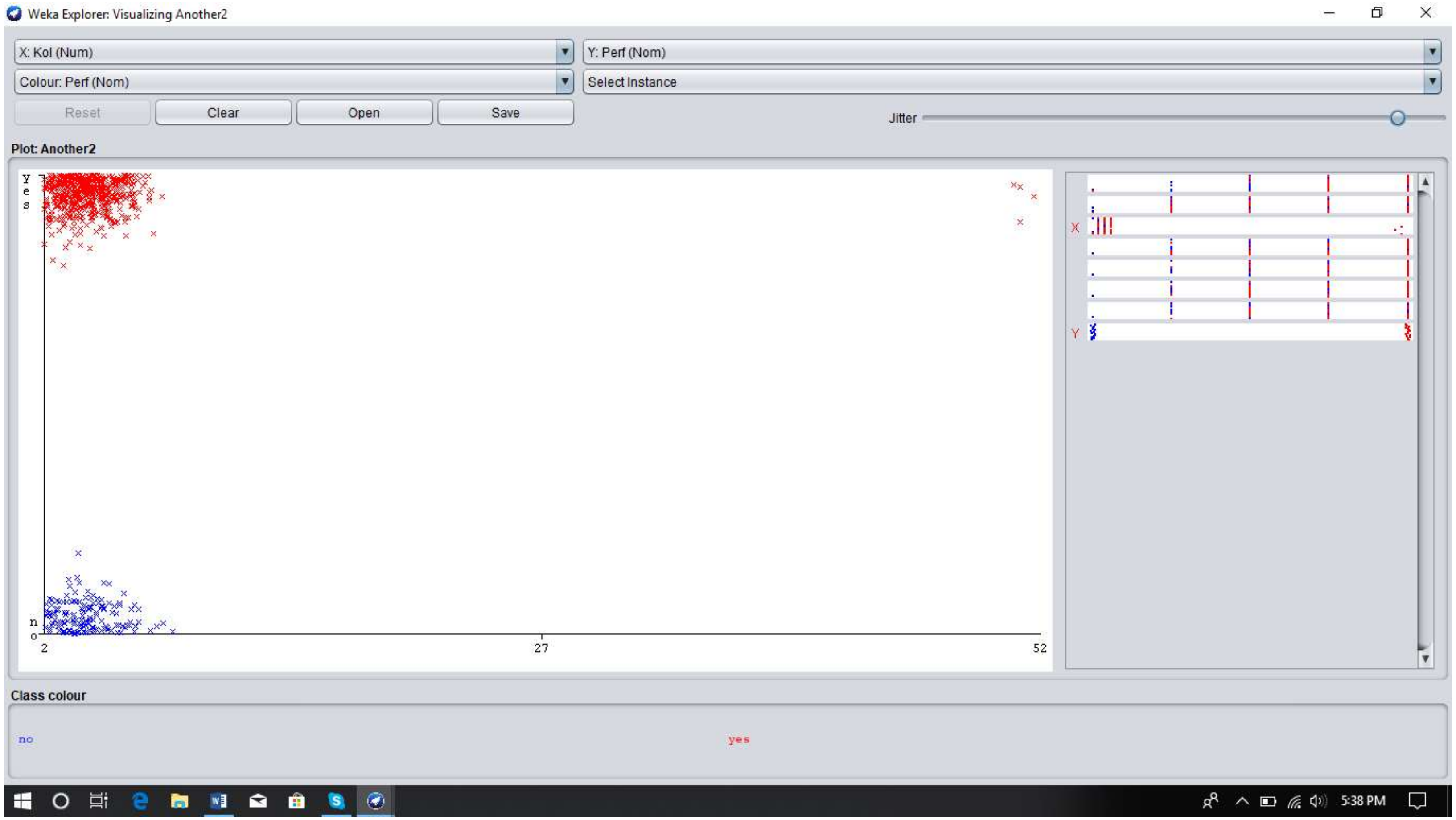

Figure I-6 *Learning pattern with knowledge of internet (KoI) versus performance (Perf)*

This pattern presents a different approach to student learning patterns. It implies that the level of knowledge of internet technology in all the students is low. The students performance is divided into two, those with little knowledge about the technology and do not perform well and those with little knowledge about the technology and perform well. The latter group of students form the majority in this pattern since the students still used the technology even when they had minimal knowledge about it. Consequently, this attribute was not considered in the decision tree generated to give the visualized output with the *Perf* class.

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Appendix J: Testing Internal Consistencies

```
######

import numpy as np



def svar(X):
   n = float(len(X))
   svar=(sum([(x-np.mean(X))**2 for x in X]) / n)* n/(n-1.)
   return svar



def CronbachAlpha(itemscores):
   itemvars = [svar(item) for item in itemscores]
   tscores = [0] * len(itemscores[0])
   for item in itemscores:
     for i in range(len(item)):
        tscores[i]+= item[i]
   nitems = len(itemscores)
   print("total scores=", tscores, 'number of items=', nitems)

   Calpha=nitems/(nitems-1.) * (1-sum(itemvars)/ svar(tscores))

   return Calpha

def ReadData(fileName):
   #     read the file, split by lines
   f = open(fileName, 'r');
   lines = f.read().splitlines();
   f.close();
```

```
    # initiliaze an empty list of items
    items = [];

    # arrange the columns using the delimiter
    for i in range(1, len(lines)):
        line = lines[i].split(',');
        # itemFeatures list, holds the features to be used for clustering
        itemFeatures = [];

        #     to ensure that the data is of float data-type
        for j in range(len(line) - 1):
            # convert to float as follows
            v = float(line[j]);
            # add each row to the empty itemFeatures list
            itemFeatures.append(v);

            items.append(itemFeatures);

            # shuffle(items);

    return items;

##########Test###############
itemscores = ReadData('finale2.csv')
print("Cronbach alpha = ", CronbachAlpha(itemscores))
```