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Prediction of Student Learning Styles using Data Mining Techniques

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Abstract: *This paper focuses on the prediction of student learning styles using data mining techniques within their institutions. This prediction was aimed at finding out how different learning styles are achieved within learning environments which are specifically influenced by already existing factors. These learning styles, have been affected by different factors that are mainly engraved and found within the students learning environment. To obtain the learning styles, a data mining technique was used and this explicitly involved the use of pattern analysis in order to identify the underlying learning styles in the data collected from the learners. This paper highlights the five major learning styles that describe the patterns extracted from the collected data. Therefore, considering the changed learning ecosystem, it is clear that prediction of student learning styles can be done when the various factor inputs within the student environment are brought together and analyzed to focus on learning within internet-mediated environments[1].*

Keywords: *Student learning, data mining, performance, learning style.*

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I. INTRODUCTION

The learning process plays a major role in students' performance especially within the defined learning period. To ensure an effective learning process, the use of internet technology in the learning process has been greatly embraced. 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- motivated, self-formulated and self-constructed set of steps in which the student secures ideas and concepts based on existing knowledge[1]. 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 who did not have the technology as part of their instruction [2]. The embrace of internet technology in the learning process of students always leads them to be 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 [3] [4].

Learning has mainly shifted into the world of weblogs, wikis and social software applications [5]. 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

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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 maximize 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 behaviors, their personalities and the kind of incentives they would like in order that they become loyal users of their services [6]. Appreciating the behavior of online users ensures that the products developed aim at fitting into their lifestyle and deliver satisfactorily to their needs.

Understanding the learning style that internet users exhibit while online goes a long way in trying to appreciate how the learning process takes place. A deeper look at learning 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 [7]. As a result, learning takes place within completely different spheres leading to a new approach to the students learning styles.

A learning style is defined as a conglomeration of all the learning activities that learners engage in, together with the inspirations and philosophies that govern their learning process. This gives them a unique distinction at a specific period in time. It also provides an interrelationship between a learner's reasoning ability, emotional abilities, and beliefs about learning and motivations in learning [8]. Initially the focus on the learning 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.

Student learning styles are divided into four major pillars: conception of learning, cognitive processing strategies, metacognitive regulation strategies and learning motivations [8]. The first pillar, the conceptions of learning, examines the general perceptions, opinions and philosophies that are held by learners about the teaching and learning process. This pillar can be represented using an equation as shown in (1),

$$LS_1 = f\ (P_n, O_n) \qquad (1)$$

where LS_1 is the learning style, P_n are the perceptions of the learners and O_n are the opinions of the learners.

The second pillar, the cognitive processing strategies are the amalgamations of learning activities that students use in order to acquire knowledge and competence in a specific skill. This pillar can be represented using an equation as shown in (2),

$$LS_2 = f\ (L_a\ , K_n) \qquad (2)$$

where LS_2 is the learning style, L_a are the learning activities and K_n is the student knowledge.

The third pillar, the metacognitive regulation strategies are the combinations of the available learning activities that students use to organize, keep track, direct and assess the learning processes that have led to a positive learning outcome. This pillar can be represented using an equation as shown in (3),

$$LS_3 = f\ (T_l, A_l) \qquad (3)$$

where LS_3 is the learning style, T_i are the learning activities that track learning and A_i are the learning activities that assess learning.

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. This pillar can be represented using an equation as shown in (4),

$$LS_4 = f\ (OB_l) \qquad (4)$$

where LS_4 is the learning style, OB_i are the objectives and aims of learning.

The learning style 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 styles 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 styles in a different environment. A learning style therefore becomes the prediction result obtained after combining the personal and contextual factors of the learners within a variety of given environments [9].

The use of the predictive analytics within the student learning process has been used as a helpful tool in determining student performance within a given period of time [9]. For instance, several factors such as internal and external assessments, high school background and extra-curricular activities have been considered in the prediction of the final student performance [10] [11].

II. LITERATURE REVIEW

A study undertaken by [12] revealed two major kinds of learning styles within higher learning institutions. These learning styles are directed and undirected learning styles. Directed learning styles focus on trying to find a meaningful relationship between the ideas they learn and the outside world. Learners also dedicate a lot of effort in trying to remember what they have learnt in class in order to pass their assessments. In the undirected learning styles, 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 education practice to another different kind. They try to use the learning approaches they had used previously in the former stages only to realize 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 hold on to their peers and instructors for a sense of belonging and direction. In this particular study [12] describes the typical learning styles common in the higher learning institutions in many parts of the world. Additionally, the paper also tries to describe how learners try to cope with their circumstances. On the other hand, the paper does not focus on how they can ensure that learners can benefit more from other learning activities aided by the use of internet technology within their institutions. This aspect of learning with technology brings the learners to a whole new world in their study environment.

According to [13], online learning styles are classified based on software, learning materials and educational practices. Learning styles 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 styles in educational practices has also been studied in relation to educational theories and instructional disciplines. These styles have been studied in the use of study groups, classroom environments, seminars and short course programs. In these different environments, learning styles are captured to give expert knowledge in the teaching and learning process. Online educational learning styles involve the learning outcomes and objectives that are specific to every course. Each course has its unique learning goals to be realized. The learning style 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, 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 style will ensure that the learners achieve their goals, interact with their peers amicably and get the required support from the course instructors. As much as this study focuses on software used in the learning process, it does not give information regarding how well the students perform once they use and adopt the technologies in their learning process. As a result, the major gap yet to be addressed in this paper revolves around the general student performance once the learners engage with these technologies.

Research by [14] shows that understanding the learning styles 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 styles 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.

[15] carried out a study to establish the relationship between student learning styles and the academic achievements among secondary school students in Kenya. In his 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 used different learning styles depending on their circumstances. There was need to present the content to be learnt using different and diverse multimodal approaches, hence this presented a major challenge. The paper did not give any indications regarding whether students performed better considering the use of the different learning styles. The paper did not also focus on the use of technology in the schools, aiming to give the learners a better learning experience. Therefore, there is need to check whether the learning styles actually contributed to better student performances or not.

III. METHODOLOGY

In this paper, a prediction technique was used in the determination of the student learning styles. This technique applies a data mining approach to the data collected for the sole purpose of predicting new observations. As a result, this data about the different learning activities was collected, profiled and used to predict the learning styles of the learners while they use internet mediated platforms in their learning process. Therefore, there was need to examine some of the existing ways of handling the large datasets being generated by considering different approaches such as data mining techniques in the prediction process. Educational data mining techniques are the most recently developed approaches which take into consideration the use of statistics in decision making and yet they are least frequently used [16][17] [18].

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 [19].

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 [20]. Data mining approaches are also used in other fields, for instance, in anomaly detection, dependency modelling, pattern tracking, clustering and summarization. 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. In this paper, the data mining approach used is the pattern tracking approach.

Pattern tracking is 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 tracking 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 [21].

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 [22].

In describing a simple pattern, this pattern holds for a function given by for all the data points . In this pattern, all the input values give a pattern as the output. In defining an exact pattern for a given dataset, this is described as a non-trivial function (non-zero function) for all the data points x that can arise from a source [20]. An approximate pattern for a given dataset can be defined as a non-trivial function 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.

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). 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 analyzed 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 $\in f(x) \approx 0$ (5)

where the expectation $\in$ is defined 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. Pattern tracking presents one of the basic techniques employed in data mining that helps in getting information about trends that are exhibited by the data points in the specific dataset under consideration. This data mining approach identifies the patterns that occur either at a specific point in time or over a certain specified long period of time. The patterns exhibited could involve some kind of unusualness in the data that mainly happens at regular intervals or an ebb and flow of a certain variable over time. In this particular paper, the patterns in the data collected were generated at a specific point in time using the WEKA (Waikato Environment for Knowledge Analysis) workbench.

The use of WEKA version 3.8.3 (c) 1999 – 2018 assisted in the generation of the patterns that give the student learning styles. WEKA presents a series of machine learning algorithms and visualizes its results as well. This assists with resolving day-to-day data mining challenges. Feature selection was performed on the dataset. This involved the process of selecting features in the provided data in order to assist in model development [23] [24]. All the different attribute values 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 WEKA supports correlation-based feature selection with *CorrelationAttributeEval* technique that requires the use of a Ranker search method. 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 style.

IV. RESULTS AND DISCUSSION

In order to generate the patterns that assisted in defining the different learning styles required in this paper, WEKA's *Visualise* panel was used. This panel allows a user to visualize a dataset prediction patterns in two dimensions. When the user selects a nominal attribute as the coloring attribute on the panel, then each attribute is drawn in the color that corresponds to the to the discrete of that attribute at the specific instance. If the user selects a numeric attribute to color on, then the points are colored using a spectrum ranging from blue to red (low values to high values). The specific class used in the *VisualizePanel* takes the form:

weka.gui.visualize
Class VisualizePanel
java.lang.Object
java.awt.Component
java.awt.Container
javax.swing.JComponent
javax.swing.JPanel
weka.gui.visualize.PrintablePanel
weka.gui.visualize.VisualizePanel
All Implemented Interfaces:
java.awt.MenuContainer,
java.io.Serializable,
javax.accessibility.Accessible,
PrintableHandler
Direct Known Subclasses:
ThresholdVisualizePanel

Using the above algorithm, the patterns were generated using WEKA's Visualize panel. WEKA's visualization allows you to visualize a 2-D plot of the current working relation and hence use it for the prediction process. Visualization is very useful in practice, it helps to determine the difficulty in the learning problem. WEKA can visualize single attributes (1-d) and pairs of attributes (2-d). WEKA has "Jitter" option to deal with nominal attributes and to detect "hidden" data points [24]. To open the Visualization screen, one is required to use the *Visualize* tab. Then, one selects a square that corresponds to the attributes one would like to visualize. In the data collected from the surveys, there were seven variables namely Perceived usefulness (PU), Perceived Ease of Use (PEOU), Task Technology Fit (TTF), Attitude (IAtt), Knowledge of Internet (KoI) and Investment for use of internet technology in learning (Inv). The dependent variable was classified as Performance (Perf). The variables were then used in the identification of the different pillars involved in the identification of the learning styles as described earlier on in this paper. Hence, the variables above were divided as follows:

$$LS_1 = f\ (P_n, O_n) = f\ (PEOU, PU) \qquad (6)$$

$$LS_2 = f\ (L_a\ , K_n) = f\ (IAtt, KoI) \qquad (7)$$

$$LS_3 = f\ (T_l, A_l) = f\ (Inv, SM) \qquad (8)$$

$$LS_4 = f\ (OB_l) = f\ (TTF) \qquad (9)$$

All of the variables combined together gave the different patterns that represented the learning styles of students within the institution. For example, in this paper, IAtt for X-Axis and Perf for Y-Axis were selected. Clicking anywhere inside the square that corresponds to 'IAtt' and 'Perf' gives a visual outlook of what expected styles will look like. 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. Notice that the dots on the graphs are colored by their class value. It is good to look out for the trends in the dots, such as clear separation of the colors. For instance, considering the style generated by examining the individual attitude (IAtt) versus performance (Perf), figure 1 was obtained.

Fig. 1 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.

Hence, the learning styles 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 fig. 1 was subdivided into four main sections representing the four distinct learning styles generated at specific designated areas, mainly at x=2, x=3, x=4 and x=5 (from the left to the right).

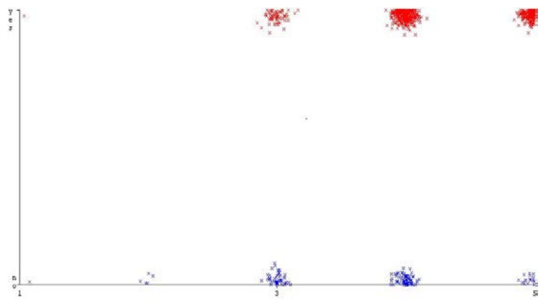

Fig.1. Learning styles generated when considering Attitude vs Performance

At x=2 the different parameters generated from the scatter plot are shown in table 1.

Table 1 Instances at x=2

Weka Instance Info	Weka Instance Info
Plot: Master Plot Instance: 366 I Att: 2.0 Inv: 3.0 KoI: 3.0 PEOU: 4.0 PU: 3.0 SM: 3.0 TTF: 3.0 Perf: no	Plot: Master Plot Instance: 385 I Att: 2.0 Inv: 2.0 KoI: 3.0 PEOU: 3.0 PU: 3.0 SM: 3.0 TTF: 3.0 Perf: no

In this learning style, 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. Hence figure 3 shows two different learning styles for students within this environment.

At x=3 the different parameters generated from the scatter plot are shown in table 2.

Table 2 Instances at x=3

Weka Instance Info	Weka Instance Info
Plot: Master Plot Instance: 151 I Att: 3.0 Inv: 4.0 KoI:4.0 PEOU: 4.0 PU: 3.0 SM: 5.0 TTF: 5.0 Perf: no	Plot: Master Plot Instance: 629 I Att: 3.0 Inv: 5.0 KoI: 4.0 PEOU: 5.0 PU: 4.0 SM: 4.0 TTF: 4.0 Perf: yes
Plot: Master Plot Instance: 590 I Att: 3.0 Inv: 3.0 KoI: 3.0 PEOU: 4.0 PU: 4.0 SM: 3.0 TTF: 4.0 Perf: no	Plot: Master Plot Instance: 705 I Att: 3.0 Inv: 2.0 KoI: 3.0 PEOU: 4.0 PU: 3.0 SM: 3.0 TTF: 4.0 Perf: yes
Plot: Master Plot Instance: 717 I Att: 3.0 Inv: 3.0 KoI: 3.0 PEOU: 4.0 PU: 4.0 SM: 3.0 TTF: 4.0 Perf: no	Plot: Master Plot Instance: 711 I Att: 3.0 Inv: 3.0 KoI: 4.0 PEOU: 5.0 PU: 4.0 SM: 3.0 TTF: 4.0 Perf: yes

In this learning style, 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. Hence figure 4 illustrates two different learning styles for students within this environment.

At x=4 the different parameters generated from the scatter plot are shown in table 3.

In this learning style, the first group of 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.

Table 3 Instances at x=4

Weka Instance Info	Weka Instance Info
Plot: Master Plot Instance: 245 I Att: 4.0 Inv: 3.0 KoI:3.0 PEOU: 4.0 PU: 4.0 SM: 3.0 TTF: 4.0 Perf: no	Plot: Master Plot Instance: 183 I Att: 4.0 Inv: 3.0 KoI: 4.0 PEOU: 4.0 PU: 4.0 SM: 3.0 TTF: 4.0 Perf: yes
Plot: Master Plot Instance: 560 I Att: 4.0 Inv: 3.0 KoI: 3.0 PEOU: 4.0 PU: 3.0 SM: 3.0 TTF: 4.0 Perf: no	Plot: Master Plot Instance: 233 I Att: 4.0 Inv: 4.0 KoI: 3.0 PEOU: 4.0 PU: 4.0 SM: 4.0 TTF: 4.0 Perf: yes
Plot: Master Plot Instance: 735 I Att: 4.0 Inv: 4.0 KoI: 4.0 PEOU: 5.0 PU: 4.0 SM: 4.0 TTF: 4.0 Perf: no	Plot: Master Plot Instance: 645 I Att: 4.0 Inv: 5.0 KoI: 4.0 PEOU: 4.0 PU: 4.0 SM: 4.0 TTF: 4.0 Perf: yes

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. Hence, figure 5 presents two different learning styles for students within this environment.

At x=5 the different parameters generated from the scatter plot are shown in table 4.

Table 4 Instances at x=5

Weka Instance Info	Weka Instance Info
Plot: Master Plot Instance: 344 I Att: 5.0 Inv: 5.0 KoI:4.0 PEOU: 5.0 PU: 5.0 SM: 5.0 TTF: 5.0 Perf: yes	Plot: Master Plot Instance: 215 I Att: 5.0 Inv: 4.0 KoI: 4.0 PEOU: 5.0 PU: 4.0 SM: 4.0 TTF: 4.0 Perf: no
Plot: Master Plot Instance: 384 I Att: 5.0 Inv: 4.0 KoI: 4.0 PEOU: 4.0 PU: 4.0 SM: 4.0 TTF: 4.0 Perf: yes	Plot: Master Plot Instance: 525 I Att: 5.0 Inv: 3.0 KoI: 4.0 PEOU: 4.0 PU: 4.0 SM: 4.0 TTF: 4.0 Perf: no
Plot: Master Plot Instance: 492 I Att: 5.0 Inv: 4.0 KoI: 4.0 PEOU: 5.0 PU: 5.0 SM: 4.0 TTF: 5.0 Perf: yes	

In this learning style, 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. 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, 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) represents a success in the utilization of the internet, that is, being in the 'using' state or in the 'not using stage'. 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) [28]. This would therefore hinder the students' use of the technology resulting in poor performance.

V. CONCLUSION

The utility 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 behavior patterns, as the TRA highlights. The attitude of the individual learner and the influence they receive from within their environments helps them acquire behavioral 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 behavior patterns have a direct influence on their learning style. Their behavior 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 style of students considering each of the mentioned factors, both within themselves and within the context of their environment.

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