Review on Bloom's Taxonomy to Identify the Cognitive Levels and Various Learning Styles and Behavioral Patterns of the Students

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Abstract: *Outcome Based Education (OBE) is the method adopted by the Technical Institutes in the country since a decade. It is a method where the outcomes attained by the students at the end of the course or degree are used to analyze the performance. The performance is actually the mapping between the course outcomes (COs) and programme outcomes (Pos). The Pos are designed based on revised Bloom's Taxonomy for Cognitive Domain and the COs are depending on the course material. The different cognitive levels in Bloom's taxonomy are arranged from lower order thinking level to higher order thinking level. There are many significant research works carried out to analyze the impact of Bloom's Taxonomy in the process of mapping COs and POs. It is also important to understand the different learning styles of the students for different cognitive levels. There are many theories of Learning Styles and Kolb's learning Theory is one among them. The learning styles can be matched with different cognitive levels.*

This review paper consolidates the work carried out on Blooms taxonomy and different Learning styles. The primary objective of this review paper is to identify the advantages, limitations and the future enhancement that can be done based on the research gaps. The learning styles can be matched with different cognitive levels. One expected outcome is, to design a cognitive models which helps the students to assess themselves and also for the teachers who can use this method to assess and monitor the performance of the students.

Keywords: Bloom's Taxonomy, Cognitive Domain, Kolb's Learning Styles.

1. Introduction

1.1 OBE and Bloom's taxonomy:

The Bloom's taxonomy plays an important role in the modern technical education scenario especially with the OBE. In OBE every course is designed with different course outcomes that must be attained by the student which is a metric to assess the performance of the student. In the processing of assessing the performance of the students, it is very important for the teachers to know the cognitive level of the students. It is known that every student has different cognitive level and so the performance of each student is different. The cognitive level of the student can be identified and can be assessed with the help of revised Bloom's taxonomy. The revised Bloom's taxonomy is shown as below in fig 1.1.

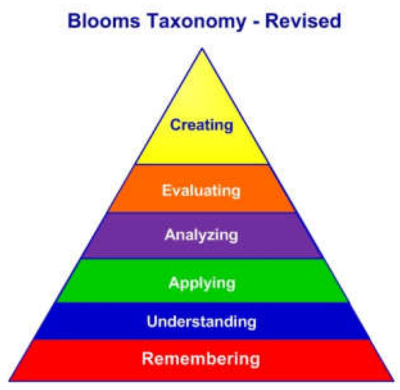

Fig.1.1

The levels from bottom to top are arranged based on the level of thinking. The bottom most level indicates lowest order of thinking and top level indicates the higher order thinking. Each level from bottom to top, increases the order of thinking and top to bottom, decreased the order of thinking. The first two levels from bottom (remembering and understanding) specifies lower order thinking, the next two (applying and analyzing) specifies medium order thinking and last two (evaluating and creating) specifies higher order thinking skills. The course outcomes of a given course have been designed based on these cognitive levels. If the progress of the student matches corresponds to the cognitive level from third level to last level, then it can be considered as remarkable. There are many different assessment methods are existed to assess this performance like, real time assignments, quiz, tests and etc. Many research works are already carried out to analyze the outcomes of the above assessment methods.

1.2 Learning Styles:

The learning style is description of the attitudes and behavior which determines an individual's preferred way of learning. In the past, several systems of learning styles have been described. Kolb Learning Style Inventory (KLSI) is one among them. KLSI is developed by David A. Kolb and it is based on his own comprehensive learning theory. The KLSI consists of four learning styles in grid format based on the quadrants results fall under. The four styles are the diverging, accommodating, assimilating and converging. The KLSI grid is shown as below in fig 1.2.

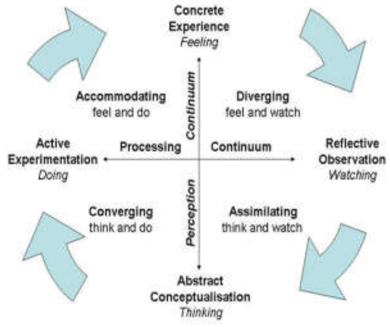

Fig 1.2

According to Kolb, the study of knowledge is based on how individuals learn, assimilate information, solve problems, and finally make decisions. Stemming from this analysis and the experiential learning theory, he created a learning styles inventory (LSI) in order to identify individual learning styles. Experiential learning is conceived as a four stage cycle, composed of:

Concrete experience (CE) or "feeling": learning through concrete experiences, getting involved. Abilities in this area include good interpersonal relations and sensibility towards personal values of all parties involved;

Reflective observation (RO) or "observing": learning through observation, seeing, listening, and internalizing;

Abstract Conceptualization (AC) or "thinking": learning through pondering, use of logic, concepts, theories, principles, and ideas. The systematic planning and consequent action is based on the intellectual comprehension of the given situation;

Active Experimentation (AE) or "doing": learning by taking action, and making decisions. The strategy is to workwith real situations and obtains practical results.

Rest of the paper is organized as follows, Section 2 contain the literature revive on, how Bloom's taxonomy is useful in identifying the cognitive levels, review on different learning styles and how they linked with the various cognitive levels. It also includes review on cognitive level/load measurement using physiological sensors like EEG, ECG, Eye Tracking, GSR and etc. Sections 3 contain the research gaps identified in all the existed works and what are the possible future enhancements.

Sections 4 contain the conclusion part and the 5 part is reference section.

2. Literature Review

D.Uma S et al., [1] presented a study which focuses on analyzing the thinking skills of students present in an assessment using revised Blooms Taxonomy standards. Different categories of courses have been considered for the analysis of complexity level present in an assessment and know the quality of the system. The study proposed a weight based data mining approach to classify the Blooms categories and the thinking levels associated with that. The thinking levels such as low, medium and high are decided based on contribution of the cognitive dimension parameters. This study helps the organization to check the quality of assessment paper and to decide whether to accept or not. The Cognitive domain parameters used in the assessment reveals whether the order of thinking as low, medium or high. In case of low or medium, one can improve by giving weightage to higher order parameters.

C. Gururaj et al., [2] proposed a study to define course outcomes based on Bloom's Taxonomy. The program outcomes are also considered. The course selected for this study is Image Processing. This study reveals that, it is the better and efficient way of defining the Course Outcomes and it resulted in good PO attainment which is the positive impact of OBE.

Afifa Yasmeen et al., [3] the purpose of the study is to assess the level of cognitive learning with the help of question paper analysis. The data collected were descriptively analyzed and presented through tables and graph for easy and quick interpretation of the results. The results showed that, out of sis courses only one course reached the highest level of cognitive learning. The study tried to measure the achievement of cognitive knowledge through levels of cognitive domain proposed by Bloom's Taxonomy. The study suggest that the teachers need to pay more attention to their teaching and assessing practices and make an effort to achieve and assess cognitive learning on all six levels. The work can be enhanced by considering the Bloom's taxonomy for psychomotor and affective domain.

Soumya K Patil et al.,[4] The proposed methodology is to make a comparative study of question bank classification based on revised Bloom's Taxonomy using support vector machine and K-NN , which helps to build cognitive skills of the learner. It also explores the effectiveness of the machine learning techniques which classifies the questions to Bloom's cognitive skill domain, which is of particular importance an in question bank management system. Using this method, the question paper can be set by the tutor, which usually covers all the type of questions and all the levels of taxonomy. The present work can be enhanced for knowledge level classification.

Arthur James Swart et al., [5] states that engineering students must enable students to acquire discipline specific knowledge with the important ability to apply theory in practice. This fusion of theory and practice enables students to progress to higher levels of cognitive development where logical reasoning and critical thinking may be promoted. Bloom's taxonomy describes six levels of cognitive development ranging from simple memory recall to complex reasoning abilities. The study revealed that the two lower levels of Bloom's taxonomy contribute approximately 58% to the total learning outcomes. The third level contributes 27% and remaining higher levels accounts for remaining 15%.

Kavita kelkar et al., [6] the objective of this study is to demonstrate interaction feature mapping to affective state. The work carried through sensor free, non intrusive affective learning system. This system determines the affective state like confusion and confidence of the learner with 80% accuracy. The system is designed with questionnaire based on Bloom's taxonomy cognitive levels. The study presented an approach for establishing relationship between cognitive level test performance of learner and affective state using random forest algorithm.

Dino Capvilla et al., [7] the study proposed DiCS-Index for predicting student performance in computer science by analyzing learning behaviors. The study also reveals that the better performance of the students who prefer learning through abstract conceptualization compared to study through concrete experience. The study was conducted based on Kolb's Learning Style Inventory (KLSI).

Gunathilaka T.M.A U et al., [8] proposed that learners are in different knowledge levels according to the capacities of their mind. Each learner shows different level of aptitude for different subjects, different prior knowledge, different learning styles, different kind of memory, different motivation to learning, different family background, different habits etc. These variations influence in their patterns and preferences of learning. This work presented a model identifying the dynamic and the static learning behavior of the students to personalize the learning environment according to the individual's learning preferences and the style of learning [based on Kolb's Learning styles].

Mauricio Dziedzic et al., [9], the study considered three questionnaires for assessing learning styles, Kolb's, Honey-Alonso and Felder–Soloman. The aim of the work was to determine which questionnaire would be preferred by respondents based on ease of understanding questionnaire , the time needed to complete the questionnaire and how the results are presented. Based on the study, Felder –Solomon learning style was preferred by the respondents.

Mohamed Soliman Halawa et al., [10] states that, E- learning has become an essential factor in the modern educational system. E-Learning must recognize the differences in student personalities to make the learning process more personalized. The model provides vital information for educators, equipping them with a better understanding of each student's personality. Using this knowledge, educators will be more capable of matching students with their respective learning styles. Some of the machine learning techniques are used for the accurate classification which includes, Naïve Bayes, Kstar, Random Forest, j48, One R, KNN , Decision table etc.

Rajat Das et al.,[11] according to the study, use of EEG signals in measuring cognitive load is widely practices area and falls under BCI technology. These EEG devices of medical grade are normally expensive as well not user friendly for regular use. This work proposed a methodology to compare low cost wireless EEG devices for application in cognitive load /level detection. This method proved to be non invasive in nature and portable and brain signals provide a more direct way of measuring cognitive load.

Rahul Gavas et al., [12] Cognitive load corresponds to the amount of working memory demanded while performing a certain task. Estimation of cognitive load is crucial to many domains and the usage of pupil size dilation to accomplish this is widely researched. However, existing approaches suffer severely as they are largely based on the raw pupil size. The work proposed a cognitive load metric based on the power and frequency relations at the mean frequency of the variation in pupil size. The stimulus used is a mental addition task which is designed in a manner to induce low and high cognitive loads on the participants. Results show good separation in the metric for the tasks inducing low and high mental workloads in contrast to the state of the art methods.

Debatri Chatterjee et al., [13] Cognitive load primarily depends on how an individual perceives, assimilates and responds to an external stimulus. They intended to create Electroencephalogram (EEG) models for the cognitive skills defined in the Bloom's taxonomy using low cost, commercial EEG devices. This could be applied in educational psychology to provide individual assistance according to one's learning style and abilities. The major challenge in using low resolution EEG device lies in signal analysis with reduced number of channels. This paper, presented the signature of EEG signals for such low cost devices using three basic tasks namely, number matching; finding characters in text; finding hidden patterns and figures. These tasks map with understand, remember and analyze sub categories of Bloom's taxonomy. Different brain regions are activated while performing the above tasks. However, the EEG signals observed on the scalp are the manifestation of the combined effects of various brain regions. The cleaned EEG signals are analyzed using unsupervised clustering of features obtained from different frequency bands. The study is performed on 10 subjects using 14 lead Emotive neuroheadset, so that one can get further insights on how an individual perceives certain cognitive tasks.

Zahid Ullah et al., [14] According to the study, assessment of students in computer programming is a challenge for instructors, especially at the introductory programming level, where the number of student enrollment is typically high. Therefore, this study presents a novel approach to assessing students' competency in programming using Bloom's taxonomy. The novelty of the presented approach is based on some rules that quantify the attained competencies with respect to the cognitive levels of Bloom's taxonomy. Existed studies shows that cognitive levels were used as a scale for making the questions while the competency assessment was manually performed, in this study, the rule-based assessment method uses the automatic decision-making process to map the students competency level directly to the corresponding cognitive levels.

Nazre Bin Abdul Rashid et al., [15] Advancement in neuroscience like EEG technology had been serving in education – related research with immense contributions. On the other hand Learning style had emerged as an important study in education frontier. In this study, the classification of participants LS is implemented using EEG Beta Summative Power Spectrum Density and Kolb's Learning Style Inventory (KLSI). The research findings had shown that EEG Beta Summative PSD being successfully utilized to classify the participants based on their LS.

Farouk Lawan Gambo et al., [16] this paper proposed a conceptual framework for detection of learning style from facial expression using Convolution neural network. Identifying student's learning styles allows them to learn better and faster through several means. Traditionally, a test (use of questionnaire) is usually conducted for automatic detection and prediction of student's learning preferences particularly in e-learning. This approach though valid and reliable in detection of learning styles, but it is also associated with many challenges; learner self-report bias, individual earning styles may vary over time, Students not aware of the importance or the future uses of the questionnaire. This research proposes a framework capable of recognizing student's affective states and infer learning styles from them through;

- Developing of an algorithm for efficient recognition and classification of emotion based on facial expression.
- Identifying and mapping emotional classes onto specific learning style that positively correlates with different learning style
- Developing learning style predictive model from feature extracted in the learning style emotive database.
- Evaluation of the predictive model for recognition and prediction of the learning style using square mean error.

This work presented a conceptual framework that will use student facial expression, extract feature using configured CNN to recognize emotion and used them to classify student's learning style. If this novel approach is fully implemented; it is hoped to provide a better, more accurate and relevant studies in detection of learning style.

According to Ananthu S Kuttattu et al., [17] the learning style can be referred to as the way a student prefers to acquire, process and retain information. The prominent learning style classification model is the VAK model. According to this model visual, kinesthetic and auditory are the three major kinds of learning styles. Many research have shown that people prefer more than one way of learning, hence categorizing a person to just one of the above types as done in traditional methods is not accurate. A method to identify our learning styles more accurately is required. Machine learning can be applied in this field to achieve our aim in the most efficient way. Once we have accurate information about learning styles, we can use it to suggest career options. This research aims to predict the learning style combinations of students and suggest field of study using algorithms like k-means, SVM and decision tree.

Mirnali Sogy et al., [18] E-leaning, today is recognized as a big platform for learning and is considered better as compared to the conventional classroom learning. Personalized e-learning is one of the most researched areas, because courses online require a proper structure such that it is created keeping in mind the students it is being created for. Not only can the online courses be structured, but even the traditional classroom courses can be structured. This paper focuses on the research on analyzing the Learning Styles of students. This paper consists of analysis done with the help of a Website particularly designed for the analysis of the learning style of the students. Various interactive activities have been designed to evaluate the students' behavior. Further, this paper would depict the analysis that is done via Data Mining on the datasets created during the interactive activities sessions.

CHIH-HUNG WU et al., [19**],** study anticipated whether students with different learning styles have significant differences in learning motivation, learning emotions, learning outcomes, and problem-solving steps. The learning portfolio data can be used to classify the student learning style through the results of the student's operation of the physical balance game, and then complete the development of the learning style recognition system. Feldman, Monteserin also confirmed that the learners of the sensing learning style are more creative, so they can achieve better results in the open learning method of digital games. Therefore, from the research results of this study, it is expected that the effective game will be a learning style recognition system. Future researchers can develop different learning style recognition systems through different forms of games, through the learning process of the game, and with different deep learning algorithms.

Hsiao-Hui Liet al., [20] Teaching norms are taught through the way of large class teaching. Nowadays, most of the teaching method is still dependent on physical classes. Therefore, it's hard to design individual lesson based on different students' ability to achieve fundamental education. Good teaching is" According to the ability, ambition and interest of different learners, give appropriate teaching methods". Therefore, this paper is analysis students learning effectiveness through artificial intelligence adjusting the learning content and curriculum according to different learners to give learners the most appropriate learning style. The design can achieve personalized learning and auto-didacticism and instant feedback to meet the learners' different learning styles and thus improve the overall learning benefits.

3. Research gaps identified for future analysis

3.1 Related to Bloom's Taxonomy:

Most of the work carried out related to Bloom's taxonomy is only with respect to curriculum revision, question paper classification and analysis and some are related to finding cognitive level of thinking and again it is based on question paper analysis. Yet there are some works to be done and they are as follows.

1. Measuring the attainment of learning outcomes using the other two domains of Bloom's taxonomy i.e. psychomotor and affective domain
2. Different question paper classification techniques using machine learning can be implemented with more accuracy.
3. Can still improve the accuracy in establishing relationship between cognitive level test performance of learner and affective state and relationship between different cognitive levels and different learning styles can be established. A machine learning algorithm for the same may be suggested to build a cognitive model.
4. Instead of analyzing Bloom's taxonomy using question papers, dynamic stimuli can be given to the subject and reading physiological signals may be modeled.

3.2 Related to Learning styles:

1. By establishing relationship between cognitive levels and learning styles, e - learning can be personalized with more accuracy.

2. A cognitive data model can be designed to identify both the student learning behavior and preferred cognitive level.

4. Conclusion

The survey has been conducted on how Bloom's taxonomy is being used from long time to analyze the cognitive levels and also to improve the thinking capacity of the students in their learning process. For the purpose, the colleges are following different assessment tools for analyzing the learning behaviors through test and exams, offline and online quiz, in LMS and etc. The colleges are following different rubrics for different levels of Bloom's Taxonomy while setting internal assessment QPs and also while setting semester exam QPs. Even for evaluating regular assignments, colleges have adopted rubrics system based on Bloom's taxonomy. The survey also studies about what are the different theories of learning styles and how they can impact the performance of students. This has been a helpful tool for both teachers and students. Students can assess themselves and teachers can use suitable teaching methodologies based on student's learning styles. As already mentioned in part three, there are many limitations identified in many of the previous works carried out on Bloom's taxonomy and learning styles.

1. Different machine learning techniques are being used to classify the learning styles based on the input given. They worked out well. Still there is a need of more accuracy in the classification and this will be concentrated in the further studies.
2. Low cost physiological devices can be used in a better way to read the signals (E999EG, ECG, GSR, Eye tracker and etc.) and can be analyzed for the better classification of cognitive levels and also learning styles. A map can be done with good accuracy between the cognitive levels and learning styles of the students. This is going to be very useful for the teaching fraternity in the process of analyzing and improving the academic performance of the students.

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