EEG Based Learner's Learning Style and Preference Prediction for E-learning

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***Abstract*-The prominence of diagnosing a learner's Learning Style is necessary has to demonstrate success in a teaching and learning process. At the same time, the learner's preferences on MultiMedia Content (MMC) are also being keenly examined in consistent attempts to understand learner in a more adept way. For the above competence in emergence of Electroencephalography (EEG) technology, learner's brain characteristics should be observed directly and the consequence may well support the learning style and preferences. In this study, Learners are categorized by David Merrill's First Principles of Instruction (FPI) which contains four phases namely Activation, Demonstration, Application and Integration. Also it is assessing learning preference by identifying the type of multimedia content the learner prefers. The proposed approach proposes to use participant's commitment level measured with an EEG system, the neurosky mind wave instrument. The main advantage of proposed system is that it enables continuous assessment of various learners with MMC for predicting learning style and preferences.**

Keywords: EEG, First Principles of Instruction, Multimedia Content, Learning Style, Learning Preferences.

I. INTRODUCTION

E-Learning has become an important learning method that provides the same resources to all learners although different learners need different information according to their level of knowledge, requirements, expectation of media, ways of learning style and learner preferences. Learner's different learning styles will affect the way they learn all courses including communication languages. Some learners are interested towards listening and talking. Some at some other time, prefer to analyze text or study with the help of visual support. For identifying the Learner's learning style and Learning Preferences, Learner EEG data can be more contributing.

EEG stands for Electroencephalography and is defined as electrical activity of an alternating type recorded from the scalp surface after being picked up by metal electrodes and/or frequency band contained discriminating information about numerical processing (14).

II. REVIEW OF LITERATURE

EEG data had been captured using MindPeak's WaveRider instrument. Participants are connected to the instrument through electrodes. The brain signal then be recorded in the computer notebook using a direct USB input from the instrument using the "WaveWare" version 2.5 software. The software configuration allows segregated recording of the brainwaves bands from both sides of the participant's scalp (1).

Adopting the same methodology outlined by Sulaiman et al. (25), the EEG data from RFH (Right Prefrontal Hemisphere) and LFH (Left Prefrontal Hemisphere) channels were analyzed off-line. The eye movements and blinks artifacts were removed by setting threshold values of 100/39. The EEG data filtered using band pass filter set from 0.5 Hz to 30 Hz to produce common EEG frequency bands of Delta (0.5 – 4 Hz), Theta (4 – 8 Hz), Alpha (8 – 13 Hz) and Beta (13 – 30 Hz). The 1024 length Fast Fourier Transform (FFT) with Hamming window set to 256 with 50% overlapping was applied to calculate the power of each EEG frequency band. Finally, the Energy Spectral Density (ESD) computed by dividing the area of Spectral Power Density curve with frequency range of each band. In the experiment, each participant was put through a twice 5 minutes (300 seconds) sessions where they were placed into resting condition of Open Eyes and Close Eyes state on each occasion. They are required to be in relax sitting position and given 10 seconds break between experiments (1, 2).

To identify the learning style or preferences of the learners, the David Merrill's FPI approach can be used. These principles are interrelated to one another with four-phase cycle of instruction consisting of activation, demonstration, application, and integration (3, 5).

Using Learner EEG data, the Learner's learning preferences can be identified by learning content and is evidenced from the work of Pei-Chen Sun et al. (24). The learner's needs for multimedia instructional material in e-learning recently has been shown to attract learner's attention and interests (4, 24). Multimedia content mainly contains video, audio, movies, animation, images, text and graph. The development of multimedia e-learning content has been employment of intensive process, requiring a team of web designers and developers responsible for the technical development of these resources, thereby limiting its widespread implementation. The powerful and expressive multimedia that can capture and present information. Instructional videos are extensively used in e-learning (10). These Learning Style and Learning

Preferences can be more useful for arriving at recommendations for E-learning.

A. E-learning System

E-Learning is an application which revolutionizes traditional education, as it could provide faster access to materials at minimal cost. E-learning is an application where learner can gain knowledge by accessing learning materials. It is one of the way in which a learner can have access to a topic in different form of materials like jpg, pdf, ppt, video, etc. (16).

B. Learning Style

Learning Styles (LS) reflect the Cognitive, Affective and Physiological characteristics of learners, which to certain extent, determine their perception, interaction and reaction style (13). From the cognitive perspective, learning styles determine how the learner assimilate and process new information to construct meaning. Likewise, the learning style of a learner defines the cognitive strategy that he or she will invoke in assimilating new information and in retrieving the acquired knowledge for later use.

Kolb's Learning Style Inventory (KLSI) is based on the Experimental Learning Theory, comprising four learning modes that are Concrete Experience (CE), Reflective Observation (RO), Abstract Conceptualization (AC), and Active Experimentation (AE) (7). These learning modes when combined yields a bi-polar spectrum (i.e., vertical and horizontal dimensions), discerning on how a learner takes in and deals with experience. Referring to the bi-polar score, a particular LS could be ascribed to the learner, namely Diverger (CE and RO dominant), Assimilator (RO and AC dominant), Converger (AC and AE dominant) and Accommodator (AE and CE dominant) (8).

Neil Fleming's VARK model expanded upon sensory modalities. The four sensory modalities in Fleming's model are: Visual learning, Auditory learning, Read/Write learning and Kinesthetic learning (12).

National Association of Secondary School Principals (NASSP) formed a task force to study learning styles. The task force defined three broad categories of style Cognitive, Affective, and Physiological and 31 variables, including the perceptual strengths and preferences from the VAK model of Barbe and colleagues; but also many other variables such as need for structure, types of motivation, time of day preferences, and so on were also considered. It is a composite of internal and external operations based in neurobiology, personality, and human development and reflected in learner behavior. Cognitive styles are preferred ways of perception, organization and retention. Affective styles represent the motivational dimensions of the learning personality; each learner has a personal motivational approach. Physiological styles are bodily states or predispositions, including gender-related differences, health and nutrition, and reaction to physical surroundings, such as preferences for levels of light, sound, and temperature (17).

Learning style as cognitive characteristics, affective and psychological behaviors that serve as relatively stable indicators of how learners perceive, interact with and respond to the learning environment. Hence, learning style could use an FPI approach which contains four phases of instruction that are Activation, Demonstration, Application and Integration (19).

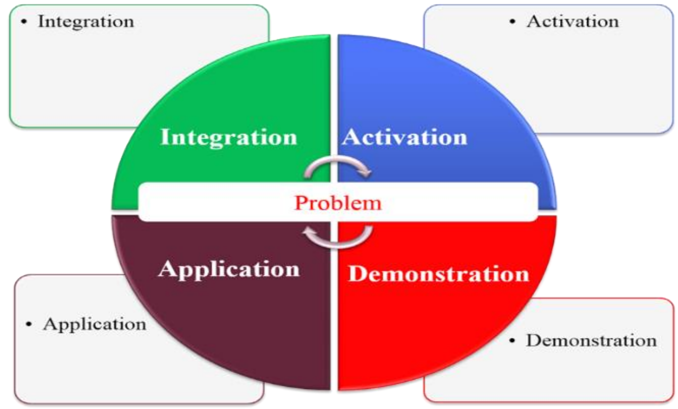

Figure 1: Problem-centered instruction and include four phases of effective instruction

Figure 1 provides a conceptual framework for stating and relating the first principles of instruction. The first principle relates to problem-centered instruction that ideally suits e-learning environment. Four more principles are stated for each of the four phases for effective instruction. Learning is promoted when learners are engaged in solving real-world problems. Problem is engaging in some form of simulation of a device or situation. Problem-centered instruction is contrasted with topic-centered instruction where components of the task are taught in isolation before introducing the real world task to the students. Activation recalls the prior knowledge or experience and create learning situation for the new problem. Demonstration show a model of the skill required for the new problem. Application applies the skills obtained to the new problem. Integration provides the capabilities and to show the acquired skill to another new situation (21).

C. Learner's Learning Preferences

Learner needs multimedia learning contents in the form of video, audio, images, text, etc. as a learning material in E-learning. The use of multimedia based teaching material enhances students learning and increases productivity. It is therefore important for faculty, not only understand the concepts behind the development of multimedia but to also have a good grasp of how to implement some of the processes involved with courseware production (23).

D. EEG

EEG denotes the process of recording electrical brain activity with the help of electrodes placed on the human scalp (15). The recorded EEG signal is collected as multiple individual fluctuations at different frequency bands or brain waves. While characteristics for all of these waves of fluctuations may be present in the overall EEG signal; at the same time, one or another are usually leading during certain states of cognizance or different activities (9).

Various researchers have discovered the possibility of using EEG as a means for detecting or differentiating between human basic emotions such as happiness, joy, distress, surprise, anger, fear, disgust and sadness, (22, 26) or between learning related emotions such as commitment, boredom and frustration (6, 18, 11). In multimedia-related research areas, EEG has been used for automatic implicit emotional tagging of multimedia content, as an alternative to explicit approaches that require users to tag the clips themselves. Furthermore, the possibility of using EEG for assessing user's perceived multimedia quality has also been explored (9).

EEG technology, used successfully in related disciplines, seems a viable technology in harnessing the brain waves in educational research (20, 19). The results of previous studies suggest that this technology, when carefully and craftily utilized, could be an efficient tool to detect and process brain signals for educational purposes. More precisely, EEG technology when used in some innovative ways could capture brain signals, which would be processed to determine the LS of learners during learning. Studies identified that the EEG data is used successfully in detecting the learners learning style and learning preferences and the correlation between them.

Based on the vast existing works and experiments, it is understood that use of EEG data for identifying the learner characteristic would be more viable and hence the proposed work.

III. PROPOSED APPROACH

From the above literature using learners EEG data (frustration log) has been taken for identifying the learners learning style and multimedia content quality assessment. In this study, EEG data captured can be used to identify learners learning style by David Merrill's problem-based FPI approach and assessing the multimedia content requirement according to learners learning preferences.

The proposed approach is as represented in Figure 2. Learners EEG data are captured through Neurosky Mind Wave Instrument (Emotive, MindPeak's WaveRider). This instrument capture five type of frequencies that are delta, theta, alpha, beta, and gamma. In particular, the work focus on alpha brain waves for analyzing the learners learning styles and preferences. Learners are to be categorized using David Merrill's FPI. The four phases are considered as the learning methods for the learners. Learner should be classified as various levels namely Beginner, Low level learner, Middle level learner and High level learner.

Learning style identified by David Merrill's FPI approach is as follows:

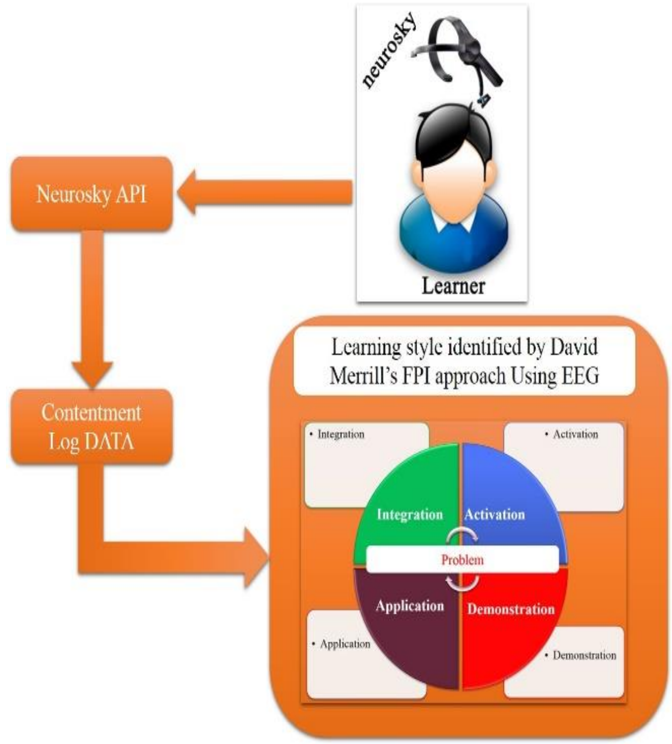

Figure 2: Learning style identified by David Merrill's FPI approach using EEG Data

1. *Activation*: Learners have limited prior experience; learning is facilitated when the instruction provided relevant experience that can be used as a foundation for the new knowledge.

2. *Demonstration*: Learning is facilitated when the instruction also shows descriptions of the information.

3. *Application:* It provides opportunity for the learner to apply the new knowledge to new specific situations. It involves solving whole problems or doing whole tasks and is more than merely answering questions about one step, one action or one event in the whole.

4. *Integration*: Instruction provides an opportunity for the learners to create, invent or explore new and personal ways to use their new knowledge and skill.

Figure 3 shows the process of as to how the learning preferences identified from multimedia content usage. The process beings while the learner wear a neurosky mind wave instrument at one end and the multimedia content is ready for learning at the other end. Both the multimedia content and neurosky mind wave instrument are synchronously started.

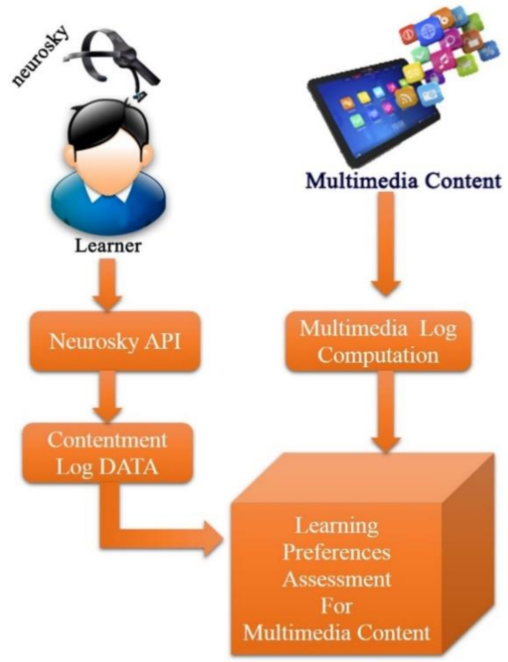

Figure 3: Learning Preferences Assessment for Multimedia Content

Now the learner starts learning from multimedia content. Here the neurosky application receives the signals from neurosky instrument and start preparing for contentment log data including time scale. On the other hand, multimedia content log computation has to be performed with time scale. Finally, contentment log data and the result of multimedia data log computation can be compared using time scale to evaluate the learning preferences assessment for multimedia content.

Figure 4 explores as to how the Learner's learning Styles and Preferences are established using Learner EEG data captured from the Neurosky mind wave instrument. Here the contentment log should be captured through the learner interest and the level of the learner. The FPI approach is used for identifying the level of learner with respect to FPI and the learning preferences are identified by multimedia content assessment through multimedia log computation. Finally, this learner level and learning preference are to be used for proposing the recommendation for E-learning.

A. Scope and Objectives of the Proposed Approach

Certainly a human behavior cannot be predicted for longtime. However, a short period of time like seconds and minutes can be predicted based on past and present context of mind and thoughts. In that way, to provide a list of recommendation for assisting the e-learning system to offer the learning environment suitable for an e-learner, the proposed system would suffice. Proposed system covers the broad set of objectives such as:

- It enables assessing and measuring the effect of various factors on learner's Emotions in that Learners do not have to provide input on their perceived experience.
- Ultimately the present state of mind of the learner can be synchronized to offer the learning content.
- It matches the present subjective assessment methods, being particularly useful in circumstances when continuous assessment is necessary.
- It enables advanced monitoring and interpretation of Learner and Learning environment optimizing the entire learning assessment procedure.
- It would ensure the prospective for finding commitment and attention using only the EEG band.
- The cognitive characteristics of learner are captured from learner EEG data.
- It would propose a recommendation for the e-learners in the context of respective e-learning environment.

B. Feasibility of the Proposed Work.

It is seen from the literature that a vast list of experiments have been conducted and succeeded in observing and assessing the human thoughts and emotions. Hence, the e-learners can be assessed of their kind just before actually entering into learning to predict the needs and requirements with more accuracy and so the best matching content be offered for learning use. As it is possible to employ EEG to capture emotive thoughts; FPI to devise learning styles and preferences, the viability and feasibility of this work is well confirmed.

C. Applications of Proposed Work

In the vide spectrum of applications, the proposed approach is more suitable and required in the context where and all human are involved. Thus, every field of work relating to the study, observation, creation, assembling and production, driving, stimulating, experimenting, experiencing, etc. kind of circumstances, this work would be more appropriate and found useful. The list of applications cannot be listed as an exhaustive one but to mention a few:

- Medical diagnosis
- Sports Predictions
- Gaming Applications
- Human-health study
- Social Interaction
- Child health monitoring

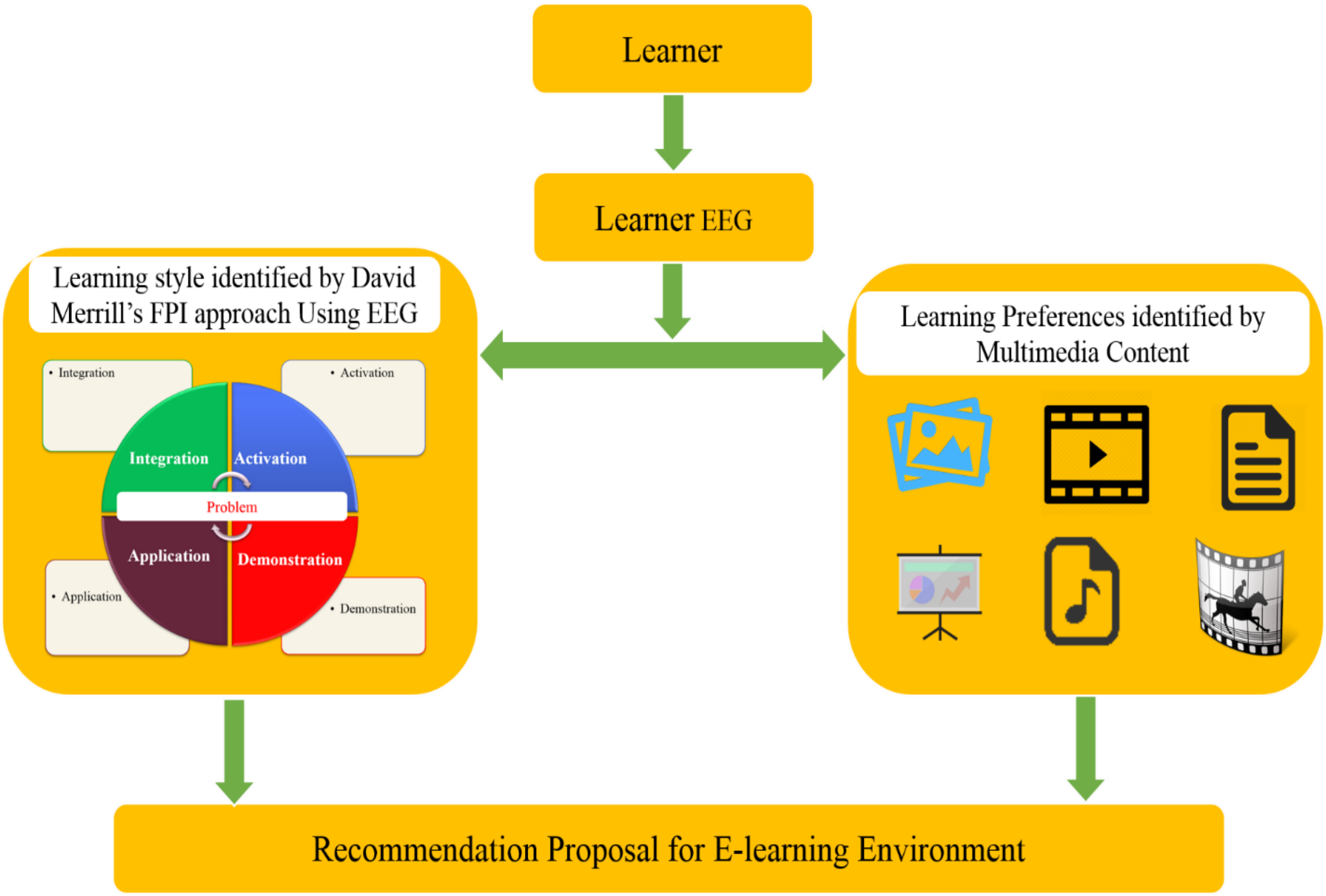

Figure 4: Recommendation Proposal for E-learning Environment

- Driving Assistance
- Simulation Applications
- Workers Hazardous Work Environment
- Space Research
- Underwater Study
- Animal-Behavioral Study
- Disaster Recovery

IV. CONCLUSION

This paper works around predicting the learners learning style and learning preferences using Learner EEG data. Using EEG data, one can easily identify the learning related emotions that is commitment of the learner. EEG data are captured by taking the type of signal as input for identifying the cognitive characteristics of learning style as per FPI approach. The FPI approach is suggested to be used to categorize the level of the learner. Multimedia content is used to predict the learner‘s learning preference of the learning style. Thus this proposed system would be useful to propose a recommendation for the e-learners in the context of that e-learning environment wherein above such experiment is conducted.

As understood from the list of applications mentioned above, the proposed work may be experimented with real-time applications covering any item of the above list or the similar one. Therefore, the wide scope of future extension or diversion of the proposed work is established.

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