Streamlining-Learning Through Bio-Inspired Brain-Computer Interface Chatbot

Dr.Senthilkumar.R
Associate Professor,Computer Science and Engineering
Shree Venkateshwara Hi-tech Enginering College
Erode,Tamilnadu,India.
svhecrsk@gmail.com

Kanithkumar.S
IV year-BE –Computer Science and Engineering,
Shree Venkateshwara Hi-tech Enginering College
Erode,Tamilnadu,India.
kanithkumar76@gmail.com

Logeshkumar.V
IV year-BE –Computer Science and Engineering,
Shree Venkateshwara Hi-tech Enginering College
Erode,Tamilnadu,India..
logeshkumar894@gmail.com

Sakthimanikandan.C
IV year-BE –Computer Science and Engineering
Shree Venkateshwara Hi-tech Enginering College
Erode,Tamilnadu,India.
sakthisakthi79199@gmail.com

***Abstract*—The rise of Massive Open Online Courses (MOOCs) and e-learning platforms like Coursera, EdX, and Udemy has democratized access to education. However, a major hurdle remains: high dropout rates, with some studies reporting figures as high as 96% [1]. This research investigates the potential of Brain-Computer Interfaces (BCIs) to revolutionize e-learning and tackle dropout rates. BCIs can measure brain activity, and research suggests a correlation between beta waves (14-30 Hz) and learner alertness [2]. Building on established methods for personality and learning style classification, this work proposes a Bio-Inspired Learning style Brain-Computer Interface (BIL-BCI) framework. Traditionally, researchers have employed Neil Fleming's VARK model (Visual, Auditory, Read/Write, Kinesthetic) to categorize learners [3]. Additionally, Carl Jung's theory of introversion and extroversion provides valuable insights into personality traits [4].The BIL-BCI framework leverages a chatbot equipped with a modified VARK questionnaire to classify learners as introverts or extroverts. Following this classification, learners engage with two minutes of visual and auditory content. During this time, their beta brainwaves are recorded at one-second intervals, generating a rich dataset for analysis. Machine learning algorithms such as Naïve Bayes, N48, and Canopy are then used to validate the dataset. The BIL-BCI framework aims to enhance the accuracy of learner classification, paving the way for personalized learning recommendations and ultimately reducing dropout rates in e-learning environments.**

Keywords*— MOOCs, Dropout Rate, Brain-Computer Interface (BCI), Beta Waves, Learning Styles, VARK Model, Introversion/Extroversion component.

I. INTRODUCTION

The internet's reach is expanding globally, with average speeds increasing. This growth has made educational technologies more viable and transformed higher education through the use of advanced techniques and tools. Modern technologies are facilitating easier access to learning. E-Learning and MOOCs are changing the way individuals learn online. MOOCs allow a large number of learners to study at their own pace, using open course materials and peer feedback to interact with the courses. Universities worldwide are offering learners the opportunity to study their relevant courses through MOOCs.E-Learning caters to individual learning needs and goals, allowing learners to choose their own learning paths and pace. If learners can decide what and when to learn, they are more likely to continue with the courses. E-Learning has many advantages over traditional learning systems. However, a recent study by MIT found a high dropout rate of about 96% in online courses over the last five years. Many MOOC courses have less than 30% completion rates, and the majority of learners who participate in MOOCs do not obtain their completion certificates. According to a study by Rivard, the reasons for not completing registered MOOC courses by E-learners include no real intention to complete, low motivation, lack of attention, lack of time, course difficulty, expectations, and starting late. It is recognized that people learn in different ways. To improve the learning process and help people become efficient learners, a personalized approach is needed. There are two common types of learning environments: Individual Learning environments and Group Learning environments. Individual learners learn more effectively on their own, while group learners learn more effectively in groups. Separate course contents should be prepared for individual and group learners to meet their respective learning needs. Individual learning became popular in the 1970s and, despite criticism, has greatly influenced education. In recent years, learning styles have gained attention across different age groups and learning environments. Many researchers are considering the preparation of course contents using learning styles. Human learners differ in their learning styles. Many theories have been proposed to classify humans based on their learning styles. Different psychological characteristics indicate how individuals

Iinteract and respond to the learning environment. Scientists who have conducted extensive research have criticized various learning style approaches. The major critique to the Learning Style Inventory (LSI) is the lack of learning style measurement. Web services have some unavoidable limitations, one of which is that they produce less reliable responses compared to face-to-face or telephonic surveys. Learning experiences are becoming smarter with the advent of new technologies. A new learning culture has been introduced with Artificial Intelligence-powered Chatbots, which aim to engage users. However, the information in this abstract is current only up to the year 2021, and there may have been advancements or changes in the field since then.

The advent of new technologies has led to smarter learning experiences, with a new learning culture being introduced through Artificial Intelligence-powered Chatbots. These Chatbots elevate the level of personalization, aiding e-Learning providers and educators in achieving their educational objectives. The personality traits of Introversion and Extraversion, as proposed by Winnie Frances Leung, play a significant role in this context. Extraverts, who are outgoing and comfortable working in large groups, prefer exchanging ideas and have a social learning style. They are often the first to volunteer for assignments and projects, demonstrating strong verbal learning styles and effective team management skills. On the other hand, Introverts are more reserved and reflective. They prefer to think thoroughly before taking actions and enjoy solitude. Their learning style is unique as they prefer to solve problems independently and seek theoretical explorations before tackling a problem. Interestingly, these personality traits respond differently to the neurotransmitter dopamine in the brain. While Extraverts are more activated with more dopamine in crowded places, making them more talkative, Introverts and Extraverts have the same amount of dopamine in their brains. However, the activities of dopamine differ due to the reward network, with the dopamine in the brains of Introverts being more active when they are alone. The proposed work aims to classify learners into Introverts or Extraverts for the Learning Style Inventory (LSI). This is achieved by implementing modified VARK questionnaires as a Chatbot to interact with learners. Following the classification, learners are given two minutes of visual and auditory content to watch in a silent atmosphere, during which their Beta brain waves are recorded. This data is then processed and trained using machine learning algorithms like Naïve Bayes and J48 tree classification algorithms available in the Weka 3.8.3 data mining tool. The accuracy of the proposed method is compared with the accuracy of the Fleming's VARK online questionnaire method regarding the classification of learners. The experiment involves learners of different age groups and both genders from SRM Institutes of Science and Technology, Kattankulathur, India. The Chatbot and the two-minute visual and auditory contents are tested with 118 learners, and common assessment results have been recorded. Please note that the information provided here is based on the details available at the time of writing and may need to be updated to reflect the most recent findings in the field.

E-Learning

Unlimited participation and open access via web are the features of an E-Learning. In addition to traditional course materials in E-Learning readings, video lectures and text. In E-Learning, interactive courses have emerged to support the community interactions between learners and teachers. This will enable the learners to provide immediate feedback to quick quizzes and assignments. The addition of learning styles in E-Learning enables to customize E-Learning platforms. The recent researches are emerging to find out the classification of the learners in E-Learning to reduce the dropout rates of E-Learners.

Learning styles

This model lays out a comprehensive set ofelementsthatcaninfluencealearnerinsteadofprescribingafixedstyleforeachlearner.For improving performances especially in higher education Kolb's learning style Model [12] is accepted.

The combination of two separate earning styles decides the learning style preference itself. Based on the work of Kolb, learning style model [13] was developed by Peter Honey and Alan Mumford. Four distinct learning styles Activist, Theorist, Pragmatist and Reflector are identified by them. The above four learning.

II. BIG FIVE PERSONALITY TRAITS

These are a widely recognized model in psychology, proposing five fundamental dimensions of personality:

Openness: This trait features a broad appreciation for art, emotion, adventure, unusual ideas, curiosity, and variety of experiences. Open individuals are creative, open-minded, and willing to entertain novel ideas. They tend to be adventurous and interested in culture. However, a very high level of openness can sometimes lead to a lack of focus and an inclination for risk-taking.

Conscientiousness: This dimension denotes a person's degree of organization, dependability, and work ethic. Highly conscientious individuals are reliable and methodical, often with a strong sense of duty. They are planners and like to live according to routines and schedules. On the downside, they can sometimes be perceived as inflexible or obsessive.

Extraversion: Extraversion is characterized by sociability, talkativeness, assertiveness, and high amounts of emotional expressiveness. Extroverts draw energy from interacting with others, while introverts, who score lower on this trait, expend energy in social situations and prefer more solitary or quiet environments.

Agreeableness: This trait reflects a person's tendency towards altruism, kindness, and affection towards others. Agreeable people are cooperative and get along well with others, often showing a high level of trust and a desire to help others. Those with low agreeableness may prioritize their own needs over others and can be competitive or challenging.

Neuroticism: This dimension relates to the tendency to experience negative emotions, such as sadness, anxiety, and irritability. High scorers on neuroticism may be more prone to experiencing mood swings and stress. Conversely, those with low scores tend to be more emotionally stable and resilient to stress.

These traits are considered the building blocks of personality and have been linked to various aspects of life, including learning styles and behavior patterns. As people age, their levels of conscientiousness tend to increase, while other traits may show different patterns of change.

III. BLOOD TYPE AND HUMAN CHARACTERISTICS

ExtravertsandIntrovertsareassociatedwiththeirrespectivebloodtypes.JapaneseProfessorTokejiFurukawa[29]published a paper claiming that each blood type reflects the personality of a person. The four primary blood types, A,O,B and AB are differentiated from each other based on their antigens.

In general, people differ in their blood types [30]. 'A' bloodtypepeoplearecooperative,emotional,passionate,sensitiveandclever.Theyareverypatientandloyal.Butthesepeoplebecome overly sensitive sometimes. These people take their time to make decisions and are too organized in all spheres of life. They like things to be neat, clean and put at the right place.

People with blood type 'A' are get stressed easily and thushaveahighlevelofcortisolhormone.Thesepeopleareverycreativeandquickdecisionmakers.Buttheyarenotgoodattakingorders.Theyputeverypartofthemselvesintosomething they want to focus on. They have a very strong desire and drive to be the best of everything they do. These people are not good at multi-tasking.

They are also not good at taking orders. They put every part of themselves into something they want to focus on. They have a very strong desire and drive to be the best of everything they do. But just like the'A' blood type, these people are also not good at multi-tasking.Peoplewith'B'bloodtypearethoughtfulandempathetictowardsothersandmakegoodandreliablefriends.

Table 1 Blood type and chances of Introvert and Extravert types

SI.NO	Blood type	Chance of Introvert	Chance of Extravert
1	TypeA	High	Low
2	TypeB	Low	High
3	TypeO	High	High
4	TypeAB	High	Low

IV. HUMAN BRAIN WAVES

MIT's Earl K. Miller [32], a Professor of Neurosciencesaysthat,thedistinctneuralsignaturesshouldguide researchers as they study the underlying neurobiology of how humans both learn motor skills and work through tough cognitive tasks. There searchers Freedman[33],Nieder [34]

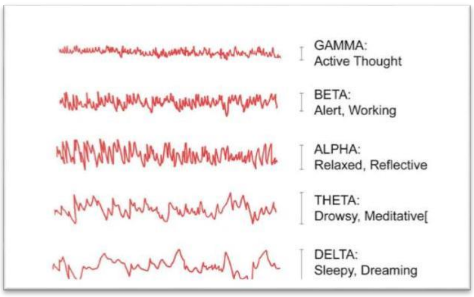

Figure1 Healthy adult brainwaves

Pasupathy [35] found that different types of behaviors are accompanied by different patterns ofbrainwaves.Figure1showsdifferentbrainwavesproduced for a healthy adult.

Learning engages all the senses and taps the emotional side of the brain through methods likestorytelling,humor,group activities and games. Human brain contains morethan100billionnervecellscalledneuronsandeachneuronindividually is linked to other neurons through axons and dendrites. Basically, a small amount of electric signal in micro amperes range moves from one neuron too ther neuron [36] to carry out the numerous activities of the brain.

These signals produced by the brain can be divided intofivefrequencieslikeGamma,Beta,Theta,AlphaandDeltaas giveninTable2.

A. Table2 Brainwavesandtheirassociatedactivities[37]

Brainwaves	Frequency Range	Associated state of mind
Gamma	30 -100Hz	Anxiety, Depression, High Arousal, Stress
Beta	14-30 Hz	Alert, normal alert consciousness, Active conversation, Making decisions, Learning.
Alpha	8-13Hz	Yoga ,Just be for efalling a sleep, Being creative and artistic.
Theta	4-7Hz	Deep meditation Daydreaming.
Delta	<3.5Hz	Sleep, Dreaming

A. MACHINE LEARNING FOR PERSONALIZATION

Machine Learning is said to be learning from past experiences with respect to some class of tasks, and thelearningimproveswiththeexperience[43].Machinelearning makesuseofalgorithmsthataredesignedtoimprove over time depending on the new data they will be tracking.

Chatbot for learning platform

One of the most thriving E-Learning innovations is the Chatbot technology [45]. Chatbot works on the principle of interacting with users in a human-like manner .Artificial Intelligent and Content based Chatbot are becoming essential parts of E-Learning environment .Learners are exposed to Chatbot andother virtual assistants on their personalized devices. These intelligent bots are often deployed as virtual assistants. Chatbot provides conversational answers and serve as a quick reference guide.

B. MACHINELEARNINGAPPLIED TOE-LEARNING

Studies [44] found that learners who are taught according to their identified learning styles do no better than

earners who are not matched to their learning styles. In the past decades, many learning style models have been proposed, and some of these learning style models have been found more suitable for E-Learning .However ,research on Learning style inventories might be a way for learners to develop E-Leaning contents that keep them interested and engaged in the learning process and this may find useful for the learners to discover their learning preferences. For example Visual learners might be more interested with symbols, graphs, and other visual information while studying the E-Learning materials. Machine Learning (ML) provides many eeffective ways to analyze learner's engagement data and identify patterns that suggest which content could be better redesigned, or to provide more support to learners who are failing to complete a MOOC course. ML and BCI are the emerging technologies that can apply machine learning algorithms to classify learners and deliver the appropriate E-Learning contents to increase the engagement of E-Learning courses.

IV. PROPOSED METHOD

The proposed system embarks on a two-pronged investigatory approach to discern and categorize learner typologies. The inaugural experimentation delves into the development of an AI-driven chatbot designed to taxonomize learners based on their predilections and aversions within the learning domain. This intelligent agent probes into learner preferences encompassing habits, chromatic affinities, and proclivities towards collaborative learning modalities. Extrapolating from established psychological paradigms, the system leverages tendencies such as extroverts' preference for group learning and introverts' inclination towards the color blue, thereby enabling the classification of learners into these two primary personality categories.

The subsequent experimentation ventures into the realm of terotechnology with the design of a Brain-Computer Interface (BCI) system. This sophisticated apparatus scrutinizes learning styles through the meticulous analysis of electroencephalographic (EEG) signals. Employing machine learning classifiers, the system distinguishes between visual and auditory learners. The experimental protocol involves exposing participants to a multimedia presentation containing stimuli catering to both visual and auditory learning styles while simultaneously recording their EEG signals, thus generating a comprehensive dataset for analysis.

The initial phase of learner classification utilizes a modified VARK questionnaire administered via the aforementioned chatbot. This interaction aims to ascertain

The proposed system adopts a content-based approach to learning style identification, aligning with the widely recognized VARK model. Despite critiques and a dearth of empirical validation, the VARK model maintains its relevance due to its intuitive and practical approach within adaptive e-learning environments.

Prior to engaging with the educational content, learners u ndergo an assessment of their learning preferences through th e administration of the VARK questionnaire [17]. This instru ment requires learners to select the response that most accura tely reflects their individual inclinations by encircling the cor responding letter. In instances where a single answer fails to encapsulate the learner's perception, the option to select multi ple choices is provided. Should a question prove too challeng ing, the learner may opt to leave it unanswered, with the cave at that a minimum of 10 out of the 13 questions must be com pleted to ensure the validity of the assessment.

Table 3 contains the VARK learning style and its prescribed learning contents.

S. No	Learning styles	Prescribed Learning contents
1.	Visual Learners	Pictures, Text, Animation, Diagramsetc.
2.	Auditory Learners	Voice Narration, Audio books, Music, Video etc.
3.	Read /Write Learners	Self-study by text, Own notes etc.
4.	Kinas the tic Learners	Physical actions and Sense of touch etc.

Table3 prescribed learning contents for VARK learning style

Table 4 contains the sample VARK Learning Style Inventory(LSI) chart. The VARK learning style is used in most of the recent E-Learning systems.

Categories / Questions	A Category	B Category	C Category	D Category
1	K	A	R	V
2	V	A	R	K
3	K	V	R	A
4	K	A	V	R
5	A	V	K	R
6	K	R	V	A
7	K	A	V	A
8	R	K	A	V
9	R	A	K	V
10	K	V	R	A
11	V	R	A	K
12	A	R	V	K
13	K	A	R	V
14	K	R	A	V
15	K	A	R	V
16	V	A	R	K

Table 4 Sample VARK Learning Style Inventory chart

Based on the aforementioned assessment, the learner in question exhibits a dominant visual learning style, as ascertained through the VARK model and its corresponding Learning Style Inventory (LSI). It is important to acknowledge the limitations of the e-learning environment, which precludes the effective implementation of read/write and kinesthetic learning modalities .Further corroborating the initial classification, research by Chris [51] highlights the chatbot's categorization of learners into introverts and extroverts, the subsequent phase of the experiment involves exposing participants to a two-minute multimedia presentation encompassing both visual and auditory elements within a controlled, silent environment. During this exposure, the learners' beta brainwave activity is meticulously recorded at one-second intervals, facilitating the creation of a comprehensive dataset for subsequent analysis.

The proposed chatbot employs a series of concise, single-line questions to efficiently gather data on learner preferences. These questions are strategically categorized into three distinct segments:

1. Chromatic Preferences: Exploring learners' likes and dislikes regarding colors.
2. Unique Habits: Delving into daily routines and individual peculiarities, such as caffeine consumption preferences.
3. Learning Modalities: Assessing preferences for individual versus group learning environments.

The chatbot's architecture comprises three fundamental components: Natural Language Processing (NLP), Natural Language Understanding (NLU), and a Decision-Making Engine (DMG). NLP facilitates the generation of questions and responses, while NLU extracts meaningful information from user input. The DMG governs the chatbot's responses, determining whether to provide an immediate answer or await further input. All conversational data is meticulously stored within a dedicated database.

Figure 4 elucidates the data flow and underlying principles of the chatbot, illustrating the dynamic exchange of questions and answers between the bot and the learner. Based on this interactive dialogue, the extroverts. To evaluate the efficacy and generalizability of the chatbot, an experiment was conducted across diverse age groups. A total of 118 learners from the SRM Institute of Science and Technology in Chennai, India, participated in the study by accessing the chatbot via a designated URL [49]. The implementation of the chatbot leveraged the Landbot online tool [49], which provides a user-friendly drag-and-drop interface for creating interactive chatbot experiences.

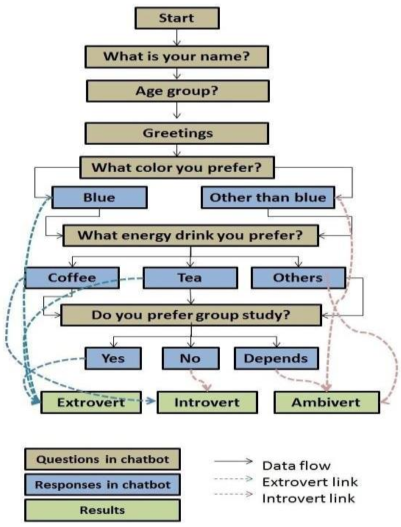

Figure 4 elucidates the data flow and underlying principles of the chatbot

V. RESULTS

Experiment 1 employed a modified VARK questionnaire implemented as a chatbot to categorize learners into introverts, extroverts, and ambiverts. The chatbot's design was inspired by the concept of "Bio-Inspired blood group prediction" [62], aiming to extract pertinent information from learners' daily routines and preferences. The chatbot functions as a decision-making tree, commencing with simple inquiries about daily activities and culminating in the identification of the learner's personality type.

Comparison table between proposed method and machine learning classification.

Experiment 2 employed machine learning algorithms to classify learners based on EEG BCI signals, leveraging the WEKA Tool for both classification and clustering processes. EEG BCI signals offer a high degree of reliability for discerning learner characteristics.Table 15 presents a comparative analysis between the proposed Bio-Inspired Chatbot method and machine learning classification techniques. Additionally, Table 16 compares the Bio-Inspired Chatbot method with Canopy clustering, a specific machine learning clustering algorithm. The results demonstrate that the Bio-Inspired Chatbot achieved superior classification accuracy compared to existing online learning style inventories.

VI. CONCLUSION

Researchers in the field of e-learning are increasingly turning to machine learning to gain deeper insights into learner behavior and preferences. Among the various approaches to learning style classification, Neil Fleming's VARK model remains a prominent framework. Complementing this, the exploration of personality traits, such as introversion and extroversion, as described by Carl Jung, provides another dimension for understanding learner differences. Notably, research by Soomin Kim [63] highlights the potential of chatbots as effective tools for gathering quantitative data.

This research investigated the correlation between introversion/extroversion personality types and their corresponding learning styles. The study employed a modified VARK questionnaire implemented as a Bio-Inspired Chatbot to classify individuals, yielding high-quality data from participant responses. Subsequent to chatbot classification, learners were exposed to visual and auditory content while their beta brainwave activity was recorded. This neurophysiological data was then analyzed using machine learning algorithms, including Naïve Bayes, N48 tree, and clustering techniques, demonstrating improved classification accuracy compared to existing methods.

The proposed Bio-Inspired Chatbot offers a time-efficient approach to learner classification and forms the basis for the Bio-Inspired Learning style Brain Computing Interface (BIL-BCI) framework. This framework serves as a valuable recommendation system for e-learning content developers, enabling them to categorize learners into an "Introvert-Extravert learning style inventory" and tailor educational materials accordingly.

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