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Modeling the Human Learning Process Using an Industrial Steam Boiler Analogy to Design a Psychophysiological-Based Hypermedia Adaptive Automation System

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by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
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Dedication

I want to dedicate my doctoral degree to many people as a testimony of my love and gratitude for their support and contributions they have made throughout my academic journey.

First, I dedicate my doctoral degree to God and my parents in Heaven, Heriberto and Julia, whose infinite inspiration and sacrifices shaped my values throughout my life. To Tata, my nanny, the purest love. To my husband Omar and my beloved children, Pablo, Natalia, and Santiago, whose unconditional love and support motivated me to initiate this long voyage and remain resilient in the face of challenges. To my brothers and sisters: Heriberto, Marco, Jose, Julio, Noris, Norka, Mirian, and Nancy, and to my extended family and friends, who stood by me with their encouragement, motivation, and uplifting words. To Venezuela, my loved country.

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List of Acronyms

Acronym	Definition
AHS	Adaptive Hypermedia System
AI	Artificial Intelligence
ANSI	American National Standard Institute
BCI	Brain Computer Interface
CL	Cognitive Load
CNN	Convolutional Neural Network
DNN	Deep Neural Network
EEG	Electroencephalography
EL	Extraneous Load
Eng	Engagement
ERP	Event-Related Potential
F	Frontal
FOC	Focus
GL	Germane Load
GUI	Graphical User Interface
H	Enthalpy
HR	Heart Rate
Hz	Hertz
IL	Intrinsic Load

IM	Instructional Material
Int	Interest
IoT	Internet of Things
ISA	International Society of Automation
K	Knowledge
LSTM	Long Short-Term Memory
LTM	Long Term Memory
MED	Meditation
MIMO	Multi-Input Multi-Output
O	Occipital
P	Parietal
P	Pressure
P&ID	Process & Instrumentation Diagram
PPHAAS	Psychophysiological Hypermedia Adaptive Automation System
RNN	Recurrent Neural Network
SCADA	Supervisory Control and Data Acquisition
SpO2	Oxygen Saturation
St	Stress
STEM	Science, Technology, Engineering and Math
STM	Short Term Memory
T	Type of Task
T	Temperature
TD	Task Difficulty

U	Internal Energy
V	Volume
WM	Working Memory
α	Alpha Waves
β	Beta Waves
γ	Gamma Waves
θ	Theta Waves
ρ	Correlation

Abstract

This dissertation aims to address the existing gap in the integration of various dimensions within the student learning system, encompassing cognitive, emotional, and physical variables. The primary objective is to construct a Personalized Learning Adaptive Automation model using Electroencephalography (EEG) technology.

To provide deeper insight into the intricate nature of the Human Learning Process, this study introduces a novel analogy with an Industrial Steam Boiler. This analogy serves as a distinctive contribution to research in the field.

The research methodology involved the collection of brainwaves data from engineering students while they undertook educational tasks of varying levels of difficulty, categorized from easy to difficult. The EEG data acquired from the experimental group underwent rigorous analysis to identify statistical patterns associated with beta, alpha, and theta brainwaves at specific sites (F3, F4, P7, and P8). These findings are instrumental in establishing the psychophysiological variables relevant to students' learning processes in order to be able to analyze the students' cognitive, emotional, and physical states when selecting the difficulty level of the task that the proposed Hypermedia Adaptive Automation System will deliver accordingly.

The envisioned outcome of this research is the development of a Psychophysiological Hypermedia Adaptive Automation System Model. This model holds significant promise as an optimal, multidimensional, and personalized learning environment. It stands to enhance student development by considering emotional, physical, and cognitive factors, thus offering a holistic

approach to education, particularly through the proposed Personalized Learning Adaptive Automation model.

Chapter 1: Introduction

The adaptive automation of systems that can adapt in real time to a user's changing requirements is an important and expanding field. Industry 5.0 is rapidly changing due to the development of recent technologies, industrial production, and social behaviors imposed by 21st-century challenges. Meeting these challenges requires the integration of advances in communications, processing, system security, interconnectivity, and Artificial Intelligence (AI) into platforms such as the Internet of Things (IoT), which involve smart automation and human factors concepts. The possibility of measuring users' real-time, psychophysiological variables through non-disturbing/invasive sensors is opening new horizons for research in the industry because the user's collected data can be utilized to manage the user's cognitive workload. Analogous to industrial applications, this approach can be applied to the development of future educational systems aimed at enhancing student performance within a framework of personalized learning. Measuring significant variables such as Cognitive Load (CL) and Engagement (Eng), among others, which are present when students perform academic tasks, will permit an evaluation of the impact of teaching styles, learning strategies, or environmental variables affecting student performance. Many CL surveys have been developed by neuroscientists, psychologists, and educators [1] and, for quite a long time, those surveys were the standard instruments or self-assessment evaluations to measure student CL because they can be used to report students' feelings, emotions, or moods in a learning environment. The evolution of electronic devices has permitted the acquisition of brain signals using Electroencephalogram (EEG), an important area of research in human behavior and psychology. Different physiological measures obtained by recording signals from the heart and lungs, the eyes, the skin, and the brain [2] have been used to analyze students' CL. Studies using brain signals have demonstrated that cognitive functions are associated with specific brainwaves that have been acquired by placing leads on well-defined brain partitions that are then processed for CL analysis. Having a multivariable model of the learning process that is analogous to an industrial process will facilitate the implementation of adaptive automation for the delivery of instructional material in terms of Task Difficulty (TD) levels, CL, and Type of task (T), as well as the management of human factors in order to keep the student Engaged while acquiring knowledge. The human learning system involves an incredibly intricate and complex process. Building analogies can simplify and facilitate its understanding. Engineers can relate to the complexity of the human learning process by creating analogies between it and another control system. By drawing parallels between complex concepts and more familiar or relatable situations, we can break down the barriers to comprehension. Part of this research's contribution to a state-of-the-art in the application of Engineering to the field of neuroscience is the creation of a novel analogy between the human learning system and a steam boiler, a well-known industrial process. This novel representation of the human learning system as an industrial multivariable model will be used to develop a Psychophysiological-based Hypermedia Adaptive Automation System (PPHAAS). The PPHAAS's contribution will be to automatically manage the students' cognitive and emotional states in real-time by monitoring and controlling CL while they are performing an academic task.

Chapter 2: Literature Review

2.1 Automation for Educational Processes

An assumption in the use of EEG for adaptive automation is that some aspects of the EEG's signals may be used as an indication of mental workload that can play a role as modulators of task parameters [3]. In this research, I have created an analogy between the automation pyramid for industrial processes and educational processes to align hierarchical levels, see Figure 1.

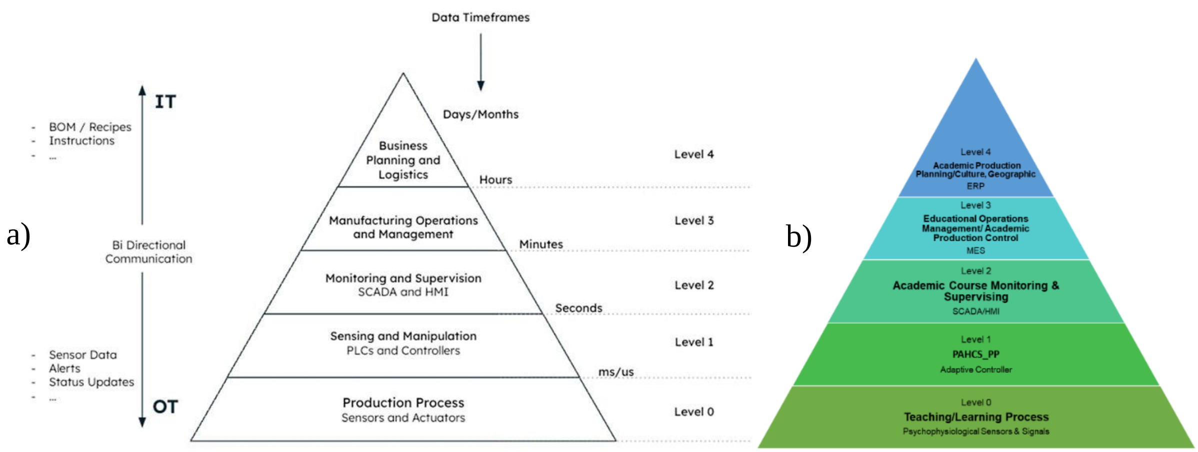

Figure 1. a) ANSI/ISA-95, or ISA-95 Model Developed by the International Society of Automation [4] and b) An Analogous Educational System.

There are several advantages to using psychophysiological indices in an adaptive system [5]. Psychophysiological measuring is a continuous process and doesn't necessarily require an explicit response from the operator. This is important because operators usually have a supervisory role and are rarely required to press a button or given any other specific input, even though they might be engaged in significant cognitive activity. Additionally, psychophysiological measures have the potential to reveal the state of the operator as well as of those functional areas of the brain. Understanding Personalized and Precision Learning using psychophysiological feedback can be enhanced using the fundamentals of Control Systems.

For many years, emotions associated with the learning process have been studied, including the measurement of brainwaves using EEG signals. Furthermore, facial recognition, abnormal head rotation, and shoulder movements [6] have been considered negative behavior and clear signs that show the student is not interested in the topic or is bored [7].

Interest in the development of devices for recognizing human emotions in the learning process has increased continuously. Using electroencephalography (EEG), it has been proven that electrical brain activity represents a useful methodological tool for understanding cortical processes that underlie students' performance and engagement in learning activities.

Much research has been done showing different methods for measuring variables present in a learning environment, for example, Engagement, Cognitive Load, and Attention, among others. Most of those investigations utilize surveys as instruments to collect student data before and after a particular task, forcing the academic intervention or control to remain on hold until the next task session. In terms of control theory, this type of process is called batch processing. Continuous systems require a much higher level of control than batch processes since the use of technology plays a key role in the automation of continuous systems, facilitating real-time data collection. Monitoring real-time psychophysiological variables in students while they are performing a learning task will help the educational system manage their academic performance by delivering instructional materials in accordance with their cognitive and emotional states [8]. The goal of academic systems is to improve the outcomes of students' learning experiences by implementing proper interventions from each of the authorized hierarchical levels, just as an industrial system does. For instance, in a university setting, data acquired from students can be made available in real-time to professors, department chairs, college deans, and administrative support staff, e.g., program advisors, to optimize the institutional response. This research is expected to open new opportunities for promoting future research contributions to the development of educational control processes based on Supervisory Control and Data Acquisition (SCADA) approaches to improve the management of student's learning processes in educational institutions, as shown in Figure 2.

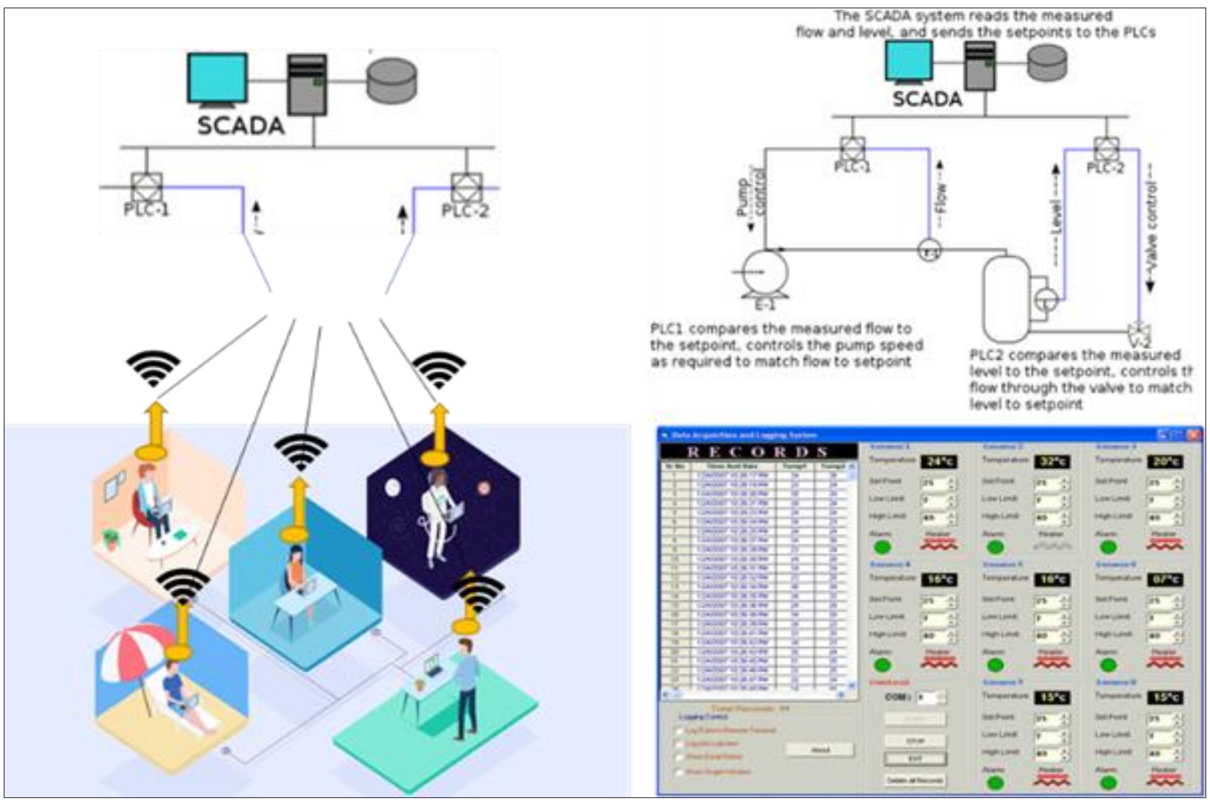

Figure 2. Future Supervisory Control and Data Acquisition (SCADA) [9] for an Academic Geographical Zone.

From a worldwide perspective (see Figure 3), the possibility of incorporating other variables for geographic zones such as culture, economics, ethnicity, etc., by using a control systems methodology will create other opportunities for holistically analyzing the Teaching/Learning process.

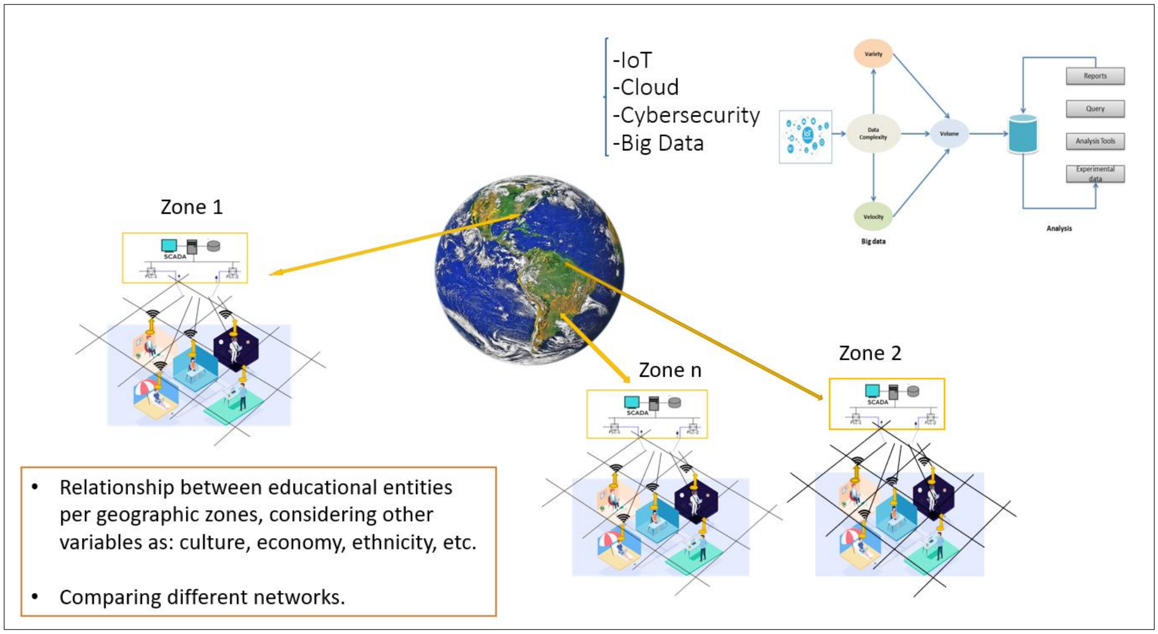

Figure 3. From a Global Perspective, Future Supervisory Control and Data Acquisition (SCADA) for Educational Zones Are Geographically Distributed [10].

2.2 Engagement and Cognitive Load

Student Engagement is a multidimensional construct that can be analyzed from all the different dimensions that are dynamically interrelated. It typically includes three major dimensions: Behavioral Engagement focuses on participation in academic, social, and co-curricular activities; Emotional Engagement focuses on the extent and nature of positive and negative reactions to teachers, classmates, academics, and school; and, Cognitive Engagement focuses on students' levels of investment in learning [11]. Cognitive Engagement is susceptible to being affected by the levels of Cognitive Load imposed by a task. Consequently, Cognitive Load increases when excessive demands are imposed on the cognitive system. If the Cognitive Load becomes too high, the transference of information to the brain memory is obstructed and, therefore, learning is obstructed. Such demands include inadequate instructional methods while educating students about a subject, as well as unnecessary environmental disruptions. Cognitive load theory aims to clarify how the information processing load stimulated by learning tasks can affect students' proficiency in processing new information and building knowledge in long-term memory. This fundamental argument posits that human cognitive processing is heavily restricted by limited working memory, which can only process a limited number of information elements at a time [13]. Working memory capacity can be increased and, thus, help the processing of more intellectual activities like problem-solving, and the storing of knowledge in the form of schemata, i.e., knowledge organized by chunking. Therefore, the objective of training must be to support the construction of schemata in working memory but not overload its capacities [14]. Mental state changes due to the level of imparted cognitive load: a subject's performance may become drastically reduced if the load surpasses a critical point. Growing task difficulty and mental workload increases the heart rate [15]. Basic cardiovascular measures like heart rate have been found to significantly increase with increased attention and mental workload. Accordingly, the blood oxygen concentration and heart rate can be measured and correlated with students' emotional and cognitive states. Recent studies have increasingly applied objective measurements like eye-tracking, time-on-task, and physiological measures using brainwaves because they are more accurate for measuring student Cognitive Load than questionaries and surveys, which are considered subjective measurements. EEG measures the voltage change caused by the movements of ions in the brain's neurons [16]. The proliferation of wireless EEG devices and advances in computational intelligence techniques have contributed to Brain-Computer Interface (BCI) development [17]. Emotional states are also associated with directly impacting learning objectives.

In this research, a compact EEG headband that integrates dry sensor technology, Bluetooth, and significant advances in digital signal processing has been used to access brainwaves signals in order to measure and analyze multiple dimensions of students' learning that could be affecting his/her performance.

2.3 Dimensions of Student Learning

Student learning is influenced by a complex interplay of various factors, including emotional, social, cognitive, and physical elements (see Figure 4). Below are some key factors within each of these dimensions:

1. Emotional Factors:
    - Motivation: A student's motivation, whether intrinsic (internal) or extrinsic (external), plays a significant role in their learning. Motivated students are more likely to Engage with educational material and persist in the face of challenges.
    - Emotional Well-being: A student's emotional well-being, including his/her mental health, stress levels, and overall emotional state, can impact his/her ability to focus and learn effectively.
    - Self-esteem and Self-confidence: Students with higher self-esteem and self-confidence are often more willing to take on challenges and have a more positive attitude towards learning.
2. Social Factors*:*
    - Peer Interaction: Positive relationships with peers can enhance learning through collaboration, discussions, and the sharing of ideas and knowledge.

- Teacher-Student Relationship: A strong and supportive relationship with teachers can motivate and Engage students, making the learning experience more meaningful.
- Family Support: Family support and involvement in a student's education, including encouragement, a conducive learning environment, and resources, can significantly affect learning outcomes.
- Cultural Background: A student's cultural background can shape his/her learning style, values, and perspectives, influencing how they approach education.
- Classroom Environment: The overall classroom environment, including its inclusivity, safety, and the teacher's teaching style, can impact a student's comfort and Engagement.

3. Cognitive Factors:
    - Prior Knowledge: A student's existing knowledge and cognitive abilities provide a foundation for new learning. Building on prior knowledge is essential for meaningful learning.
    - Learning Style: Individuals have different learning styles, such as visual, auditory, or kinesthetic. Understanding one's learning style can enhance the learning process.
    - Critical Thinking and Problem-Solving: Developing critical thinking skills allows students to analyze, evaluate, and apply information effectively.
    - Metacognition: Awareness of one's own learning process, including goal setting and self-monitoring, can improve learning outcomes.

- Executive Function: Executive function skills such as organization, time management, and planning help students manage their learning tasks and responsibilities.

4. Physical Factors:

- Health and Nutrition: A student's physical health, including nutrition and overall well-being, can influence his/her ability to focus and learn.
- Sleep Patterns: Adequate and quality sleep is essential for cognitive function and memory consolidation.
- Physical Activity: Regular physical activity can enhance cognitive function and overall well-being.
- Learning Environment: The physical learning environment, including lighting, seating, and classroom design, can affect a student's comfort and focus.
- Access to Resources: Access to educational resources such as textbooks, technology, and materials can impact a student's ability to Engage with the curriculum.

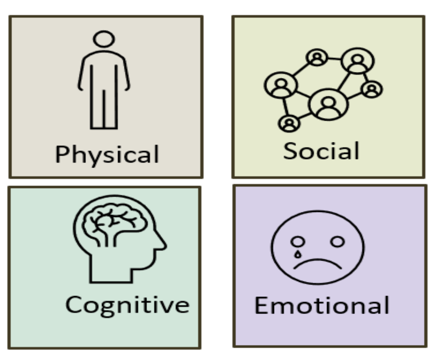

Figure 4. Dimensions of Student Learning.

It is important to recognize that these factors are interrelated and that the influence of each factor may vary from one student to another. Effective education and support systems consider and address these various dimensions to create a well-rounded learning experience that accommodates the diverse needs of students. Table 1 shows some previous research.

Table 1. Previous Work Considering One or Two Dimensions of Student Learning.

Reference	Using Technology	Survey Based	User self-evaluation	Decision making based on	Intervention	Application Field
Improving Cognitive Decision-Making into Adaptive Educational Systems through a Diagnosis Tool based on the Competency Approach [18]	Yes	Yes	Yes	Cognitive	Real-time	Education
Students' Metacognition and Cognitive Style and Their Effect on Cognitive Load and Learning Achievement [19]	Yes	Yes	Yes	Cognitive	Real-time	Education
Recounting the Role of Emotions in Learning Economics: Using the Threshold Concepts Framework to Explore Affective Dimensions of Students' Learning [20]	Yes	Yes	Yes	Cognitive and affective	No	Education

2.4 EEG and Brainwaves

The connection between the brain and behavior is explained by a comprehensive mapping of its structure and functions. In terms of its structure and functions, the brain is divided into four primary lobes along with the cerebellum. The frontal lobe, represented as (F), prominently holding the Prefrontal Cortex, serves as the epicenter for intricate human functions, including but not limited to thinking, planning, logic, and decision. This lobe encompasses the frontal region of the brain.

The parietal lobe, denoted as (P), plays a pivotal role in the processing of sensory information and the awareness of the body's spatial orientation. It is situated at the top of the brain, positioned just above the occipital lobe.

Auditory information is processed in the temporal lobes, designated as (T), with two of these lobes situated on opposing sides of the brain.

Lastly, the occipital lobe, marked as (O), is dedicated to the complex task of processing visual information. It is located towards the posterior part of the brain.

An EEG measures the brain’s electrical activity; it does not measure thoughts or feelings. During an EEG, small electrodes and wires are attached to a subject’s scalp. The electrodes detect the brainwaves, and the EEG device amplifies the signals and records them. Usually, electrodes are positioned within a cap, typically comprised of 8–14 channels, placed respectively at locations AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, according to the International 10–20 EEG standard.

No central lobe exists, the letter ‘C’ is used to identify the central line from ear to ear. The ‘z’ (zero) refers to the electrodes located on the midline, transversal to the central line. Even numbers (2,4,6,8) refer to electrode sites in the right hemisphere and odd numbers (1,3,5,7) refer to electrode sites in the left hemisphere.

The literature-motivated frequency bands and channel selection are shown in Figure 5:

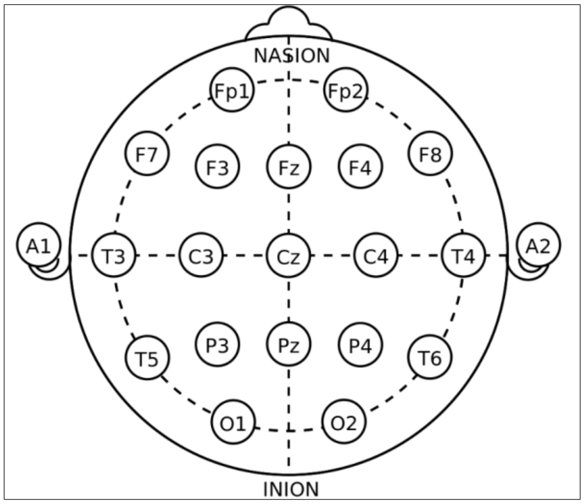

Figure 5. Location of Electrodes: 10/20 System Positioning [21].

Students can experience specific emotional states within a learning experience such as enjoyment, engagement, etc., which contribute to reaching high levels of student focus and attention, as was shown in the work of [22], where using gamification teaching strategies enhanced students' learning motivation and academic performance by adjusting cognitive load.

2.5 Working Memory and Brainwaves

Working Memory (WM) involves the ability to maintain and manipulate information over short periods and can be subdivided into the initial encoding of information, and maintenance and retrieval of WM items. Since WM is centrally involved in many aspects of higher cognitive functions, a substantial amount of research has been dedicated to identifying the neuronal substrates of different WM processes. [23]. From the perspective of neuroscience, it has been established that working memory activates the frontoparietal brain regions, including the prefrontal, occipital, and parietal cortices [24]. Cognitive load is the load imposed on working memory by the cognitive processes that_learning materials evoke, which can be measured at different task levels. The CL is the relative demand imposed by a particular task in terms of mental resources required, also called mental load or mental workload [25]. According to cognitive load theory, academic tasks can impose three types of Cognitive Load (CL) on a learner's cognitive system: task difficulty and the learner's prior knowledge determine the Intrinsic Load (IL), instructional features that do not contribute to effective learning determine the Extraneous Load (EL), and instructional features that are beneficial for learning contribute to Germane Load (GL).

IL should be optimized in instructional design by selecting learning tasks that match learners' prior knowledge and by minimizing EL in order to reduce ineffective load on learners so they can engage in activities imposing GL [26]. Many researchers have found an association between theta, alpha, and beta channels with task difficulty. Most neurocognitive EEG research focused on Event-Related Potential (ERP) indices. ERPs reflect brain responses to certain events and are calculated by averaging the continuous EEG signals over many trials, so that the oscillatory background activity, considered noise, is canceled out. The described mental workload uses a set of features that include instantaneous workload, peak workload, average workload, accumulated workload, and overall workload. Instantaneous load indicates the changes in CL, which fluctuates continuously while performing a task or set of tasks. When the time interval is fixed, both the accumulated workload and the average workload should be proportional to the overall mental workload [27]. In [28], the authors performed high-resolution EEG topographic maps showing the deblurred topography of the frontal midline theta rhythm during the performance of easy and difficult versions of tasks. On average across the subjects, theta signal was higher in amplitude in the more difficult task conditions than in the easy task conditions.

The most pronounced and reliable task-related modulation of spectral power occurred in the theta (4–7.5 Hz) and alpha (7.5–14 Hz) bands. As suggested by the power spectra measures, the highest amplitude individual bursts were observed in the most difficult task conditions.

In [29], it was found that by performing several experiments, the alpha frequency varies as a function of memory performance. These results indicate that alpha frequency may be a permanent and not only a functional parameter that controls the speed with which information can be retrieved from memory.

Changes in alpha band power (amplitude) further reveal that the upper alpha band is particularly sensitive to semantic memory demands while the lower alpha band, on the other hand, appears to reflect attentional processes.

The literature review suggests that cognitive load variations for tasks having different difficulty levels are most clearly visible if the frontal and parietal lobes [30] are considered. The researchers [31] have reported that there are seven leads (Cz, P3, P4, Pz, O2, PO4, F7) that are most important for Cognitive Load. Cognitive load considering alpha and theta waves from the four selected channels will get a simple measurement of Cognitive Load [32].

In the work performed by [33] and [34], authors considered the use of a portable Emotiv headset (14 channels) to collect brain signals. They reported that alpha power decreases with increased cognitive load. This effect is most prominent at the central Parietal (Pz) location, whereas theta power increases with increased cognitive load and is most prominent at the central Frontal (Fz) location. Since Emotiv does not have any sensors at Fz or Pz locations, P7 and P8, I will choose from the parietal lobe and F3 and F4 from the frontal lobe in my research because they are the closest representatives of Pz and Fz (see Figure 6). I will average the theta wave variations at frontal lobe F3 and F4, and alpha wave variation in parietal lobe P7 and P8.

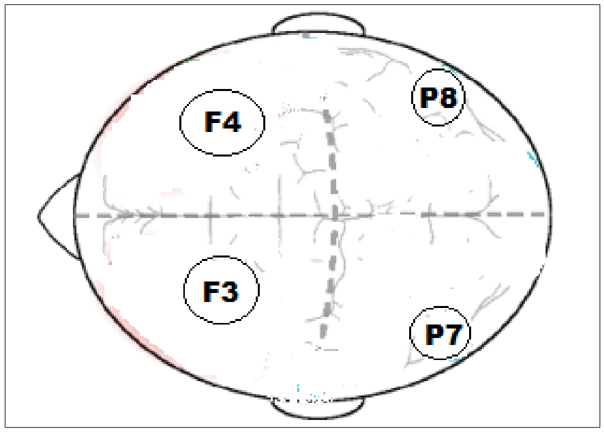

Figure 6. Measuring Cognitive Load F3, F4 from Frontal Lobe and P7 and P8 from the Parietal Lobe

The increased beta response in healthy subjects under cognitive workload implies that beta oscillations could move the system to state of attention and have an important function in cognitive activity. Beta activity is an important operator in brain cognitive processes. The results support the hypothesis that the increase in beta responses is also related to attention and the cognitive process [35].

In [35], the authors demonstrated, as other previous studies have, that, “independent of stimulus modality (auditory or visual), beta responses increase beta oscillations increased upon negative emotional stimulation, upon high arousal stimulation, upon multisensory stimulation and also upon cognitive load. The common mechanism between these different stimulations might be the need for increased attention.”

The relationship between psychophysiological measures and the response of these measures to high workload is shown in Table 2.

Table 2. The Relationship Between the Psychophysiological Measures and the Response of these Measures to High Workload.

Psychological or physiological measures	Response of measure to high mental workload or cognitive load	Reference
Heart rate	Increases	[36]
Oxygen saturation (SpO2)	Increases	[37]
Theta waves (from EEG)	Increases	[38]; [34]
Alpha waves (from EEG)	Decreases	([38]; [33]; [34]
Beta waves (from EEG)	Increases	([35] [39])

Brainwaves, frequency bands, and functions in unconscious and conscious states are shown in Table 3.

Table 3. Brainwaves, Frequency Bands, and Functions

Unconscious	Conscious				
Delta	Theta	Alpha	SMR	Beta	Gamma
Instinct	Emotion	Consciousness	Focused	Thought	Will
Survival, deep, sleep, coma, repair, complex, problem solving	Drives, feelings, integration of feelings, alert and peaceful, reading, mediation	Aware of the body, integration of feeling, alert and peaceful, reading, mediation	Mental alertness, physical relaxation	Perception mental activity, thinking, focusing, sustained attention	Extreme focus, energy, ecstasy learning, cognitive processing

2.6 Emotion–Cognition Interactions and their Impact on Learning

Cognitive state is a state of mind that can vary widely. Emotional information appears to enhance Long-Time Memory (LTM) with the pronounced effects deriving from positive emotions when compared with negative emotions [40]. Researchers have studied emotions during many years by measuring brainwaves using ECG signals, facial recognition (eyes, mouth) and shoulder movements using image processing and computer machine learning techniques [17]. The face provides a real picture of emotions because humans are programmed to express and communicate emotions through facial expressions. Studies are mostly trying to interpret basic emotions such as anger, disgust, happiness, fear, sadness, and surprise; to analyze successful Engagement in social interactions. Typically, students can experience specific emotions in a learning environment such as feeling concentrated or interested, confused, bored, frustrated, anxious, and ashamed. Specific emotional statuses at a time of learning like enjoyment, concentration, or interest have been associated with learning success. On the other hand, emotions such as confusion, boredom, frustration, anxiousness, and shame are associated with learning failure. Figure 7 is a product of a long-term observation performed by the author of this research during a higher-education course which shows students' body communication in a classic lecture.

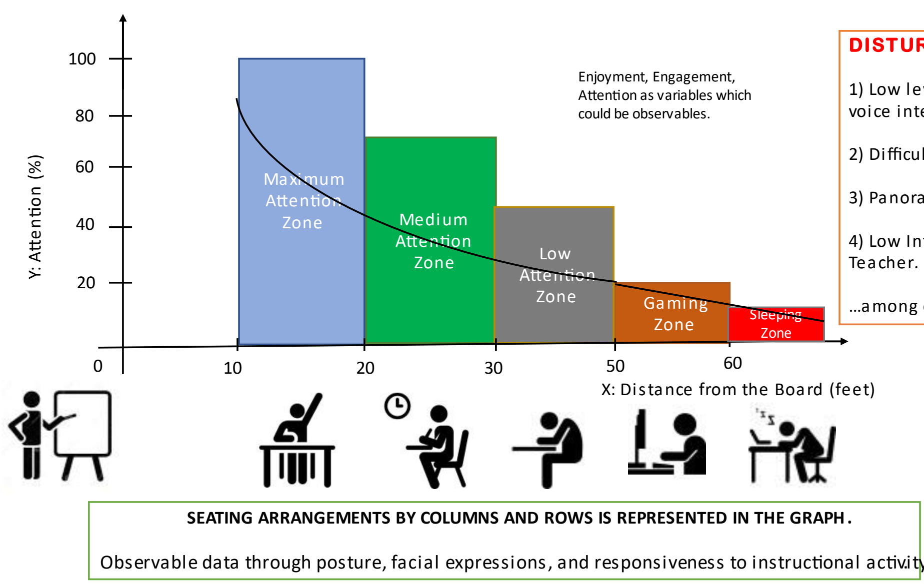

Figure 7. Body Communication in a Classic Lecture.

In my research, somatic responses will be used in parallel by measuring cardiac pulse and oxygen saturation (SpO2) as part of the control variables. Typically, emotions will affect human cognition, which is how people process information. Different channels have been used to define cognitive states and emotions. By using a portable EEG headset [41] it is possible to get student performance metrics by measuring levels of stress, engagement, focus, relaxation, among others.

Engagement (Eng) is qualified as attentiveness and the conscious direction of attention towards task stimuli. Engagement is characterized by increased physiological arousal and beta waves along with attenuated alpha waves. The greater the attention, focus, and workload, the greater the output score reported by the detection. On the other side, Stress (St) measures how comfortable is the student with a task. High stress can cause failure to complete a challenging task. Generally, a low to moderate level of stress can improve productivity, whereas a higher level tends to be destructive and cause long-term consequences for health and well-being. Focus (FOC) is a measure of fixed attention on one specific task. A high level of task switching can cause poor focus and distraction. Relaxation (MED) is a measure of the ability to switch off and recover from intense concentration. Persons who meditate can reach extremely high relaxation scores.

Chapter 3: Research Design and Methods

Brain Computer Interface (BCI) design for educational purposes requires trans-disciplinary knowledge and skills from fields such as neuroscience, engineering, computer science, psychology, physiology, and education, among others. The methodology to be used in this research is based on Neuroscience from a Control Systems perspective. Figure 8 shows the steps followed to develop this research:

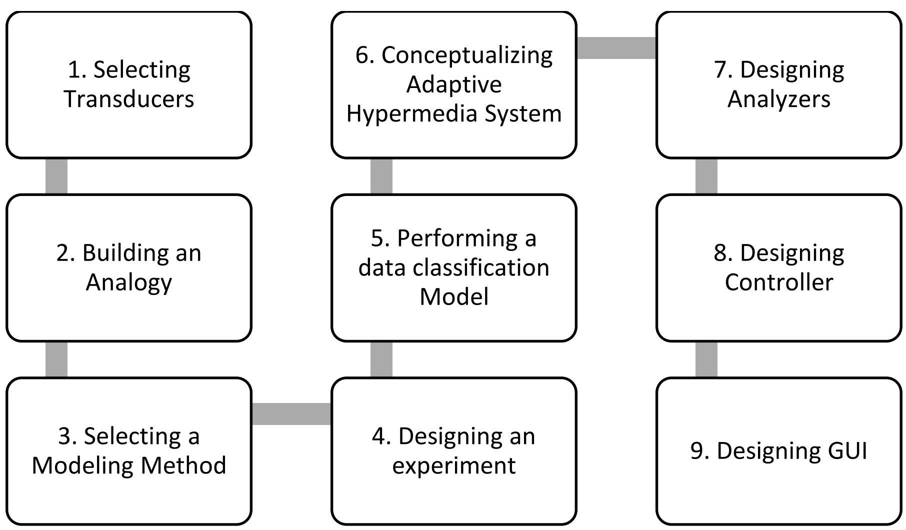

Figure 8. Steps Followed to Develop this Research

3.1 Selecting Transducer Devices

Recent developments in BCI technologies have enhanced the capacity to personalize learning, taking into account not only students' cognitive state, but also a multidimensional perspective that encompasses factors such as emotional, affective, and health states. From a holistic point of view, developing an automation system for monitoring factors impacting student performance in real-time is challenging due to limitations on the use of sensors and transducers to acquire electrical signals in order to infer students' emotional, cognitive, and physical states.

This research will be considering commercial health devices such as EEG, Heart Rate (HR) and SpO2, as the basis (Level 0) of the Automation for Educational Process pyramid that will permit the modeling of a higher level of automatic academic system to supervise and control (Level 1) student performance. Having defined the boundaries and limitations of the commercial devices to be considered in this research. Figure 9 shows the dimensions of learning incorporated into the proposed model.

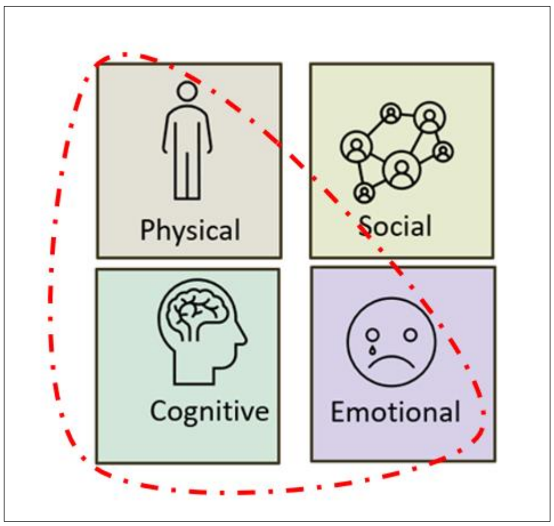

Figure 9. Three Dimensions of Learning to Be Considered in the Proposed Model.

Modeling is a fundamental step in the design and analysis of control systems. This includes understanding their physical components, interactions, and the purpose of the control system by identification of the relevant variables and parameters that describe the system.

Modeling the human learning process is a complex task that involves various aspects, including physical, cognitive, and emotional elements, among others. While these principles and theories can guide the development of mathematical models for human learning, it's important to highlight that modeling the human learning process is by its own nature highly trans-disciplinary and often requires combining insights from psychology, neuroscience, education, and computer science. Since it is not always possible to directly apply physical laws like those in classical mechanics or electromagnetism, there are some fundamental principles and psychological theories that can be used to develop an approximated model for human learning [42] from a Control Systems Engineering perspective.

3.2 Synthetizing the Human Learning System Using Analogies

Analogical thinking involves transferring understanding from one domain to another for the purpose of comparison. For instance, electrons revolving around an atom's nucleus can be compared to how planets orbit the sun. This approach is more accessible because it introduces planetary orbits before examining atomic chemistry. Analogies, though invaluable tools for conveying complex ideas and bridging understanding, inherently possess imperfections due to the essential differences between the objects or concepts being compared. While analogies serve as effective aids in illustrating similarities and facilitating comprehension, their limitations underscore the need for critical thinking and discernment, acknowledging that no analogy can perfectly encapsulate every aspect of the concept it seeks to elucidate.

The power of analogies can be effectively employed for imagining and governing systems using emerging technologies. In [43], the author states that a productive imagination contains existing knowledge that can be transformed by virtue of imagination. That research concludes regarding how analogical imagination and a boosted analogical sense for framing can foster accountable research and innovation. Analogies are not to be understood as a one-way mapping from one domain onto another: this process cannot be seen as a static one but instead as a continual and interactive creation of connections between various instances [44]. Analogies depend on the nature of domains considered to be analogous. There are two types of domains: relation-rich and object-rich domains. Their classification depends on the ratio of objects to relations present in each domain. A greater number of objects than the number of relations is an object-rich domain; otherwise, it is a relation-rich domain. Relation-rich domains are frequently the subject of debate and analysis in discussions about analogy and analogical reasoning. They usually have only a few objects, but many different relations, and the relations hold only between some, but not all, objects. The use of analogies helps to understand some processes within a context, simplifying complex ideas to make them more relatable. Engineers frequently deal with novel and complex problems to solve and often use analogies for conceptualizing the understanding of those systems. In mathematical terms, an analogy can be categorized by an isomorphism where every object of the source is mapped onto a unique object of the target, and every object of the target is assigned an object of the source. By relating the human learning process to an industrial process, it is possible to apply problem-solving techniques and methodologies that have been successfully used in industry to the field of education or human cognition. Analogies allow the transfer of knowledge and best practices from one domain to another by mapping similarities between them. Mapping is nothing but a transformation [45]. But not every transformation keeps all properties of the original object. For example, Gentner's analysis of Rutherford's analogy between an atom and our solar system is based on the two domains consisting of the objects sun, planet, and nucleus, electron: the binary predicates attract and revolve around [46]. Analogies can be valuable, but there are limits to how far the comparison between two domains can be stretched.

In this research, an axiomatic characterization of the analogy has been realized to assess the structural correspondence of the two domains in terms of axioms that, when appropriately interpreted, are true in both domains. These statements then express commonalities between the domains, that is, the positive analogies. Transference of knowledge is used in this research to leverage the author’s expertise in industrial processes control in order to improve educational processes. Similar to how industrial processes incorporate quality control measures to ensure the reliability and performance of their outputs, drawing analogies from these industrial processes can facilitate the creation of tools and metrics for evaluating the quality and effectiveness of educational processes.

3.3 Modeling Using Control System Techniques

To develop a multivariable model of the human learning process from a control systems perspective by considering only three dimensions of learning, which are cognitive, physical, and emotional, it is necessary to evaluate different modeling alternatives in order to select the more suitable model for the target system. Some systems can be represented by mathematical models, by using various modeling techniques and representations depending on the system's complexity, nature, and the purpose of the analysis or design. However, since mathematical models are common and often used in Control Systems Engineering, due to the limitations in the use of physical laws to infer emotional and cognitive behavior in humans, the use of other types of models is proposed in this investigation. Human cognition and learning are highly complex and cannot be reduced to purely industrial terms. Model representation such as block diagrams, Process & Instrumentation Diagrams (P&ID), and methods such as fuzzy logic and machine learning have been used to facilitate the analysis and design of the human learning system. These model representations and modeling methods may be employed when the system's fundamental physics or dynamics are not well understood but can still be controlled effectively. The choice of representation depends on the specific characteristics and requirements of the control system.

3.4 Design of the Experiment Using EEG, Oximeter, and HR Monitor

Student data is collected while performing an Engineering task. The student's cognitive load and emotional state will be inferred through the measurement of brainwaves using EEG. These measurements will then be processed and analyzed by the student diagnosis module. The analyzers of the student's states send the information to the controller to identify the automatic intervention in the teaching-learning system. These measurements are then processed and analyzed by the student diagnosis module after the student completes the task, e.g., reading material, watching videos, assessments, and others, which will be up to 15 minutes long. Learning objectives are presented to the student in a lecture session using a succession of short tasks during the entire session, varying the task level of difficulty, accordingly. Tasks and terms of difficulty will be organized in a pre-defined matrix. In this study, real-time refers to the duration of a class session. However, the student diagnosis module will be processing student's states after each of the short tasks, taking the time to analyze the student's emotional, cognitive, and physical states in order to adjust the difficulty level or type of task involving the academic content for the next task based on the student's previous state. During a lecture, analyzing the student's state for each small task is treated as a batch process. I adopt this approach because analyzing EEG data requires intensive computing power, especially due to the non-linearity of brainwaves.

The experimental set up will use an EEG Emotiv EPOC X14 (headset) and Emotiv PRO (software) to obtain the brainwaves, connected via Bluetooth to a Graphical User Interface (GUI) developed to manage the interaction between the student and the Learning System. Oximetry is the procedure for measuring blood oxygen saturation (SpO2). Wearing an oximeter while performing a task is a safe test. There are no risks associated with Oximeter and EEG, both tests are painless and safe. The psychophysiological variables that will be used that have been classified as *emotional* are Stress (St) and Interest (Int); *cognitive*: Engagement (ENG) and Cognitive Load (CL) and, *physical*: Heart Rate (HR) and Blood Oxygen Saturation (SpO2). The student's states initial conditions will be monitored during the first three minutes of the academic task. Engagement and, Cognitive Load will be computed by using the Pope equation [48].

3.5 Performing a Correlational Study to Validate the Theoretical Frame and Select Brain Channels

Available data collected using a headset equipped with a single-channel EEG sensor [47] has been used to perform a correlational study between variables and to build a preliminary classification model using machine learning techniques for the student from a complex system perspective. The existing dataset was recorded while the student was watching a collection of ten short videos that were previously classified or predefined as confusion and no confusion videos, showing different Science, Technology, Engineering and Math (STEM) topics and varying the comprehension difficulty level from low to high so that could potentially confuse the student. It was expected that the Intrinsic Load (IL) should be reflected by the intrinsic nature of the material and is dependent on the student's level of expertise. The brainwaves were collected to analyze the student confusion level during the entire video collection. In the proposed approach and based on the literature review, emotions such as confusion, frustration, anxiousness, etc., are associated with learning failures when a task imposes a high cognitive load, decreasing student engagement.

3.6 Conceptualizing the Adaptive Hypermedia Control System

Hypermedia system, as described in [48] encompasses diverse forms of information including data, text, graphics, video, and audio, all interconnected through a hypertext program.

The proposed Adaptive Hypermedia System (AHS) is designed to not only control the delivery of academic content, but also to direct the student towards relaxing activities. This is achieved by utilizing a psychophysiological decision tree architecture that is based on principles from neuroscience. This architecture consists of several modules critical to the operation of the AHS (see Figure 10). The processing, i.e., control, is centralized and shared among the sub-modules. Many of the modern AHS frameworks and architectures employ structural decomposition [49].

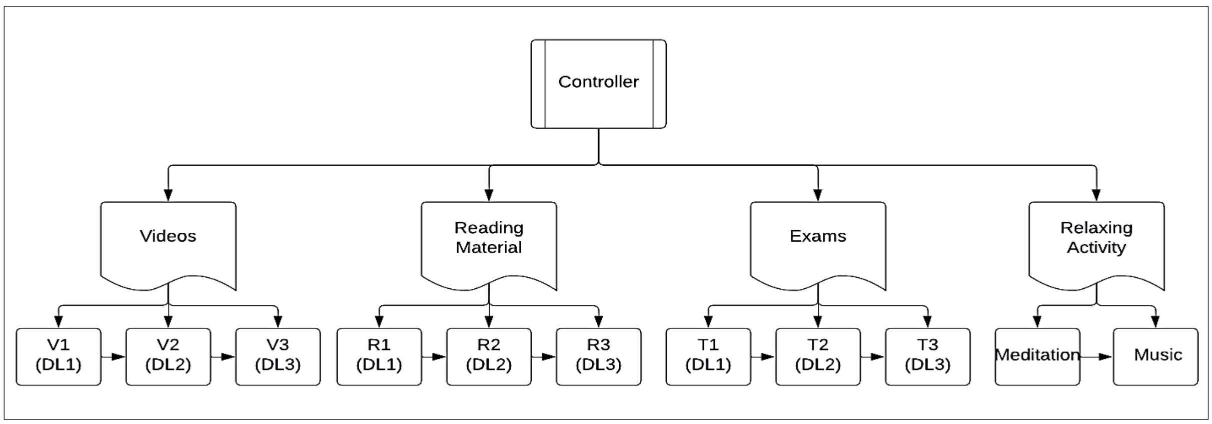

Figure 10. Example of a Structural Decomposition for the Proposed AHS.

In general, this process of decomposition is undertaken either for the purpose of gaining insight into the identity of the basic components, for example, videos, reading materials, exams, and relaxing activities; are to show a compressed representation of the global function. A task which is feasible only when the essential processes possess a certain level of modularity, i.e., independence or non-interaction.

3.7 Designing of Analyzers Using Fuzzy Logic

According to the American National Standard ANSI/ISA-5.1 for Instrumentation Symbols and Identification, the standard establishes a uniform way to identify instruments or devices, their inherent functions, and application software functions used for measurement, monitoring, and control. This standard will be followed to build a P&ID of the student learning process as a feedback control system. The analysis and processing of students' EEG data, along with other physiological variables, will be conducted using algorithms named "Analyzers." These will include a time delay to accommodate for the complexity of the required analytical operations. The analysis becomes, in effect, a batch process in which a sample is extracted from the process stream and examined, much like it would be if manually taken to a laboratory for analysis. This process can be automated and scheduled to occur at appropriate intervals. However, real-time measurement of student cognitive, emotional, and health variables poses challenges. These variables are not easily observable in the classroom by an instructor, which makes the execution of individual control operations like setpoint changes, auto-manual transfers, or on-off operations a complex process. The proposed design of the "Analyzers" of the student's emotional, cognitive, and physical states using brainwaves data and health measures is based on Fuzzy logic membership functions. The membership functions are generally represented in graphical form with value ranges in the interval [0,1]. There are certain limitations to the shapes used to represent the graphical form of membership functions. A membership function can be assumed as a technique for solving empirical problems relying more on experience than knowledge. The method of assigning membership values could be intuitive or based upon common human intelligence. Each curve is a membership function corresponding to various fuzzy (linguistic) variables such as high, medium, normal, low, etc. Knowledge of geometrical shapes is used for defining membership values. The membership functions may be defined by various shapes: triangular, trapezoidal, bell-shaped, and Gaussian [50]. Available probability information can also help in constructing membership functions.

3.8 Desing of Controller

A student’s emotional, cognitive, and physical states at a given time are determined by the current state of his/her mind. Those states can be influenced by positive or negative inputs across the human sensory system. A model of states transition was presented by [51]: that approach will be considered in this research to establish the mathematical basis of the Fuzzy Adaptive controller. The controller will determine the task difficulty and select different types of tasks based on the student's state. This includes choosing academic tasks such as videos and reading materials in the academic module, as well as relaxing videos in the relaxation module. The files have been previously classified according to a predetermined level of difficulty. Figure 11 shows the proposed model of states transition by considering dependencies between variables.

When faced with a negative input, a student's state can shift from Engaged to Stressed or Distressed. While good stress can be inspiring, motivating, and focus energy to enhance performance, bad stress, or distress, is detrimental to health.

Figure 11. Proposed Student State Transition Graph

Distress may result in anxiety, confusion, poor concentration, and a decrease in performance. When the cognitive load of a task is increased, it might cause a distressed student's Heart Rate (HR) to rise. This is due to the escalating negative influence, leading to an orderly transition of the student's emotional states. A similar process occurs with positive influences, which gradually transition the student from a state of stress to one of interest. Figure 12 illustrates the transition of student states in a precise sequence, for both positive and negative inputs.

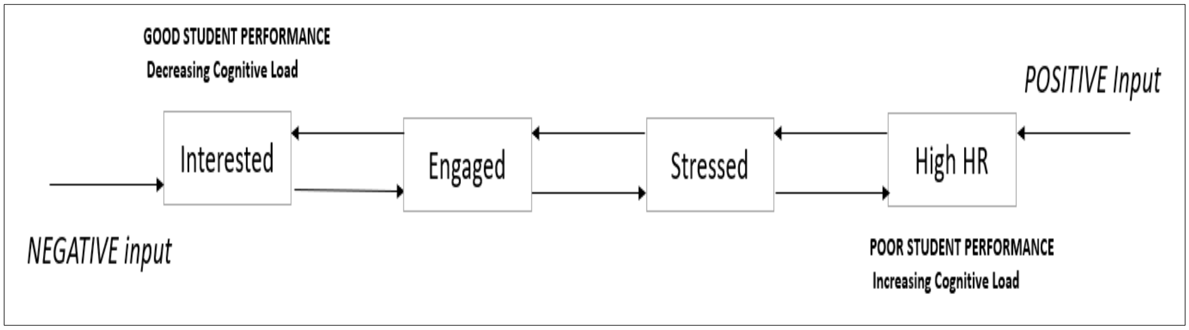

Figure 12. Transition Graph Varying Task Level of Difficulty as a Positive or Negative Input.

Considering the student state transition dynamics for i=1 to n, a complete representation of the system in terms of a vector-matrix form is shown in the following equation:

$$\mathbf{M}(\mathrm{t}+1) = \mathbf{W}.\mathbf{M}(\mathrm{t}) + \mathbf{B}\boldsymbol{\mu} - \mathbf{C}\boldsymbol{\mu}' \quad (1)$$

whereas:

M: Unnormalized membership vector of dimension nx1, whose i_{th} element denotes a singleton membership of state i at time t.

$\boldsymbol{\mu} = [\mathrm{POS}(\mathrm{strength}_k, \mathrm{t})]$ Positive influence membership vector of dimension mx1 whose kth component denotes the fuzzy membership of strength k of the input stimulus.

$\boldsymbol{\mu}' = [\mathrm{NEG}(\mathrm{strength}_l, \mathrm{t})]$ Negative influence membership vector of dimension mx1 whose lth component denotes the fuzzy membership of strength l of the input stimulus.

B: nxm companion matrix to $\boldsymbol{\mu}$ vector.

C: nxm companion matrix to $\boldsymbol{\mu}'$ vector.

The membership vector M must be normalized between [0,1] to facilitate the interpretation of state transition dynamics. The weight matrix **W** is shown in Table 4:

Table 4. Weight Matrix W

	Interested	Engaged	Stressed	HR
Interested	$W_{1,1}$	$W_{1,2}$	$W_{1,3}$	$W_{1,4}$
Engaged	$W_{2,1}$	$W_{2,2}$	$W_{2,3}$	$W_{2,4}$
Stressed	$W_{3,1}$	$W_{3,2}$	$W_{3,3}$	$W_{3,4}$
HR	$W_{4,1}$	$W_{4,2}$	$W_{4,3}$	$W_{4,4}$

In the student learning process, a ratio between Engagement and Stress will keep the flame for learning burning:

$$\mathrm{r} = \mathrm{Eng}/\mathrm{St} \quad (2)$$

A higher TD level is required for improving student performance, always having the St at proper levels.

Physiological responses such as increased blood oxygen saturation (SpO2) as well as decreased Heart Rate (HR) have been associated with good cognitive performance [52] .

As a safety factor to assure the health of the student, either High Heart Rate or Low SpO2 will be considered as an emergency condition.

$$\mathrm{Ec} = \begin{cases} \mathrm{HHR} \\ \mathrm{or} \\ \mathrm{LSpO2} \end{cases} \quad (3)$$

In the student learning process model, the delivery of academic content will be based on the CL as a controlled variable. Scaling the measured CL as a low, medium, or high; the system will assign a TD level to the next task according to the ratio: r = Eng/St. The control of the student Engagement (Eng) and Stress (St) will be considered as internal variables for the hypermedia system that will select from among three different types of instructional materials: 1) Videos, 2) Reading Materials, and 3) Exams. The time between tasks will permit the student to relax while the educational system is processing the psychophysiological data to be used as biofeedback for the controller to change the Task Difficulty (TD) level for the next task. During the relaxing time, the student will be guided to listening to music according to the level of Stress (St) presented in the previous task.

The benefits for controlling a student learning system include:

- Complete automation for "startup and shutdown" of student knowledge acquisition & control system based on cognitive load and Engagement during an academic task.
- The academic content supply is controlled precisely by adjusting the task difficulty level. With the adaptive controller, each student operates at their own pace with no-time constraints, avoiding high pressure or stress.
- The Teaching/Learning process involves areas such as psychology, physiology, and education. All these areas coexist to represent a multivariable system.

3.9 Desing of GUI

A graphical user interface has been developed for transferring and showing files using familiar icons to create an environment in which computer operations are intuitive and easily mastered by the student.

The graphical user interface must be self-descriptive, with immediate feedback, and have visual indications giving confidence and driving curiosity, as shown in Figure 13.

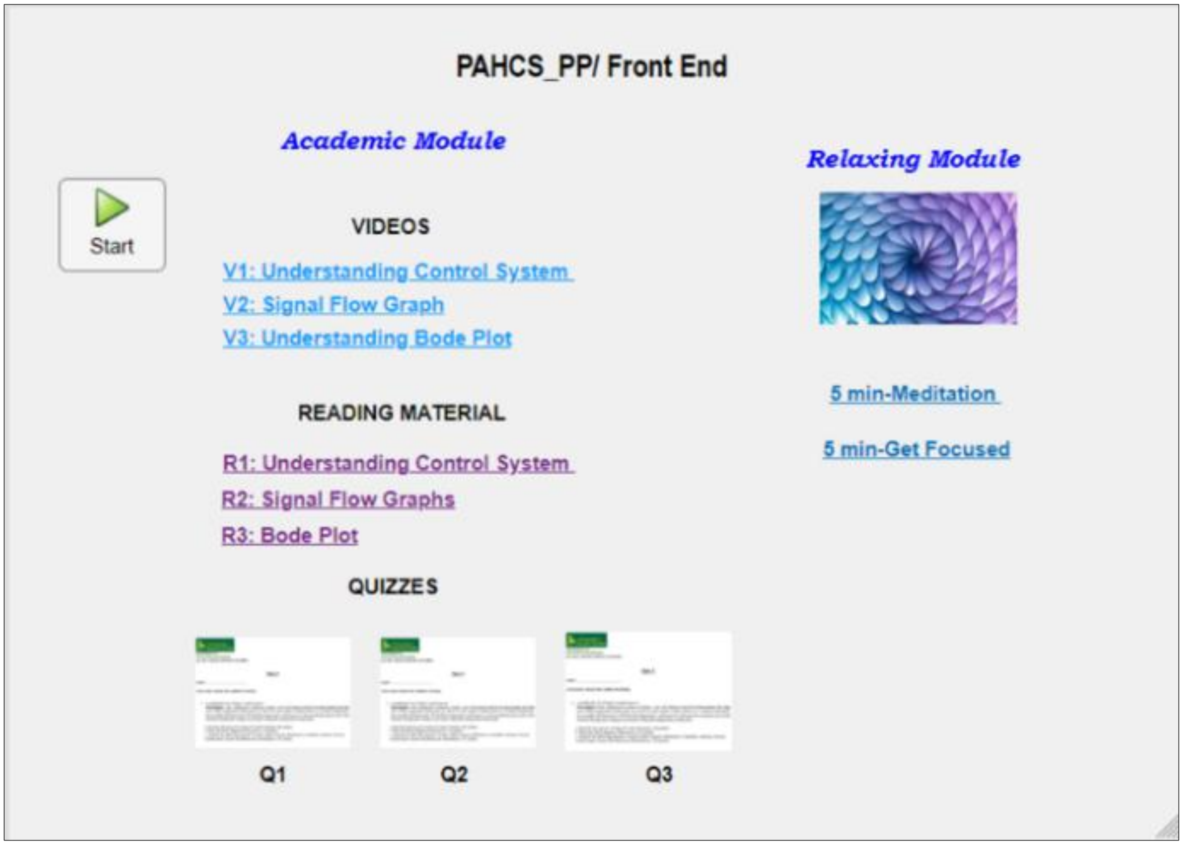

Figure 13. Preliminary Design of the GUI

Chapter 4: Building an Analogy Between a Simplified Steam Boiler and the HLS

In this section, an analogy will be presented to develop a multivariable model of the learning process, using an adaptive automation framework. This analogy compares the learning process to the multivariable control used in industrial steam boiler processes. Similar to educational systems, steam boilers are represented as Multi-Input Multi-Output (MIMO) systems in terms of process control.

The act of drawing an analogy between the process of student learning and that of a steam boiler represents an innovative research contribution. The purpose of establishing the analogy between the steam boiler and the human learning process is to gain insights into the intricacies of the human learning process as a complex system in contrast to the well-defined industrial process. This approach aims to shed light on the connections between various factors and provides a means to simplify the comprehension of this complex system.

Conventional industrial steam boilers are classified as pressure equipment. They operate by igniting a flame, created through a burner fueled by either liquid or gaseous fuel. This flame, following a heat exchange process, raises the temperature of the water within the boiler. Subsequently, this heated water can be utilized to produce steam or superheated water [53].

There are two boiler types for steam applications: firetube boilers and watertube boilers. In a firetube boiler, combustion gas travels inside a series of tubes immersed in water within a vessel to generate steam. Firetube boilers (see Figure 14) utilize a design in which combustion fumes travel through the boiler's tube bundle, transferring their heat energy to the surrounding water. Eventually, these fumes exit into the atmosphere through the chimney.

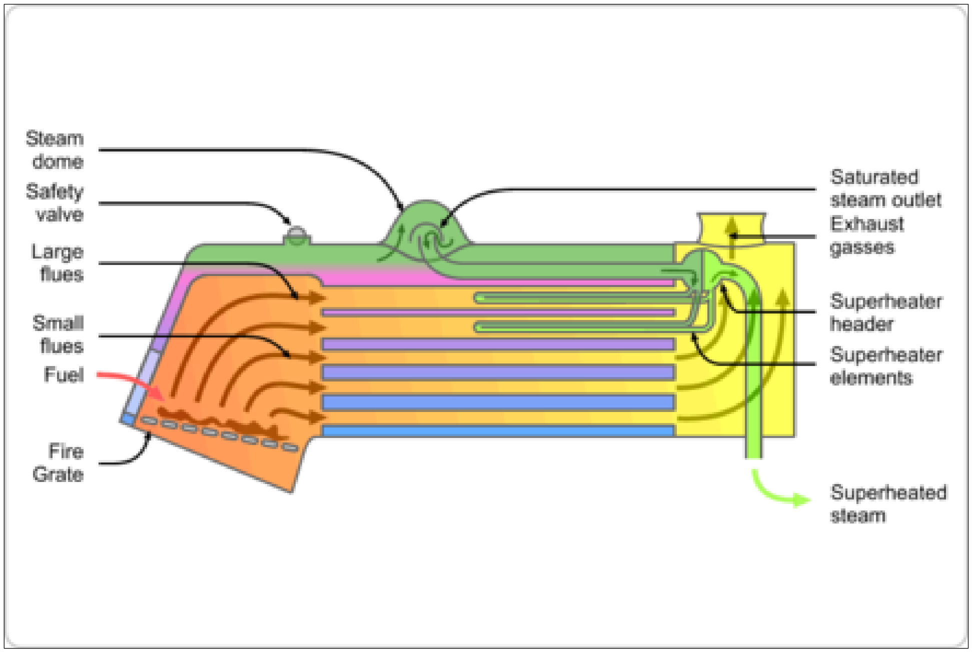

Figure 14. Firetube Boiler [54]

Key components of a firetube boiler include: a) a burner that generates combustion by mixing fuel with an oxidizer; b) a furnace or combustion chamber where the combustion flame is generated and serves as the initial location for gas/water heat exchange; c) a tube bundle gas circuit: combustion gases circulate through this region, often involving two passes; d) a firebox in this section temporarily stores and redirects exhaust gases before expelling them through the stack, typically having both front and back gas boxes; e) a water chamber: this part of the boiler is immersed in water; f) a steam chamber: located above the water chamber, it stores the steam produced, and g) a chimney/stack: an isolated duct designed to vent exhaust fumes outside.

On the other hand, in a watertube boiler, see Figure 15, water flows through a series of tubes surrounded by combustion gas, which transfers heat energy to produce steam.

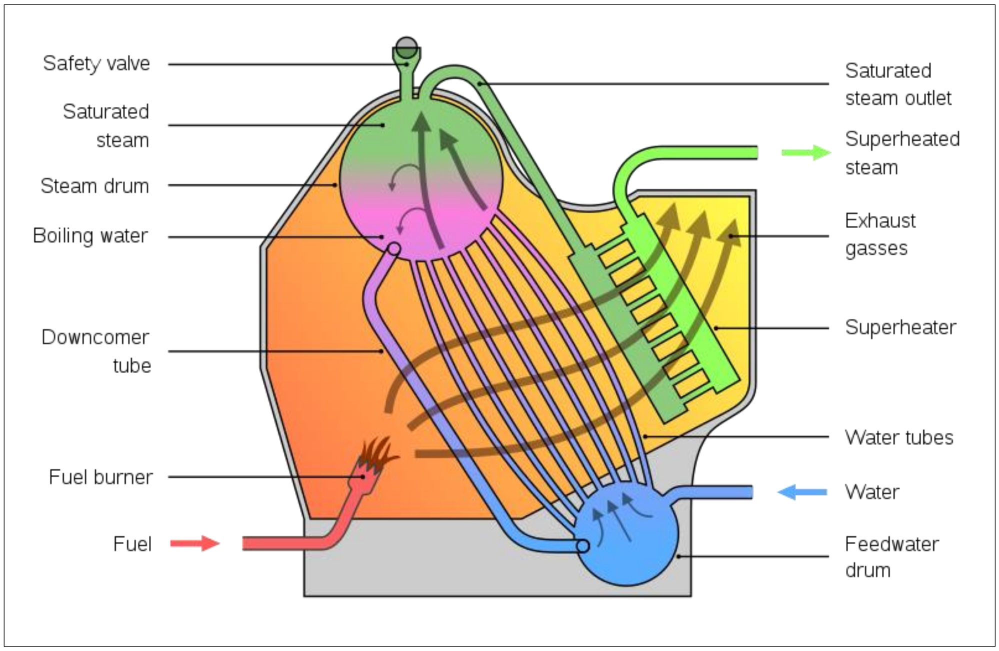

Figure 15. Watertube Boiler Diagram [55] .

In boilers, increasing the number of passes in the tube bundle of a boiler serves several purposes, and the specific reasons may vary depending on the type and the design of the boiler.

The number of passes refers to the number of times the combustion gases or hot flue gases travel through the tube bundle before exiting the boiler. Increasing the number of passes in a boiler improved heat transfer efficiency since the number of passes provides more opportunities for heat transfer from the hot combustion gases to the water or steam within the tubes. This enhances the overall heat transfer efficiency, ensuring that more heat is extracted from the combustion gases, thereby increasing the boiler's thermal efficiency. It's important to note that increasing the number of passes also has implications for boiler design, cost, and complexity. Therefore, the decision to increase the number of passes in a boiler should balance the benefits of improved heat transfer against the practical constraints and operational requirements of the specific application.

A brief description of the functioning of a boiler is as follows: The downstream process controls steam flow from the boiler. A sudden increase or decrease in demand for steam flow will change the pressure in the steam drum and boiler piping. The change in drum pressure will cause a change in the boiling point of the steam which will imply a higher water level demand. This increase in water level is proportional to an increased steam flow rate and decreased drum pressure. The steam boiler drum water level is one of the controlled variables (loop 1) and it uses the inlet water as a manipulated variable, see Figure 16. The second controlled variable is the stream pressure on the steam boiler output (loop 2) that uses the fuel flow entering the burners as a manipulated variable.

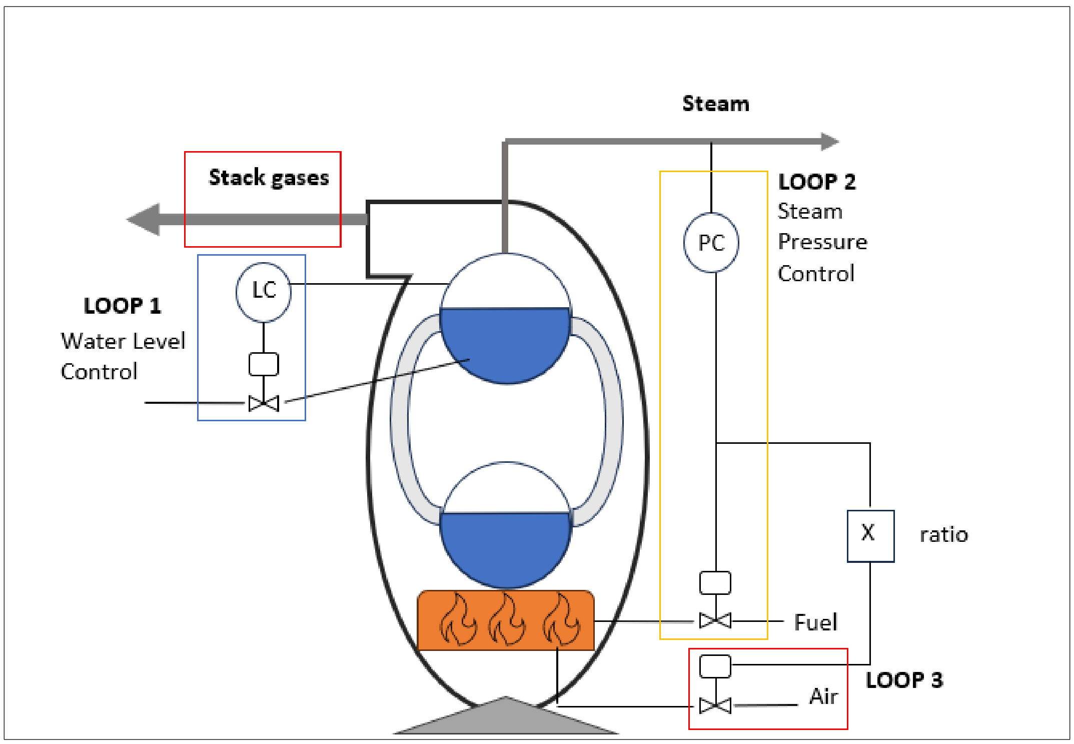

Figure 16. Control with Adjusted Fuel/Air Ratio for a Boiler.

Finally, the excess of oxygen in the outlet flow of the gas's combustion is the third controlled variable (loop 3) and, it uses the injected flow air as a manipulated variable. In the steam boiler process, a ratio control is used to regulate the air/fuel ratio entering the boiler furnace. The ratio control architecture is a strategy where one variable is manipulated to maintain a specific ratio or proportion relative to another variable [56].

Air is essential for fuel combustion. To ensure complete combustion as a safety measure, boilers are operated with excess air. Since water quality can be a limiting factor in boiler efficiency, it is necessary to filter the water for optimal operation.

Mapping variables between the boiler control system to the learning process is an important step in the process of building the proposed analogy. Thus, the downstream process (*working memory demand*) controls steam flow (*knowledge flow*) of the boiler (s*tudent learning process*). A sudden increase in demand for steam flow (*knowledge flow*) will change the pressure in the steam drum and boiler piping (*cognitive load*). The variable *knowledge* can be considered as an indirect variable proportional to *Engagement*. The change in the drum pressure will cause a change in the boiling point of the steam (*attention*) and a higher water level demand (*task difficulty*). This increase in water level demand (*task difficulty*) is proportional to an increased steam flow rate (*knowledge flow rate*) and decreased drum pressure (*cognitive load*). In the steam boiler process (*student learning process*) a ratio control is used to regulate the fuel, i.e., regulate task difficulty by manipulating Engagement (*Engagement*)/air (+*stress*) ratio entering the boiler furnace (*emotions*). Air (+*stress*) is required for the combustion of the fuel (*Engagement*). As a safety factor to assure complete combustion, boilers are fired with excess air. Figure 17 shows a comparative representation of both processes:

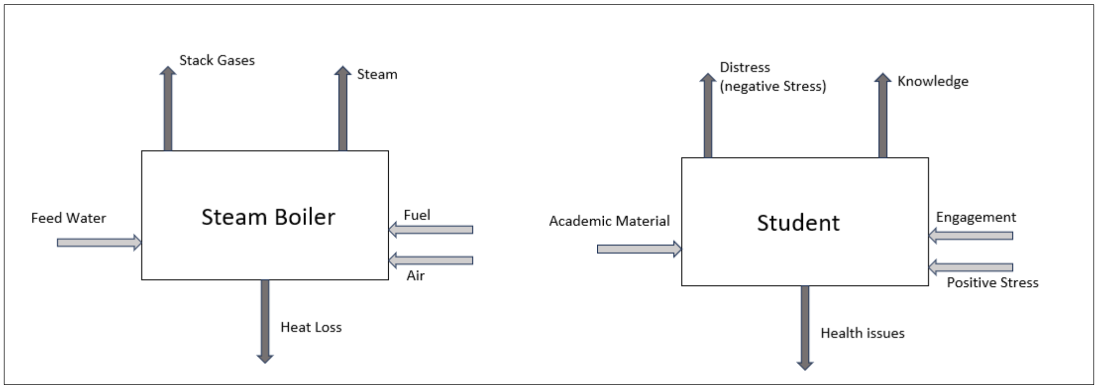

Figure 17. Boiler and Student Processes' Comparative Representation of Inputs and Outputs.

When water starts boiling, i.e., producing steam, it is equivalent to the human learning system to start transferring the knowledge from the short-term memory to the long-term memory. That energy transfer must be at a controlled rate, otherwise if the steam rate is incremented to a very high level having a limited volume in the boiler's drum (*limited short-term memory*), it could explode, analogous to the student collapses turning the alarms on. The quality of the instructional material is equivalent to the quality of the water, and it can be a limiting factor for acquiring knowledge, therefore, it also needs to be filtered to ensure that the human learning system operates most effectively, i.e., reducing the Extraneous Load (EL). On the other hand, to acquire knowledge and move the process forward, the fuel (*Engagement*) must be increased progressively, since a high fuel rate cannot be burned by the furnace, i.e., knowledge would not be stored in the limited short-term memory. If the academic system keeps feeding information to a student whose memory is already full, the information can't be processed effectively, leading to the student becoming overwhelmed potentially impacting their physical health. The "Fire of Learning" is maintained with a balanced amount of positive stress (+stress). *However,* too much distress (-stress) can turn the fire off. The steam transfer in the industrial boiler will be equivalent to the knowledge transfer from short-term memory to long-term memory in the human learning system. Since drum pressure will be represented by the *Cognitive Load* in the human learning system, if steam production continues, the pressure or Cognitive Load will be kept stable. If the Cognitive Load becomes excessive, the Engagement decreases.

The following set of equations shows the mass balance and energy balance of a general industrial boiler. The variables which are considered in the system are volume (V), relative density (ρ), internal energy (U) stored in the mass, enthalpy (H), temperature (T), mass flux (q) and heat of metal (c). In addition, the subindex, t, represents total, the total mass (mt) of the system, i.e., the mass of drum and pipes. A mass balance, also called a material balance, is an application of conservation of mass principle to the analysis of physical systems.

The equation (4) shows the Boiler Mass Balance:

$$\frac{d}{dt}(\rho_s V_{st} + \rho_w V_{wt}) = Q_f - Q_s \quad (4)$$

As an analog, the Student Mass Balance can be described as:

$$\frac{d}{dt}(\rho_K V_{Kt} + \rho_{AM} V_{AM}) = Q_{AM} - Q_K \quad (5)$$

whereas:

K: knowledge, IM: instructional material, ρ_K knowledge density which is equivalent to the # number of learning objectives learned/per task and ρ_{IM} is equivalent to # number of learning objectives taught/per task.

$$\frac{d}{dt}\left(\frac{\text{\# of object learned}}{\text{per task}}\ V_{Kt} + \frac{\text{\# of object taught}}{\text{per task}} V_{IM}\right) = Q_{IM} - Q_K \qquad (6)$$

The Boiler Energy Balance is:

$$\frac{d}{dt}\left(\rho_s U_s V_{st} + \rho_w U_w V_{wt} + m_t c_p t_m\right) = Q + Q_f H_f - Q_s U H_s \qquad (7)$$

whereas the internal energy (U) can be expressed in terms of Enthalpy (H), Pressure (P) and Volume (V):

$$U = H - PV \qquad (8)$$

As an analog, the Student Energy Balance is:

$$\frac{d}{dt}(\rho_K Int_K V_{Kt} + \rho_{IM} Int_{IM} V_{IMt} + St) = Q + Q_{IM} Int_{IM} - Q_K Int_k * Eng_K \qquad (9)$$

whereas internal energy (U) will be the intrinsic motivation or Interest (Int) and can be expressed in terms of Enthalpy (H): Engagement (Eng), Pressure (P) represents Cognitive Load (CL) and Volume (V), i.e., short-term memory capacity:

$$Int = Eng - CL * V_{Short} \qquad (10)$$

Consider the short-term memory capacity as a constant (c), CL as a function of level of Difficulty (TD), Type of Task (T), and previous Knowledge (Kprevious):

$$CL = TD * T/Kprevious \qquad (11)$$

Substitute:

$$\frac{d}{dt}(\rho_K Int_K V_{Kt} + \rho_{IM} Int_{IM} V_{IMt} + St) = Q + Q_{IM}(Eng - CL * V_{Short})_{IM} - -Q_K(Eng - CL * V_{long})_k * Eng_K \qquad (12)$$

The set of equations for the analogy between the Human Learning Process and the Steam Boiler Process represents an approximation based on the proposed analogy and the mapping of variables.

Increasing the number of passes in a boiler's tube bundle can be likened to increasing the repetition or exposure time of a student to a specific learning objective. This enhancement in the boiler design allows for more efficient heat transfer, similarly to how repeated exposure to instructional material can improve a student's ability to transfer and retain knowledge in their long-term memory. Essentially, just as more passes in a boiler provide greater opportunities for heat to be efficiently transferred, providing students with more opportunities to engage with the instructional material in an educational context, results in a more effective transfer of knowledge from the academic program to the student.

Another important concept to be considered here is the "Fire Combustion Triangle," which is a concept in fire safety that identifies the three essential components required to sustain a fire: fuel, heat, and oxygen.

Interest and motivation have a substantial influence over cognitive performance and academic success. They share a strong connection with a student's level of effort, constituting a fundamental element of intellectual involvement in the educational setting. Based on that, then, what is the analog of heat in the human learning system? Motivation could be the first variable to consider, however, due to the limitations on automating the measurement of this variable, interest in learning, or relevance of the instructional material to the student will be considered as the analog to heat in the human learning system. In a thermodynamic system, the three ways to transfer heat energy have been defined as: convection, conduction, and radiation. In a learning environment, it will be possible to use different types of tasks, for instance, videos, reading material, teamwork, presentations, game activities, among others, as ways to facilitate the transfer of knowledge to the student.

Now, an analogy between the concept of Fire Combustion Triangle and the process of learning taking into account emotional factors is being proposed in which effective and passionate learning can be described by identifying three key necessary elements for its achievement. They are described as:

- Emotional Fuel: Just as fuel is essential to ignite and sustain a fire, emotions act as the fuel for learning. When students are motivated and invested in their learning, their curiosity, interest, and Engagement become the emotional fuel that drives the learning process. Like the right kind of fuel to keep the fire going, the right emotional state can be essential for igniting and sustaining a passion for learning.
- Emotional Heat: Heat is what transforms fuel into the energy that powers a fire. In the context of learning, Emotional Heat represents the interest and passion with which students Engage with the subject matter. When students are emotionally connected to their studies, their excitement, determination, and persistence provide

the “emotional” heat that propels them to tunnel deeper into the material and overcome challenges.

- Emotional Oxygen: Just as oxygen is necessary for sustaining combustion, Emotional Oxygen in learning is the supportive and encouraging environment that pushes students to reach their learning objectives. Emotional Oxygen keeps the Fire of Learning burning brightly.

This analogy highlights the idea that effective learning is not just about the acquisition of knowledge; it is also about nurturing emotional states. When these emotional factors align, they can ignite a passion for learning and sustain it, just as fuel, heat, and oxygen all work together to sustain a fire.

Another novel contribution of this research is the analogy of the concept of the combustion triangle applied to the education field. The combustion triangle is a simple model for understanding the necessary ingredients for most fires.

A fire occurs naturally when the elements are present and combined in the right mixture. Thus, the Learning Fire Triangle, just like the Fire Combustion Triangle, requires three components to ignite and sustain the fire. In this research, those three ingredients that sustain the flame of learning have been determined as: Interest (Heat), Stress (Air) and Engagement (Fuel) (ISE), as shown in Figure 18.

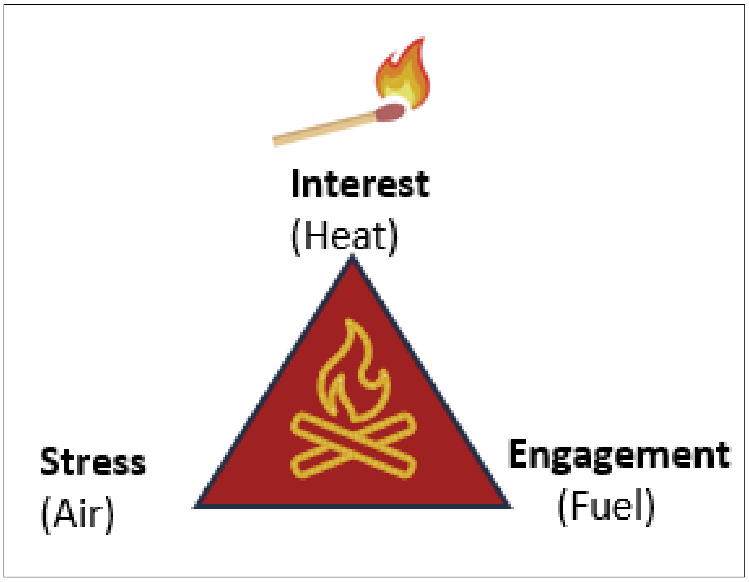

Figure 18. Learning Fire Triangle Overview.

A P&ID is a schematic illustration that shows the relationship between piping, instrumentation, and system equipment components: it has been used in the engineering field to describe the overall engineering processes of a physical process flow. Those diagrams were created by engineers to design a manufacturing process for a physical plant. P&IDs are often used in industrial projects such as Steam Boilers. From an engineering perspective, depicting the Student as a Plant aids in enhancing comprehension of the system, facilitating analysis, and enabling control over variables. Figure 19 shows a schematic of the proposed educational model based on the analogy between a Steam Boiler and the Human Learning Process.

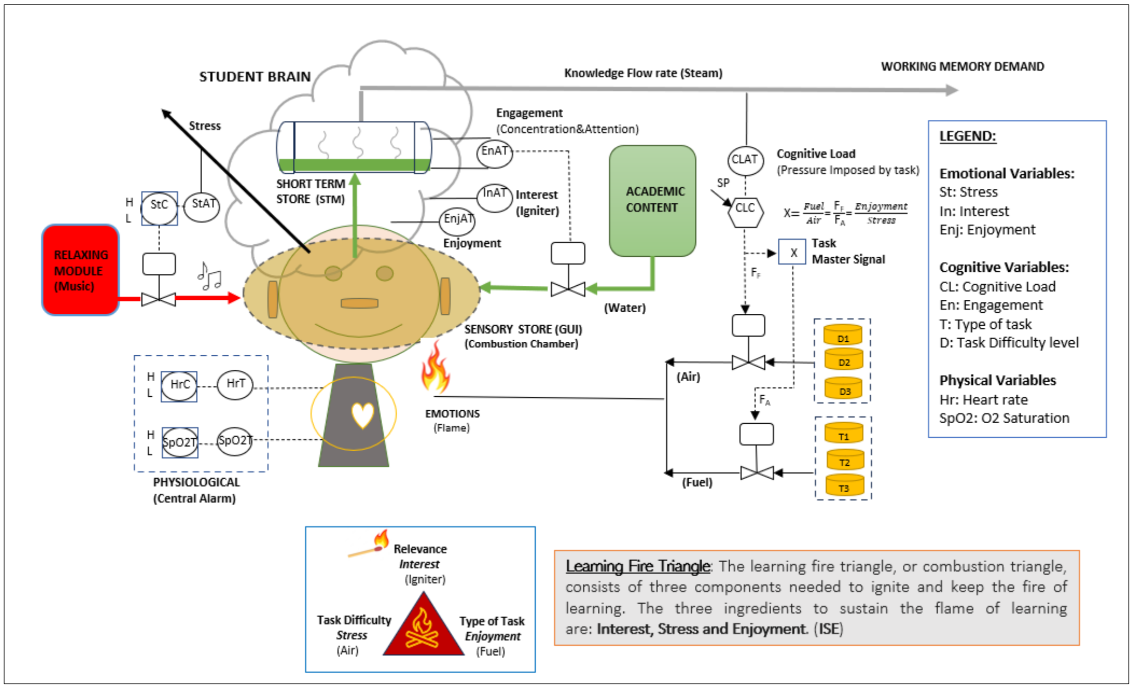

Figure 19. Schematic of Proposed P&ID Model.

Table 5 displays the variables mapping between a Steam Boiler and the Human Learning System, laying the foundation for the analogy.

Table 5. Matching Variables between a Steam Boiler and a Human Learning System

Boiler Parameter	Student Learning Parameter
Downstream Process	Working Memory Demand
Steam Flow Demand	Knowledge Flow Demand
Drum Pressure	Cognitive Load
Boiling Point of Steam	Attention
Water Feed	Task Feed
Water Level	Task Difficulty
Air Flux	Stress
Heat	Interest or Motivation

Chapter 5: Low Alpha, Low Beta, and Theta Brainwaves Bands to Predict Student Engagement Using Machine Learning Methods[1]

This chapter incorporates a published paper [46]. This chapter answers the second dissertation research question. To analyze student cognitive state in terms of 'confused' or 'not confused.' The study proposes a student cognitive load framework using Machine Learning methods, as shown in the Figure 20:

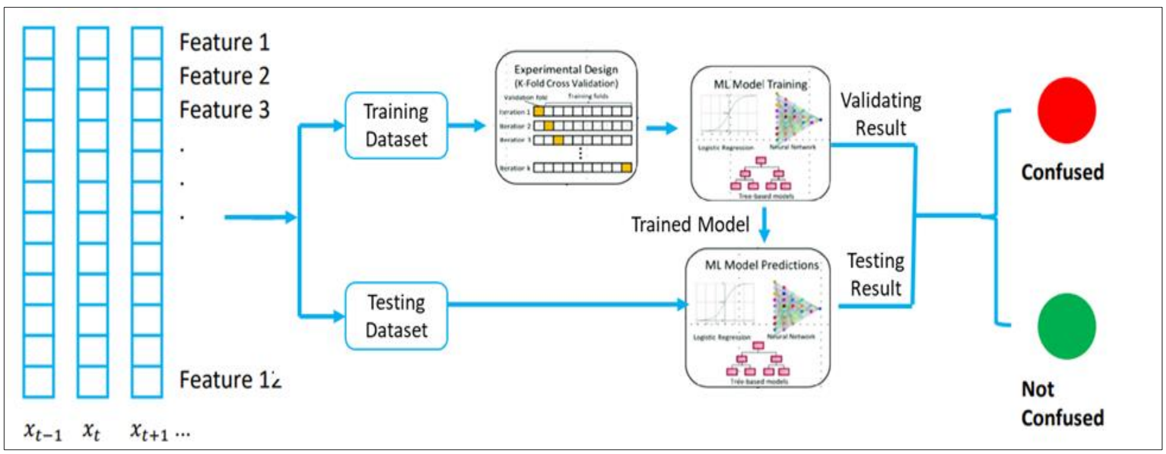

Figure 20. Framework Based on Machine Learning Methods.

The data collected from the EEG dataset is first preprocessed using the feature selection process. Feature selection is a crucial step for any data processing model. The primary purpose of feature selection is to select a subset of features that are more relevant than the target variable.

[1] Villavicencio, L.; Singh, P. and, Moreno, W (2022). "Low Alpha, Low Beta, and Theta Brainwaves Bands to Predict Student Engagement using Machine Learning Methods". International Journal on Computational Science & Applications (IJCSA) Vol.12, No.4, August 2022. [48]

Hence, by applying feature selection, the learning algorithms of the model can be improved by reducing redundant and irrelevant data. Then, different feature selection methods are applied to obtain the most relevant features; each feature is compared with the target variable to see its importance. Figure 21 shows the feature rank after using the feature selection algorithm.

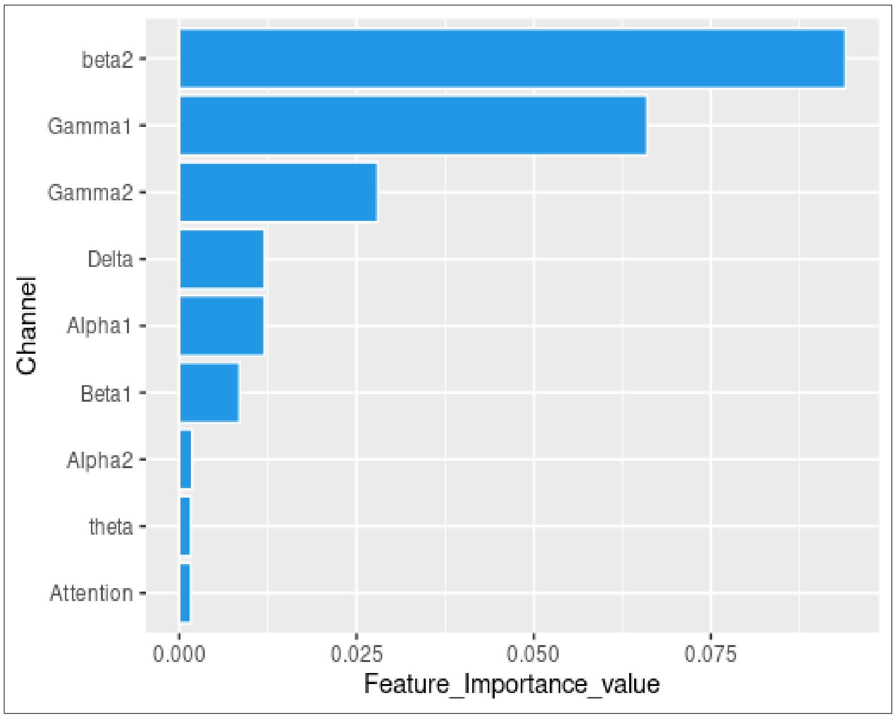

Figure 21. Filter-Based Feature Selection Evaluation

Another feature selection method implemented is a correlation matrix with a heatmap. The correlation matrix evaluates if the features within the Dataset are positively related (increase one’s value with increased value in target variable) or negatively related (increase one’s value with the decreased value in target variable) to the target variable. Figure 22 shows the correlation matrix using the heatmap:

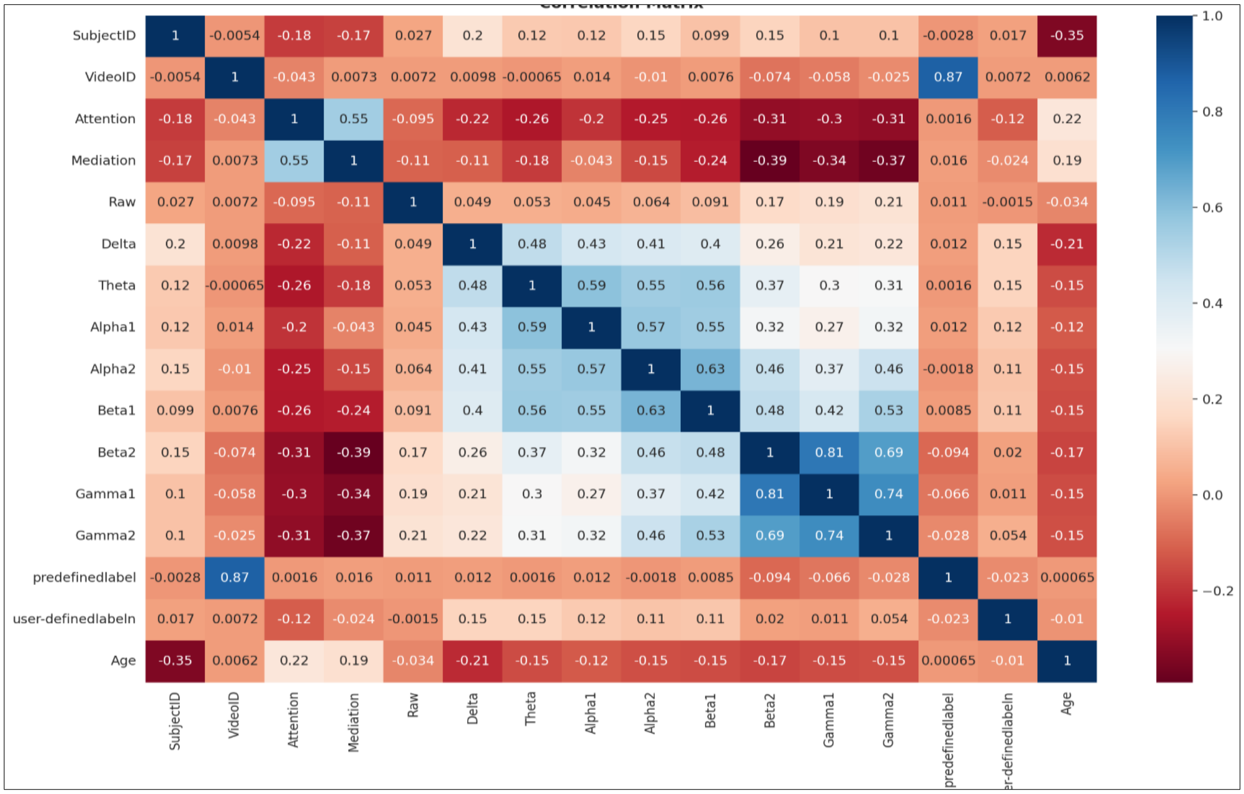

Figure 22. Correlation Matrix Using Heatmap.

To conclude regarding the correlation matrix, it can be said that beta2 is highly negatively correlated and alpha1 is highly positively correlated in the EEG channel band.

The intrinsic cognitive load is reflected by the material's intrinsic nature and depends on the student's level of expertise. The student’s comprehension level is affected by the task's intrinsic load. Task complexity level and student expertise will reflect the confused brainwave behavior while watching the complete videos. In our approach and based on the literature review, emotions such as confusion are associated with learning failures when a task imposes a high Cognitive Load, decreasing student Engagement. The data were collected on the forehead Fp1, defined by the International Electrodes Positioning System:10/20. Table 6 shows an analysis of the correlation between brainwaves and low and high CL:

Table 6. Correlation Between Brainwaves and Low/High Cognitive Load Using Neurosky Headset.

	Correlation with CL	**Waves + correlated**	ρ	**Waves - correlated**	ρ
1	Highest	$\alpha 1$	0.012	$\beta 2$	-0.094
2	Medium	$\beta 1$	0.0085	$\gamma 1$	-0.066
3	Lower	θ	0.0016	$\gamma 2$	-0.028

The highest positive correlation found was $\rho = 0.012$ corresponding to $\alpha 1$. The lower alpha band ($\alpha 1$) appears to reflect attentional processes. The second highest correlation ($\rho = 0.0085$) corresponds to the low beta waves (12–15 Hz) known as "$\beta 1$," which are associated mostly with quiet, focused, introverted concentration. This result is aligned with the literature review and the intrinsic load imposed by the task (video). According to the literature review, theta (θ) power increases with increased Cognitive Load and is most prominent at the central frontal location. All three bands are strongly correlated with CL; thus, these results show how the theoretical frame based on neurosciences is validated.

It is essential to point out that the negatively correlated brainwaves are highly correlated. To evaluate the model performance, a model design was performed using three machine learning approaches: Long Short-Term Memory (LSTMs), which are capable of learning long-term dependencies, making RNN advance in remembering things that have happened in the past and finding patterns across time to make its next guesses make sense; Deep Neural Networks (DNNs) in which data flows from the input layer to the output layer without going backward, and the links between the layers go one way, which is in the forward direction, and never touch a node again; and, also, LSTM combined with Convolutional Neural Networks (CNNs), to improve data processing.

One can see that the LSTM model achieved 65.39% accuracy with 50 epochs, the DNN model achieved 66% accuracy with 74 epochs, and CNN+LSTM achieved 75% accuracy with 100 epochs. The results are shown in the following Table 7:

Table 7. Average Accuracy Using Different Machine Learning Methods.

Type of Classifier	**Epochs**	**Accuracy (%)**
Long Short-Term Memory (LSTM)	50	65.39%
Deep Neural Network (DNN)	74	66.00%
Convolutional Neural Network (CNN) + LSTM	100	75%

The results show that CNN+LSTM outperforms the other two methods, indicating that a combination of Convolution Neural Network and LSTM can yield better results when compared with individual models such as LSTM or DNN.

In conclusion, low alpha, low beta, and theta are the bands most correlated with student cognitive confusion. Based on this, the student Engagement index was calculated using the formula beta / (alpha + theta) developed by (Pope et al., 1995). Cognitive confusion and Engagement are strongly correlated (p= 0.625). A CNN+LSTM model based on Machine Learning has been used to analyze student brainwaves correlated with cognitive confusion. The accuracy achieved by our model using the CNN+LSTM algorithm is higher than other machine learning methods.

Chapter 6: Design of the Psychophysiological Based Hypermedia Adaptive Automation System (PPHAAS)

A multidimensional model based on control systems that integrates the cognitive, emotional, and physical variables of a student, represented as a steam boiler, will provide a holistic understanding of the student's learning and well-being.

Figure 23 shows the architecture of the proposed PPHAAS:

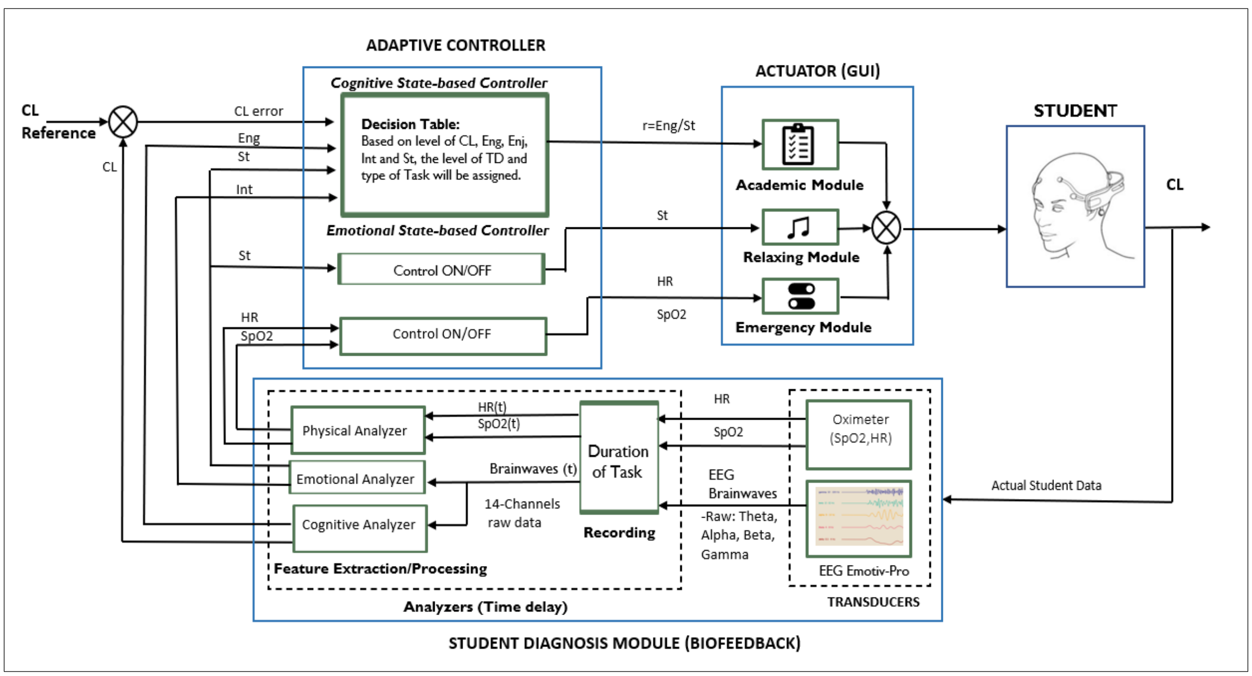

Figure 23. Block Diagram of the PPHAAS Architecture Using the Steam Boiler Analogy.

In this analogy, what are drawn are parallels between the operation of a steam boiler and the functioning of a student within an educational context. This model offers the development of personalized and adaptive educational strategies, and consider the multidimensional nature of the student's experience.

6.1 Building a Fuzzy Relational Model to Classify Student Cognitive, Emotional, and Physical States

In this section, the encoding of psychophysiological attributes and their mapping to the student learning space are described using Mamdani type implication relations. Mamdani fuzzy sets are a type of fuzzy logic system used for decision-making and control in various applications: they are characterized by their use of linguistic variables and fuzzy rule-based systems.

The Fuzzy Inference System (FIS) incorporates linguistic experiences and preferences through membership functions and fuzzy rules [57]. It comprises various stages, including fuzzification, the creation of a knowledge base in the form of if-then rules, inference, and defuzzification.

There are two primary types of fuzzy systems known as Mamdani and Sugeno. Mamdani FIS is widely used due to its inherent ability to handle nonlinear relationships between inputs and outputs. Additionally, Mamdani FIS is acclaimed for its expressive power and interpretable rule consequents, whereas Sugeno FIS may suffer a loss of interpretability.

A fuzzy relational model for detecting a student's emotional states, cognitive states, and health states using brainwaves data and other devices can be a powerful tool for understanding and managing a student's well-being in an educational context. Figure 24 shows a typical fuzzy model.

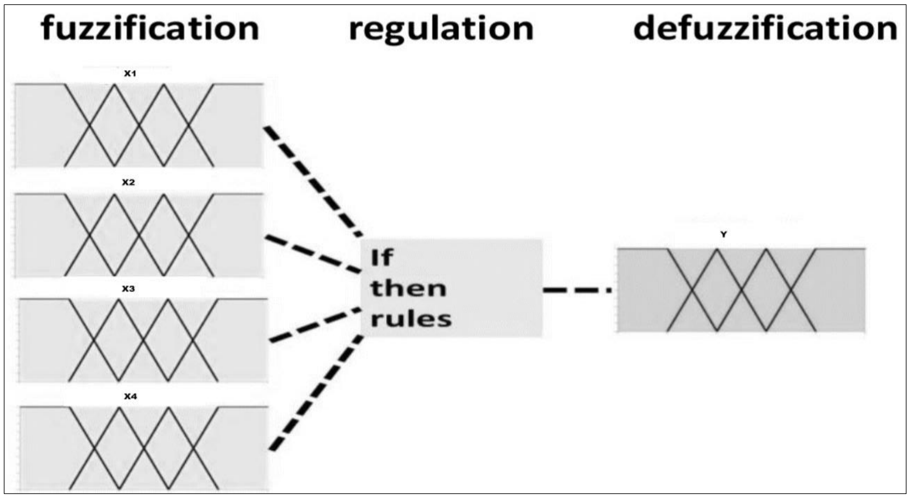

Figure 24. Typical Fuzzy Model

The measurements obtained from the calculus of emotions, Engagement, and CL through brainwaves patterns on determined sites using EEG brainwaves, among them HR and SpO2 from health meters have been encoded into three distinct fuzzy sets: Low, Medium, and High. An example of fuzzification or encoding of psychophysiological attributes is shown in Figure 25.

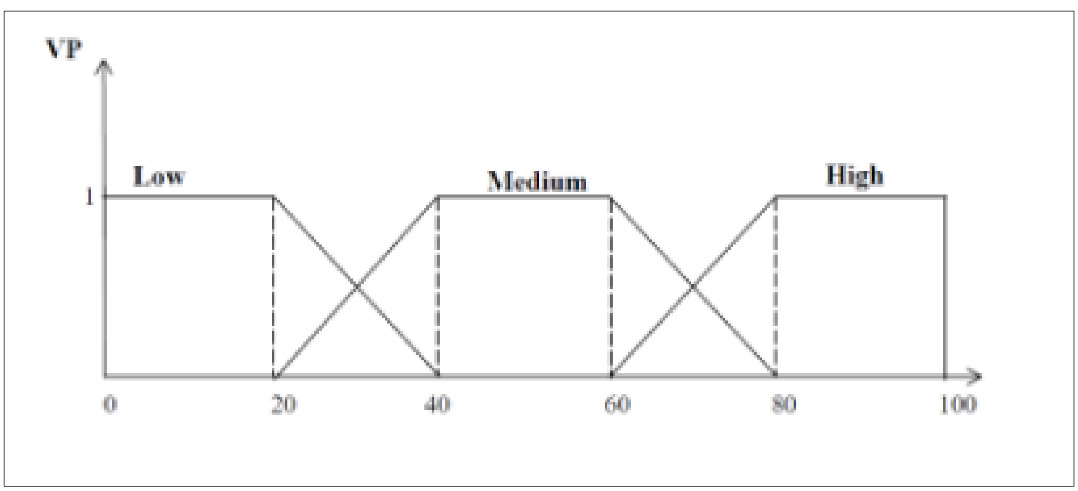

Figure 25. Example of Trapezoidal Membership Functions.

Since every individual is unique, understanding his/her cognitive, emotional, and physiological states can be complex. One approach to gaining insights into a student's state involves utilizing an experimental setup that incorporates brainwaves and health variables, considering the variability in initial conditions.

The following is a conceptual outline of the experiment setup: 1) Employ EEG (Electroencephalogram) to record brainwave activity. 2) Monitor health variables such as heart rate and oxygen saturation. 3) Collect baseline data in a controlled environment to establish individual norms.

A set of cognitive tasks or educational activities relevant to an engineering student's context was created with predefined difficulty levels of Low, Medium, and High. The type of task was defined as reading or watching videos.

The system starts using each student's initial conditions, including their baseline brainwave patterns and health metrics. This personalized data is used to establish a reference point for comparison after tasks. The system implements real-time monitoring and recording of brainwaves and health variables during consecutive tasks to detect any deviations from baseline conditions. After every task, the analyzers process the level of CL and Eng to proceed selecting based on the Instructional Matrix what will be the next type of task and level of difficulty to be delivered. Analyzers use Machine Learning techniques for analyzing EEG and other devices' data and by extracting relevant features.

A Limited Case Series was realized taking in-lab screening data to build the experimental setup and verify the theoretical frame of this research. EEG data obtained from three subjects who performed two types of Engineering tasks with two levels of difficulty were used to establish the ranges per variable in terms of percentage. The purpose of the research is educational and is not human-centered. Data collected will be used to validate the designed controller. During the experiment, students were asked to relax for five minutes watching a relaxing video before starting the experiment while wearing the EEG headset, HR and SpO2 meters, in order to get the reference values for all variables. They were encouraged to avoid unnecessary movements in order to maintain more than 93% of the device connection quality during the task's period of duration. After this time, the academic topic was presented to the students in a sequence of two different steps: i) Reading material classified as easy ii) Reading material classified as difficult.

Figure 26 to Figure 30, show some of the brainwave patterns observed in the research subjects.

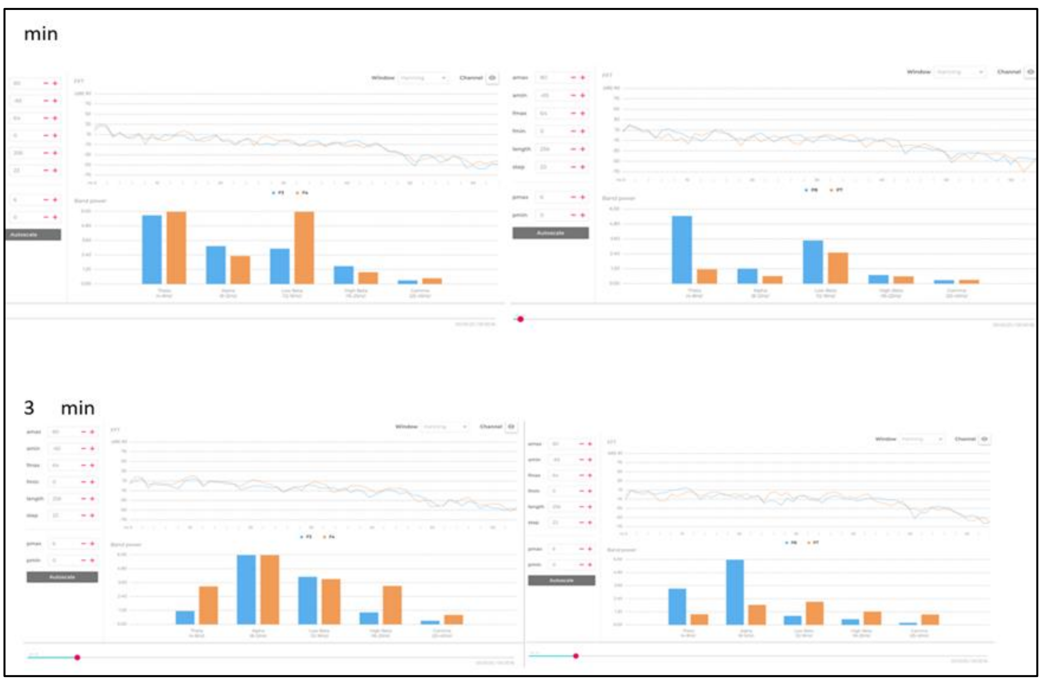

Figure 26. Identifying Brainwaves Patterns on Frontal and Parietal Lobes for Subject Initial Conditions.

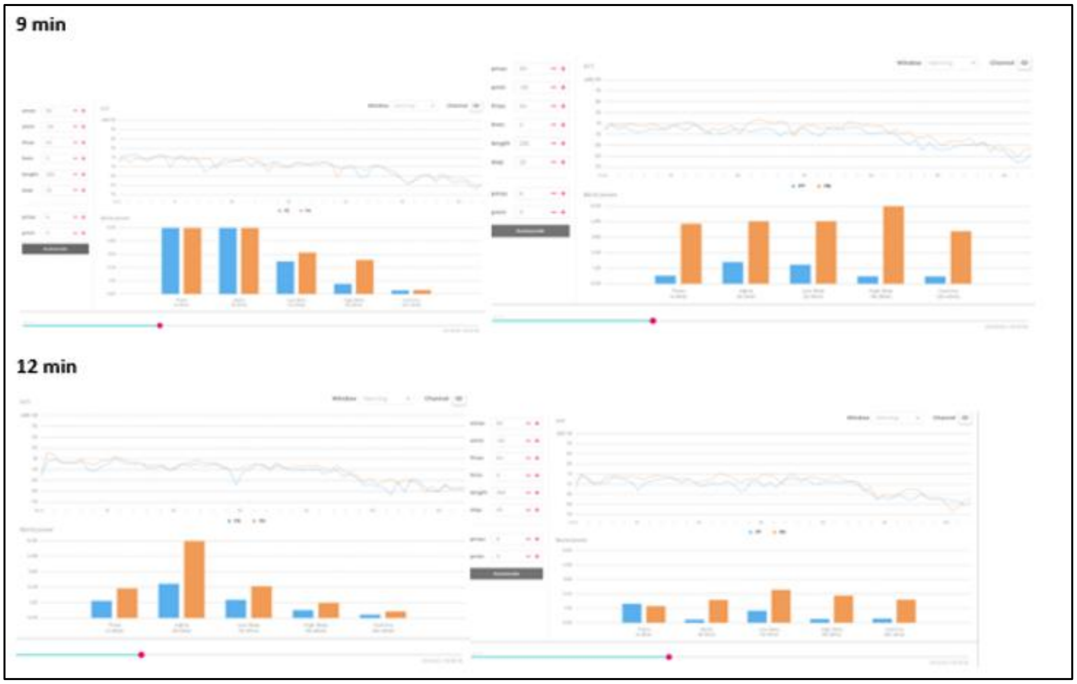

Figure 27. Brainwaves Patterns on F3, F4 Sites for Easy Task Level.

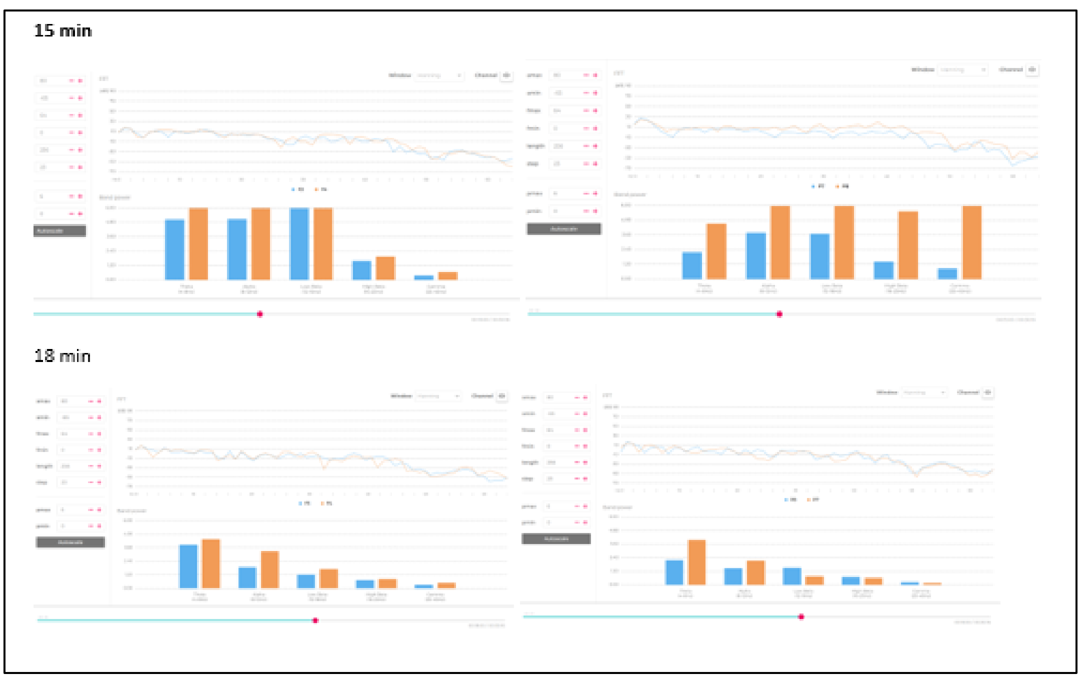

Figure 28. Brainwaves Patterns on P7 and P8 Sites for Easy Task Level.

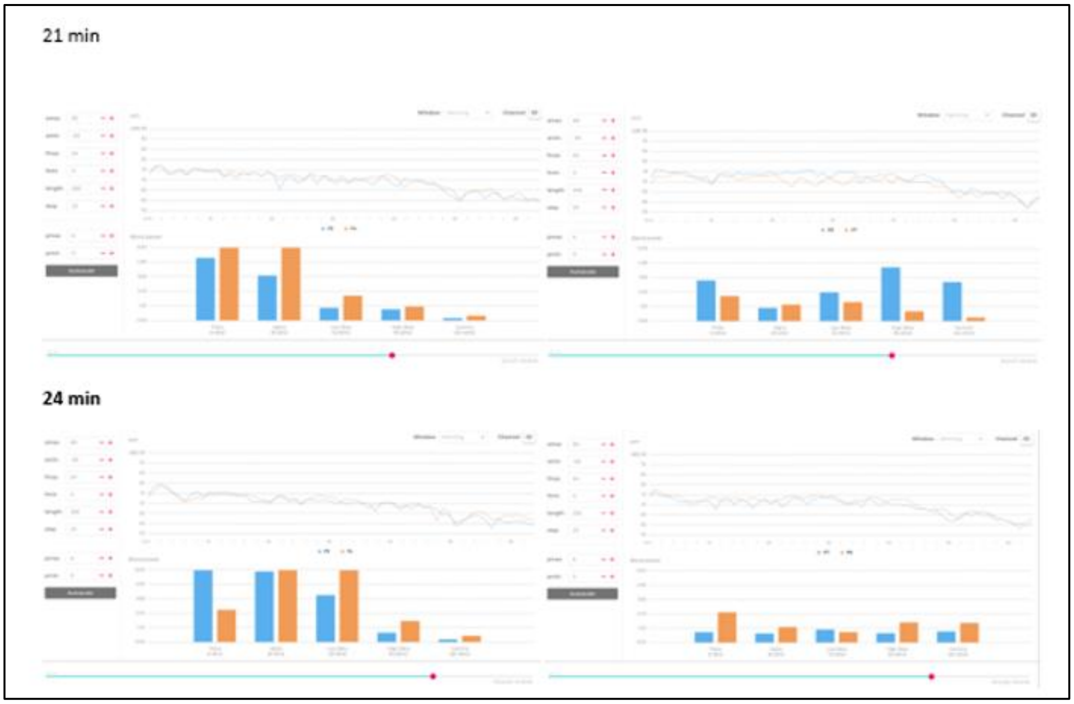

Figure 29. Brainwaves Pattern on F3, F4 Sites for Difficult Task Level.

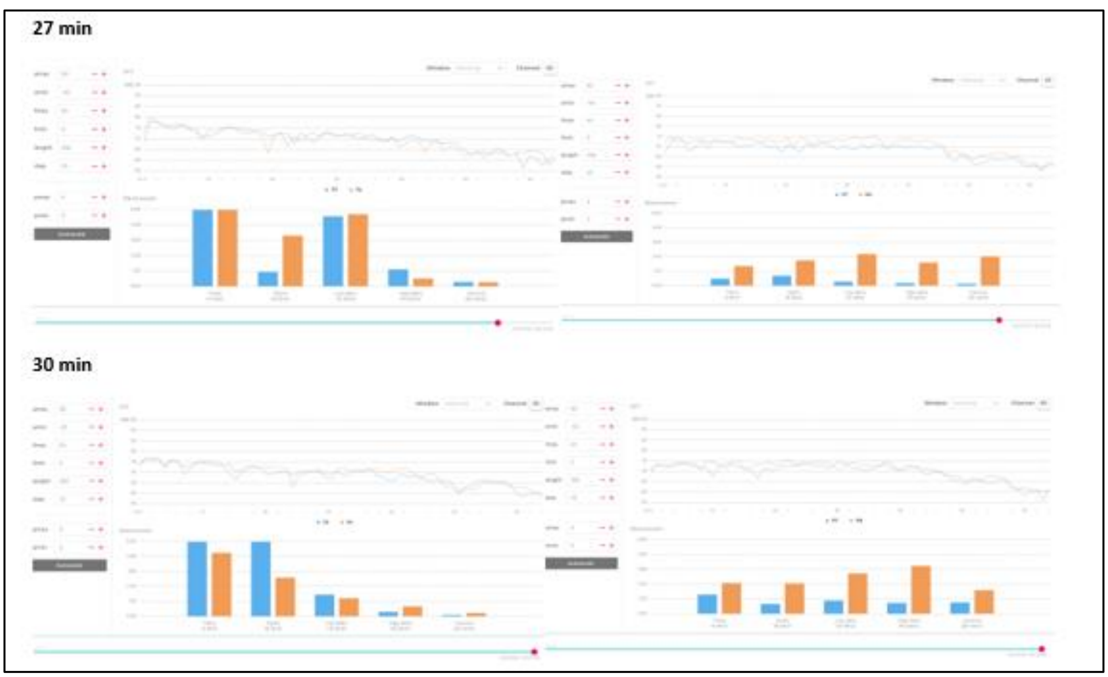

Figure 30. Brainwaves Pattern on F3, F4, P7 and P8 Sites for Difficult Task Level.

The Cognitive Load (CL) was computed after completion of the task according to the power level of the brainwaves channels and the emotional status of the students while completing each task. For the overall hypermedia system, signals from meters (EEG, Oximeter) are collected during each task time, and the system uses the period between tasks for processing and calculating the corresponding value of CL and Eng. The corresponding values of Stress and Interest are processed directly from the Emotiv software. HR and SpO2 (emergency condition) need to be collected while the student performs the task, in order to be sent to the Controller. The academic module receives the order from the Controller to deliver the proper academic material, i.e., the type of task and its level of difficulty according to the biofeedback signals. Table 8 shows the Input variables ranges.

Table 8. Ranges of the Input Variables

Variable/Range in %	High	Medium	Low
Interest	52-54	48-52	45-48
Stress	>50	37-50	<37
Engagement	>57	28-57	<28
CL	>58	20-58	<20
HR	90-100	60-90	<60
SpO2	>95	93-95	<93

6.2 Selecting the Task Difficulty Level

Intrinsic cognitive load is represented by Task Difficulty (TD) level. TD level is formulated in a way to guarantee that every single trial has a normalized difficulty in the range [0,1] in which 1 represents the highest degree of difficulty. According to [58], the TD will be set in the range of [0.4,0.8]. The difficulty level will be expressed as TD_j with {j=1, 2,…,m}, where 1 is easy, 2 is medium, and 3 is high, with a corresponding value of 0.4, 0.6, and 0.8 respectively. The controller will increase or decrease the TD in terms of j=1, 2, 3,…m. The predefined matrix contains the instructional material that will be delivered in a discrete form.

6.3 Selecting the Type of Task (T)

The amount of Extraneous Cognitive Load needs to be selected by regulating the type of task because the Extraneous Cognitive Load is going to be influenced by how information is presented to the student. A hypermedia system is used to change the type of task, providing a presentation of the data in a way that minimizes the effects on working memory and cognition, as it is shown in Figure 31. The type of task T_i will be labeled as: T_i with {i=1, 2,…n} whereas T_1:Video, T_2: Reading, and T_3: Quiz

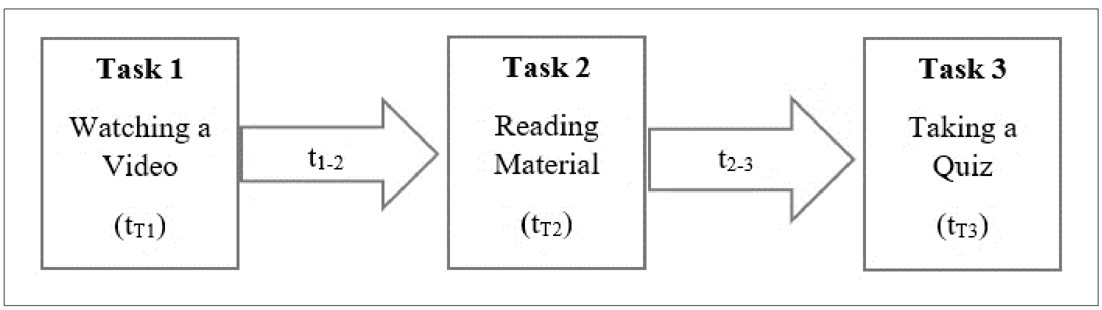

Figure 31. MATLAB GUI for Displaying Tasks, Collecting, Recording, and Processing Data.

The criteria for turning ON the emergency system are related to health parameters. Based on that, variables Stress, HR and SpO2 need to be monitored. When High stress and High HR occur simultaneously, the delivery of tasks is forced to STOP. Another important health consideration is when the blood oxygen saturation (SpO2) is low. Healthy pulse oximeter values often range from 95% to 100%, where values under 90% are considered low. However, in an educational context, a SpO2 equal to or less than 93% will be considered low.

Signal processing will be performed by the machine learning program selecting from the entire 14 channels Emotiv-EEG headset data, corresponding to the Parietal Alpha signals Pz (equal to the average between P7 and P8) and Frontal Theta Fz (equal to the average between F3 and, F4), to calculate the overall Cognitive Load during the task. Emotions coming from Emotiv Pro will be considered for processing the target variables Interest and Stress.

Each module will receive orders form the Controller as shown in Table 9:

Table 9. Controller Outputs

	Academic Module	Academic Module	Emergency Module	Relaxing Module
Output Variable	Task Difficulty	Task Type	Emergency	Relaxing
Action	D1	T1	ON	Track1
Action	D2	T2	OFF	Track 2
Action	D3			

The controller will act based on a Decision Table that has been previously built using the neuroscience literature review. The number of tasks and difficulty levels of tasks is predefined. As an example, in considering four tasks with three level of difficulty, the Instructional Material (IM) will be delivered according to following matrix, where T1, T2, T3, and T4 represent the type of task which can be a) T1: Video, b) T2: Reading Material, c) T3: Exam, and d) T4: Relaxing activity. Figure 32 shows a graph of the CL per task.

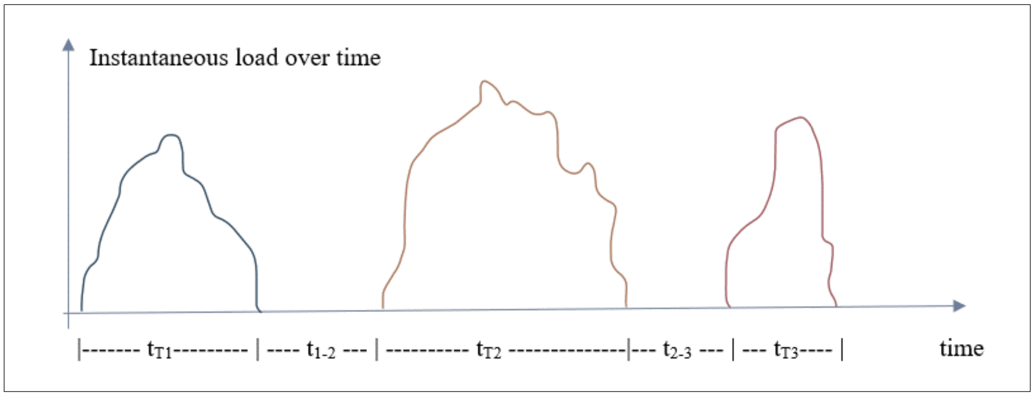

Figure 32. Graph of the Cognitive Load per Task.

$$\mathrm{IM} = \begin{bmatrix} a_1 & b_1 & c_1 & d_1 \\ a_2 & b_2 & c_2 & d_2 \\ a_3 & b_3 & c_3 & d_3 \end{bmatrix} \begin{bmatrix} T_1 \\ T_2 \\ T_3 \\ T_4 \end{bmatrix} \quad (13)$$

The matrix coefficients will classify the task difficulty level (TD) of the academic tasks as 1: Easy, 2: Medium, and 3: High. Concerning T4: a relaxing activity will be considered a mandatory task in the event the Stress reaches a very high level. The controller will select one of the relaxing music tracks. A safety interlock condition will be established to preserve the health of the student in the event the level of Stress, in conjunction with HR and SpO2 levels, reaches higher values than normal.

The overall controller design has six inputs, each one with three membership functions (L, M, H), respectively, and the four output variables, which are Task Difficulty with three membership functions (L, M, H); Type of task with two membership functions; Videos, Reading Material, Emergency with two membership functions, ON and OFF; and, lastly, Relaxing Module with two membership functions, Track1 and Track 2. The integrated adaptive controller will have a total of 729 rules. The integration of all modules i.e., Academic Module, Emergency Module and Relaxing Module in only one controller imposes an impractical implementation of the controller since computing resources must be increased to accelerate the controller's response; thus, if the total number of rules can be separated into modules such as: Academic Module with four inputs (St, Int, Eng, CL) and two outputs (T,TD); Emergency Module with two inputs (HR,SpO2) and two outputs (ON, OFF); and Relaxing Module with one input (St) and two outputs (Track1, Track2), a total of three dedicated controllers will be processing the data and reducing the response time of the overall system. In the following table, and for the purpose of this study, a reduced number of rules (only 54 rules) has been considered for the integrated controller to show a group of signals to be sent to the Graphical User Interface (GUI). In order to validate the design of the controller and the GUI, a reduced Decision Table for the controller is shown in Table 10:

Table 10. Controller's Rules Based on Evidence.

	IF																		THEN					
	Emotional variables						Cognitive variables						Physical variables						Academic Module		Relaxing Module		Emergency Module	
	Interest			Stress			Engagement			Cognitive Load			Heart Rate			SpO2			Difficulty	Type	Relaxing			
	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Normal	High	Low	Normal	High	Action	Action	Track1	Track2	Stop tasks	Continue task
Rule 1	1			1			1			1			1			1							1	
Rule 2		1		1			1			1			1			1							1	
Rule 3			1	1			1			1			1			1							1	
Rule 4	1				1			1			1			1			1		Increment	Decrement				1
Rule 5		1			1			1			1			1			1		Increment	Increment				1
Rule 6			1		1			1			1			1			1		Increment	Increment				1
Rule 7	1					1			1			1			1			1	Increment				1	
Rule 8		1				1			1			1			1			1	Increment				1	
Rule 9			1			1			1			1			1			1	Increment				1	
Rule 10	1			1			1			1			1			1			Increment				1	
Rule 11	1				1		1			1			1			1			Increment				1	
Rule 12	1					1	1			1			1			1			Increment				1	
Rule 13		1		1				1			1			1			1		Increment	Decrement				1
Rule 14		1			1			1			1			1			1		Increment	Increment				1
Rule 15		1				1		1			1			1			1		Decrement	Decrement				1
Rule 16			1	1					1			1			1			1					1	
Rule 17			1		1				1			1			1			1					1	
Rule 18			1			1			1			1			1			1					1	
Rule 19	1			1			1			1			1			1							1	
Rule 20	1			1				1		1			1			1							1	
Rule 21	1			1					1	1			1			1							1	
Rule 22		1			1		1				1			1			1		Increment	Decrement				1
Rule 23		1			1			1			1			1			1		Increment	Increment				1
Rule 24		1			1				1		1			1			1		Increment	Increment				1
Rule 25			1			1	1					1			1			1	Increment	Increment			1	
Rule 26			1			1		1				1			1			1	Increment	Increment			1	
Rule 27			1			1			1			1			1			1	Increment	Increment			1	
Rule 28	1			1			1			1			1			1			Increment	Increment			1	
Rule 29	1			1			1				1		1			1			Increment	Increment			1	
Rule 30	1			1			1					1	1			1			Increment	Increment			1	
Rule 31		1			1			1		1				1			1		Increment	Increment				1
Rule 32		1			1			1			1			1			1		Increment	Increment				1
Rule 33		1			1			1				1		1			1		Decrement	Increment				1
Rule 40		1			1			1			1		1				1		Increment	Increment				1
Rule 41		1			1			1			1			1			1		Increment	Increment				1
Rule 42		1			1			1			1				1		1						1	
Rule 43			1			1			1			1	1					1			1			1
Rule 44			1			1			1			1		1				1				1		1
Rule 45			1			1			1			1			1			1					1	
Rule 46	1			1			1			1			1			1							1	
Rule 47	1			1			1			1			1				1						1	
Rule 48	1			1			1			1			1					1					1	
Rule 49		1			1			1			1			1		1							1	
Rule 50		1			1			1			1			1			1		Increment	Increment				1
Rule 51		1			1			1			1			1				1	Increment	Decrement				1
Rule 52			1			1			1			1			1	1							1	
Rule 53			1			1			1			1			1		1						1	
Rule 54			1			1			1			1			1			1					1	

A MATLAB code was developed for the controller and GUI. To test the performance of the integrated controller and the GUI, the GUI was tested by inputting several possible combinations of inputs to observe the way in which to display the corresponding task. Figure 33 shows two combinations.

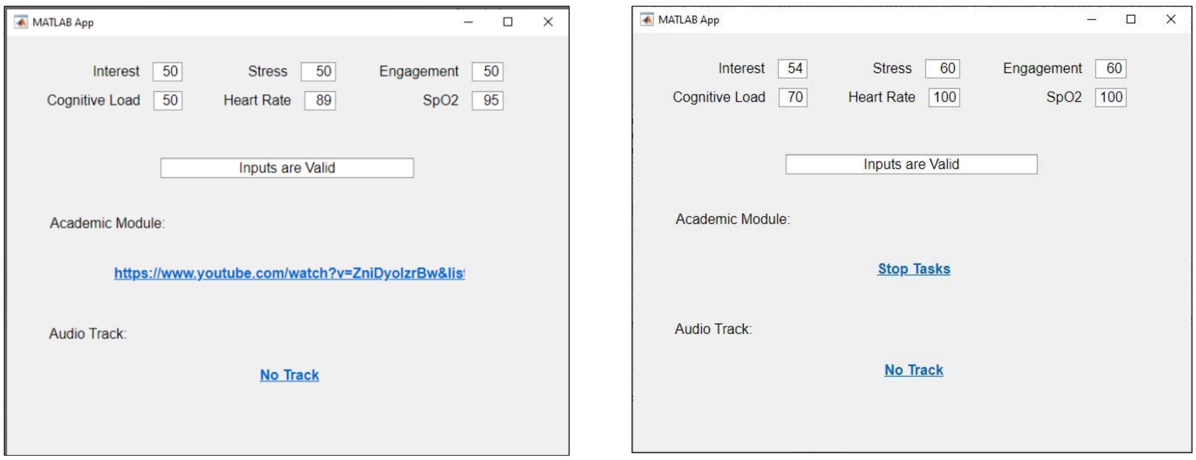

Figure 33. Controller and GUI Validation Using a MATLAB Code.

The outline of the logic and the program flow (pseudocode) in the MATLAB programming language is shown in Appendix A.

Chapter 7: Conclusions, Contributions, and Future Work

7.1 Conclusions

The comparison between human learning and a steam boiler, as viewed through the lens of neuroscience, highlights several intriguing parallels. Both systems demonstrate a remarkable capacity for adaptation and response to external stimuli. The brain's neural network, like the intricate components of a steam boiler, operates on the principles of feedback loops and equilibrium, maintaining a delicate balance between stability and change.

Neuroscience reveals that, like a steam boiler's pressure regulation, the brain employs mechanisms such as synaptic plasticity and the consolidation of memories to optimize its cognitive functions. The concept of "learning" in the human brain reflects a dynamic interplay between neurons and synapses, analogous to how a steam boiler's valves and regulators manage pressure to ensure efficient energy transfer.

Moreover, the analogy underscores the significance of controlled heat in both systems. In the case of the human brain, it signifies the importance of maintaining an optimal cognitive environment, while in the steam boiler, it symbolizes the controlled release of energy. In each case, unprofessional conduct can lead to instability and adverse consequences.

This analogy serves as a reminder of the interconnectedness of all systems, natural or man-made, and the universal principles that govern them.

Ultimately, understanding the parallels between human learning and a steam boiler from neuroscience’s perspective opens new avenues for research and insights into the complex processes that underlie our capacity to learn, adapt, and thrive in an ever-changing world.

7.2 Contributions

- Incorporating three key dimensions of learning to construct a comprehensive model of the human learning process, encompassing emotional, cognitive, and physical aspects.
- Establishing an analogy between the human learning process and an industrial steam boiler, unlocking fresh possibilities in the Engineering education field for simulating, tracking, and managing educational variables from the perspective of control systems and automation.
- Proposing the concept of the "Fire of Learning" by integrating three emotional variables into the learning framework.
- Creating a student state transition diagram that accounts for the emotional, cognitive, and physical dimensions of the learning experience, to later construct the variables' dependencies in a way that it can be implemented using a math framework.
- Outlining an initial blueprint for an adaptive fuzzy controller tailored to a multidimensional approach to human learning, aiming to enhance the efficiency and effectiveness of the learning process.

7.3 Future Work

The validation of the holistic model for the human learning system has been achieved through a comparative analysis with an established mathematical model of a steam boiler having a complete mapping of variables from the human learning system onto the corresponding components in the steam boiler model.

In the context of this verification process, the aim is to demonstrate that the emotional, cognitive, and physical dimensions of human learning can be mathematically expressed by their analogous variables in a steam boiler. However, it has been modeled by using a block diagram representation to get a simplified mass balance and an energy balance model as part of a future work. As shown in this research, emotional factors correspond to heat control mechanisms, cognitive aspects have been linked to pressure regulation, and physical factors referred to flow of resources and energy within the boiler.

By translating the human learning system into the mathematical language of the steam boiler model, the well-established principles governing industrial processes for examining the dynamics of learning can be leveraged. This comparison serves not only as a rigorous test of the developed holistic model, but also paves the way for potential insights and optimizations in the field of education by drawing on established control systems and automation methodologies.

In conclusion, the proposed holistic model that mapped variables onto an existing steam boiler model, and offers a robust method for evaluating the model's viability, was successfully implemented and verified. The proposed method opens doors to exciting possibilities in the realm of education and the multidimensional understanding of the human learning process.

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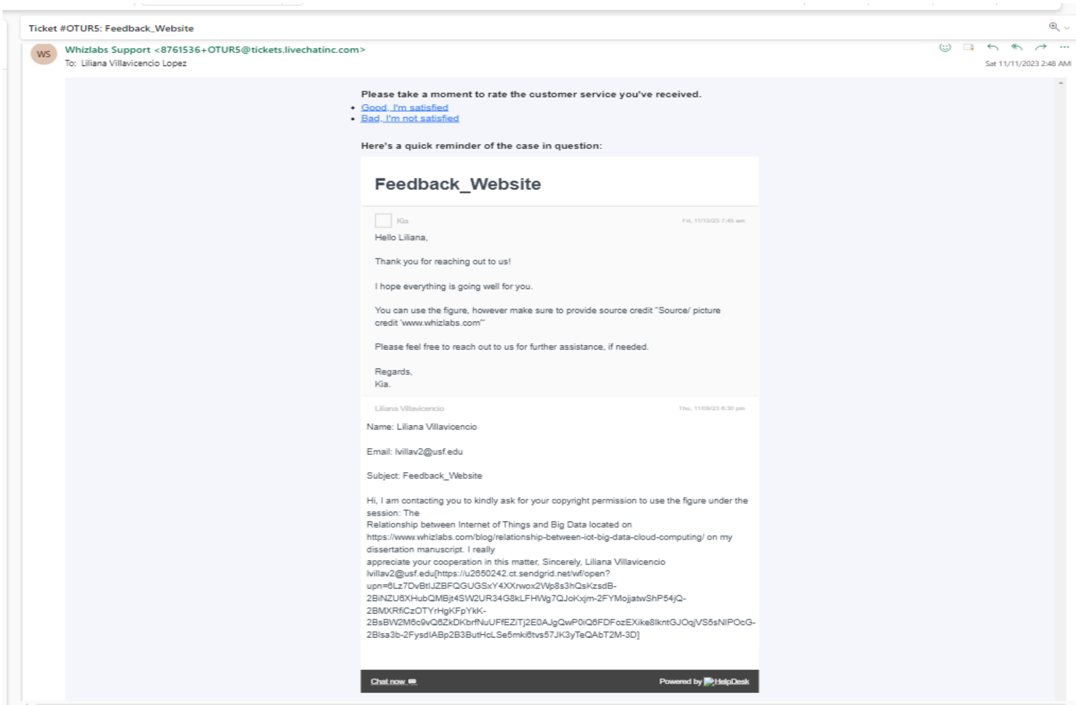

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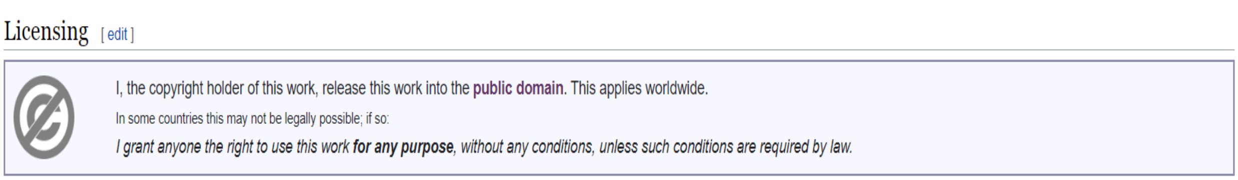

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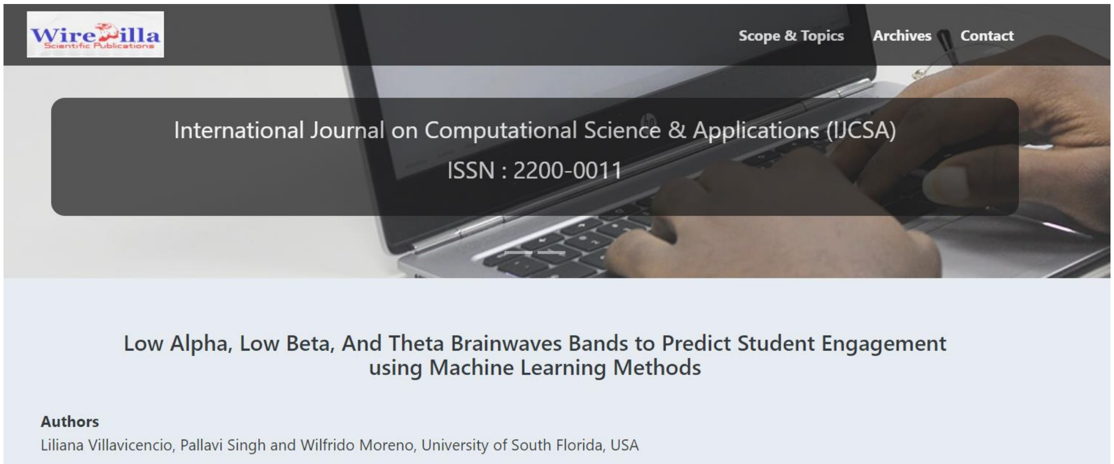

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Overall, the amount and substantiality of material used in relation to the whole ☒ supports fair use or ☐ does not support fair use.

EFFECT ON THE MARKET FOR ORIGINAL

Likely Supports Fair Use	Likely Does Not Support Fair Use
☒ No significant effect on the market or potential market for the original ☐ No similar product marketed by the copyright holder ☐ You own a lawfully acquired copy of the material ☐ The copyright holder is unidentifiable ☐ Lack of licensing mechanism for the material	☐ Replaces sale of copyrighted work ☐ Significantly impairs market or potential market for the work ☐ Numerous copies or repeated, long-term use ☒ Made accessible on Web or to public ☐ Affordable and reasonably available permissions or licensing

Overall, the effect on the market for the original ☐ supports fair use or ☐ does not support fair use.

CONCLUSION

The combined purpose and character of the use, nature of the copyrighted material, amount and substantiality of material used in relation to the whole and the effect on the market for the original
☒ likely supports fair use or ☐ likely does not support fair use.

Appendix B: Pseudo Code for the Hypermedia Controller and the GUI

The following is the pseudocode for the Hypermedia Controller and the GUI:

```
class FuzzyControllerApp:

    properties:
        interest
        stress
        Engagement
        cognitive_load
        heart_rate
        spo2
        validity_check
        current_difficulty
        track

    methods:

        function fuzzy_controller():
            # Read decision table from file
            data_table = read_table ('Fuzzy Controller Decision Table.xlsx')

            # Define a list to store column values
            cols = [NaN, NaN, NaN, NaN, NaN, NaN, NaN, NaN, NaN, NaN, NaN, NaN, NaN,
NaN, NaN, NaN, NaN, NaN]

            # Check interest range and set the corresponding column
            if interest >= 45 and interest <= 48:
                cols[1] = 1
            elseif interest > 48 and interest <= 51:
                cols[2] = 1
            elseif interest > 51 and interest <= 52:
                cols[3] = 1
            else:
                display('Invalid value for interest')

            # Check stress range and set the corresponding column
            if stress <= 37:
```

```
    cols[4] = 1
elseif stress > 37 and stress <= 50:
    cols[5] = 1
else:
    cols[6] = 1

# Check Engagement range and set the corresponding column
if Engagement <= 28:
    cols[7] = 1
elseif Engagement > 28 and Engagement <= 57:
    cols[8] = 1
else:
    cols[9] = 1

# Check cognitive load range and set the corresponding column
if cognitive_load <= 20:
    cols[10] = 1
elseif cognitive_load > 20 and cognitive_load <= 58:
    cols[11] = 1
else:
    cols[12] = 1

# Check heart rate range and set the corresponding column
if heart_rate <= 60:
    cols[13] = 1
elseif heart_rate > 60 and heart_rate <= 90:
    cols[14] = 1
else:
    cols[15] = 1

# Check SpO2 range and set the corresponding column
if spo2 <= 93:
    cols[16] = 1
elseif spo2 > 93 and spo2 <= 95:
    cols[17] = 1
else:
    cols[18] = 1

# Extract inputs from the decision table
inputs = data_table[:, 2:19]

# Initialize variables to store rule validity
valid_rule = 0

# Compare the input columns with decision table columns to find a matching rule
for jj in range(len(inputs)):
```

```
        temp = inputs[jj, :]
        if is_equal(cols, temp):
            valid_rule = jj
            break

# Define lists for difficulty levels, PDFs, and videos
difficulty_levels = ['D1', 'D2', 'D3']
difficulty_pdfs = ['PDF1', 'PDF2', 'PDF3']
difficulty_videos = ['Video1', 'Video2', 'Video3']
type_levels = ['T1', 'T2']

if valid_rule == 0:
    validity_check = 'Inputs are Invalid'
    current_difficulty = 'Invalid Inputs'
    track = 'Invalid Inputs'
else:
    validity_check = 'Inputs are Valid'

    difficulty = data_table[valid_rule, 20]
    type = data_table[valid_rule, 21]
    track1 = data_table[valid_rule, 22]
    track2 = data_table[valid_rule, 23]
    stop_tasks = data_table[valid_rule, 24]
    cont_tasks = data_table[valid_rule, 25]

    current_difficulty_index = 1

    if difficulty == 'Increment':
        current_difficulty_index += 1
        if current_difficulty_index > lEngth(difficulty_levels):
            current_difficulty_index = lEngth(difficulty_levels)

    elseif difficulty == 'Decrement':
        current_difficulty_index -= 1
        if current_difficulty_index < 1:
            current_difficulty_index = 1

    current_type_index = 1

    if type == 'Increment':
        current_type_index += 1
        if current_type_index > lEngth(type_levels):
            current_type_index = lEngth(type_levels)

    elseif type == 'Decrement':
        current_type_index -= 1
```

```
        if current_type_index < 1:
            current_type_index = 1

    current_type_level = type_levels[current_type_index]

    if current_type_level == 'T1':
        current_difficulty = difficulty_pdfs[current_difficulty_index]
    else:
        current_difficulty = difficulty_videos[current_difficulty_index]

    track1 = 'Track1'
    track2 = 'Track2'

    if track1 == 1:
        track = 'Track1'
    elseif track2 == 1:
        track = 'Track2'
    else:
        track = 'No Track'

    if stop_tasks == 1:
        cont_tasks = 0
        current_difficulty = 'Stop Tasks'
    elseif cont_tasks == 1:
        stop_tasks = 0

  return validity_check, current_difficulty, track

function updateOutputs():
  validity_check, current_difficulty, track = fuzzy_controller()

  # Update the UI components with the results
  ValidityCheck.Value = validity_check
  Hyperlink_3.Text = current_difficulty

  if current_difficulty != 'Invalid Inputs':
    url = Hyperlink_3.Text
    open_web_browser(url)

  Hyperlink_2.Text = track

  if track != 'No Track' and track != 'Invalid Inputs':
    Hyperlink_2.URL = track
    open_web_browser(track)

function InterestEditFieldValueChanged(event):
```

```
        interest = InterestEditField.Value

    function StressEditFieldValueChanged(event):
        stress = StressEditField.Value

    function EngagementEditFieldValueChanged(event):
        Engagement = EngagementEditField.Value

    function CognitiveLoadEditFieldValueChanged(event):
        cognitive_load = CognitiveLoadEditField.Value

    function HeartRateEditFieldValueChanged(event):
        heart_rate = HeartRateEditField.Value

    function SpO2EditFieldValueChanged(event):
        spo2 = SpO2EditField.Value
        updateOutputs()

    function Hyperlink_3Clicked(event):
        updateOutputs()

    function Hyperlink_2Clicked(event):
        updateOutputs()

    function StopTasksEditFieldValueChanged(event):
        # Do nothing

    function ContinueTasksEditFieldValueChanged(event):
        # Do nothing

    function ValidityCheckValueChanged(event):
        value = ValidityCheck.Value

% Component initialization
function createComponents():
    # Create the UI components
    UIFigure = create_UI_figure()
    InterestEditFieldLabel = create_label()
    InterestEditField = create_numeric_edit_field()
    StressEditFieldLabel = create_label()
    StressEditField = create_numeric_edit_field()
    EngagementEditFieldLabel = create_label()
    EngagementEditField = create_numeric_edit_field()
    CognitiveLoadEditFieldLabel = create_label()
    CognitiveLoadEditField = create_numeric_edit_field()
    HeartRateEditFieldLabel = create_label()
```

```
    HeartRateEditField = create_numeric_edit_field()
    SpO2EditFieldLabel = create_label()
    SpO2EditField = create_numeric_edit_field()
    AcademicModuleLabel = create_label()
    AudioTrackLabel = create_label()
    Hyperlink_2 = create_hyperlink()
    Hyperlink_3 = create_hyperlink()
    ValidityCheck = create_edit_field()

    # Show the UI figure

% App creation and deletion
function create_app():
    # Create the app and its components
    FuzzyControllerApp = create_FuzzyControllerApp()

function delete_app():
    # Delete the app and its components
    delete UIFigure
```

About the Author

Liliana Villavicencio holds a bachelor’s degree in electronic engineering, which she obtained from the Antonio José de Sucre Polytechnical University [*Universidad Politécnica Antonio José de Sucre*], in Barquisimeto, Venezuela, in 1993. She gained practical experience through internships at the Venezuelan Petroleum Company (PDVSA) in 1992 and the Schneider Group (formerly Telemecanique) in 1993. Subsequently, Liliana pursued two master’s degrees, demonstrating her commitment to advanced education. The first was a Master of Science in Automation and Instrumentation from the University of the Andes [*Universidad de Los Andes*], in Merida, Venezuela, completed in 2001 with the support of a Scholarship from the Gran Mariscal de Ayacucho Program. Her second master’s degree, a Master of Science in Electrical Engineering, was earned from the University of South Florida, in Tampa, Florida, in 2008. Liliana's professional journey encompasses diverse roles, including her work as an Engineer at Festo Co. in Venezuela and her role as an Associate Professor at both the AJS Polytechnical University in Barquisimeto and the Universidad de Carabobo, in Valencia. With over 30 years of experience, she is an experienced Senior Control Engineer. Her dedication to education extended to serving as a Teaching Assistant at the University of South Florida, where she contributed to the Linear Control Systems course, encompassing both theory and laboratory aspects. In addition to her academic and professional pursuits, Liliana has shown leadership qualities by assuming the role of Vice-President of the International Society of Automation-USF Student Chapter since 2021.