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Integrating Adaptive Cueing in a Physiology-sensitive Learning Platform: Exploring Design Needs

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Abstract: Adaptive cueing in currently-existing technology-enhanced learning (TEL) often prioritizes performance metrics over the cognitive load experienced by a learner, thereby losing comprehensive view to realizing learning outcomes. Cues e.g., visual, auditory, tactile cues have been shown to be effective in guiding the learner's attention and managing cognitive load. However, offering cues to promote one's skill learning based only on individual performance indicators can be misleading, since added to the performance scores, cognitive aspects and learning ability of the learner are also crucial for effective learning. Though the cognitive aspects are subtle in nature, yet these can be harnessed with the use of neurophysiological tools. Tools like Eye-gaze tracking and Electroencephalography (EEG) offer avenues to infer attention, memory load, and decision-making. Accessing such neurophysiological signals need one to deal with technical barriers, e.g., multi-modal synchronization, latency constraints, and real-time signal processing, hindering their adoption in dynamic learning environments. Here, we present the architecture that can be used to realize and overcome the technological challenges faced while integrating the cueing paradigm with synchronized multi-modal neurophysiological signal acquisition. This platform (i) estimates cognitive load through synchronized eye-tracking and EEG data during task execution, (ii) correlates it with performance outcomes, and (iii) generates adaptive cues tailored to individual cognitive profiles to optimize learning efficiency. Further, by integrating with existing platforms like LAReflecT, our approach provides actionable feedback for both learners and trainers. The broad aim is to enable implementation of cognition-aware skill learning platforms with adaptive, individualized cueing to foster effective learning.

Keywords: Technology-enhanced learning (TEL), Multi-modal cueing, Cognitive load assessment, Eye-gaze tracking, Electroencephalography (EEG).

1. Introduction

Modern technology-enhanced learning (TEL) systems increasingly incorporate data-driven adaptive cueing aimed towards personalizing cue delivery and cueing intensity in real-time based on individual learning preferences and performance indicators (Wang & Song, 2024). Cueing techniques, like visual, tactile, and auditory cues, are often integrated into such platforms aimed to enhance learning outcomes (Maćkowski et al., 2022; Xie et al., 2016b). However, offering cues to promote one's skill learning based only on individual performance indicators can be misleading, since the performance scores by themselves do not capture cognitive aspects and learning ability of the learner (Short, 2021) both of which are crucial for effective learning. This has remained largely unexplored. To address this, there is a need for a deeper investigation of interactive learning platforms that are data-driven and can generate real-time cueing while considering both the performance score and cognitive aspects of learning.

Research has shown that learning platforms augmented with cueing techniques, like visual, tactile, and auditory cues, can help in visual attention guidance, effective management of cognitive load, etc,. leading to measurable improvements in learning performance (Xie et al., 2017; Xie et al., 2016b; Lavie et al., 2004). Such cues, which can be delivered in the form of visual highlights, audio prompts, or haptic feedback, can direct the learner's focus to relevant information, reducing the cognitive effort required to recognize and process key information of a task. However, the question lies in devising architectures that can allow synchronized fusion of the cueing modalities to the learning platform that is equipped with an ability to quantify the learner's cognitive load while interacting with the platform. This can offer two-fold benefits with regard to the learner and the trainer. Specifically, the learner can get estimates on his / her cognitive load that can be cue and task-specific. Also, the trainer can understand which cues work best for the learner so that the trainer can deploy these in an individualized manner to facilitate the learning process. Such individualization or individual-centered (Xu & Woodruff, 2017) approach can facilitate effective learning.

Recent advances in neuroscience and educational technology have made it possible to assess cognition in skill learning environments. In particular, multiple modalities, such as Eye-gaze tracking and Electroencephalogram (EEG) have emerged as promising modalities (An et al., 2018; Orovas et al., 2024) for inferring attention (Vortmann et al., 2022b), working memory load (Kosachenko et al., 2023), and strategies for decision making (Rojas-Martínez et al., 2025), which are crucial during task execution. Exploiting multi-modal data, such as physiological biomarkers is important given that this data can offer signatures to one's cognitive processes that are critical for effective learning (Azevedo et al., 2022; Moon et al., 2022; Shoukry & Gobel, 2017). These physiological signals provide involuntary insights into one's cognitive aspects of learning, offering a robust complement to traditional self-report or only performance-based evaluations. Given the importance of physiological biomarkers, researchers have been investigating various indices, such as the theta/alpha ratio in specific brain regions (Tan et al., 2024; Kosachenko et al., 2023), fixation duration, saccades, pupil dilation, etc. (Ekin et al., 2025; Kosachenko et al., 2023; Rodemer et al., 2023) as indicators of one's cognitive load. However, implementing real-time, data-driven learning platforms with multi-modal sensing ability (such as integrating with different physiological sensing, e.g., Eye-gaze tracking and EEG) presents substantial technical challenges. These include meeting latency requirements of the order of milliseconds, synchronizing heterogeneous data streams across different data acquisition systems like EEG and Eye-gaze tracking running at different sampling rates, and handling computationally-intensive signal processing in real-time while maintaining data quality and user privacy (Jamal et al., 2023; Cheng et al., 2020). This opens avenues to investigate how such a learning system can be built and to address the specific technological challenges involved in its implementation.

Here we present the architecture that can be used to realize the technological challenges faced while implementing such multi-modal learning platforms capable of offering individualized cues while considering both one's performance and cognition, which are crucial for fostering effective learning. Educational platforms such as LAReflecT (Majumdar et al., 2025) offer an open platform that can be augmented by integrating the pointers to one's cognitive load acquired by processing multi-modal data. Together, the overall architecture of the platform allows for seamless integration with LAReflecT to present (i) the estimated cognitive load through acquiring physiological data, using Eye-gaze tracking and Electroencephalography synchronized with task execution, (ii) the learning outcomes in terms of task performance, and (iii) reports that help in individualized cue selection. Specifically, inputs from the physiological indices will be used to estimate one's cognitive load while identifying cues that facilitate learning instead of posing a cognitive load to the learner, adversely affecting the learning outcomes. Subsequently, the estimated cognitive load will be fused with one's task performance by a strategy generator to offer an adaptive learning environment with cues being carefully selected to foster effective skill learning by the learner.

2. Literature Review

2.1 *Role of Cues in Learning*

In the context of Technology-enhanced learning, we refer to the use of cues as a modality to promote one's physical interaction with learning materials so as to enhance a learner's comprehension and retention (Huang et al., 2024). Reports show that the choice of cue has been made with an aim to guide one's attention and manage the learner's cognitive load (Huang et al., 2024; Li et al., 2024). For example, the cues can be delivered in the form of visual highlights in a digitized environment, or as audio prompts generated by a system or the trainer, or haptic feedback triggered by a system or given by a trainer. Specifically, research shows that tactile cues that can be delivered through vibrating devices, touch/tap, are processed by the somatosensory cortical areas and influence decision making and can improve one's task performance in navigation skill learning (Romo et al., 2012). Similarly, visual cues that could be delivered via bright, attention-grabbing colors, like red, can direct a learner's attention towards salient features. These stimuli are primarily processed by the occipital lobe and are connected with attention and decision-making networks of the brain (She et al., 2024). Likewise, auditory cues, such as beeps or verbal instructions, are processed in the temporal lobe and have been shown to improve one's task performance by signaling the timing of an action or providing feedback without interrupting the visual focus on the task (Schaefer, 2014). In addition to cue selection, the learning platform needs to adaptively generate context-specific cues to foster improved learning. This is because it can bring pedagogical implications. For example, a learner performing an experiment in a virtual lab might score well in spite of facing difficulty and struggling to wire a circuit. Different physiological biomarkers, e.g., those related to EEG and eye-gaze might be used to infer that the learner is experiencing high cognitive load, though scoring well. Such task performance under high cognitive load can adversely affect the learning (Cowley et al., 2012) and retention of the skills learnt and higher order learning which in the long run might affect performance. In such a scenario, a context-relevant cue offered adaptively can foster improved learning. Specifically, visual cue e.g., a highlight on the correct wiring terminal can help provide the hints and thus reduce cognitive load. Also, such a cue can prompt the instructor to provide assistance in terms of presenting concepts of wiring to the learner. To summarize, a well-designed and carefully chosen cue offered adaptively can act as a scaffold in helping the learners improve their task performance.

2.2 *Cognitive Load due to Cues Demonstrating Disadvantages of ill-chosen Cues*

Learning is most effective when the total cognitive demand placed on a learner's working memory is optimal (Sweller, 1988; Cognitive Load Theory). While cues are often employed to reduce extraneous cognitive load by simplifying instructions and guiding attention, they can themselves become a source of extraneous cognitive load. This is particularly true when based on specific contexts, simultaneous delivery of multiple cues can be overwhelming for the learner's working memory capacity (Sweller et al., 2011) deteriorating one's learning outcomes. The nature of the cue also plays a significant role. For example, visual cues are typically processed very quickly, but can be a source of distraction if not carefully managed (She et al., 2024). Tactile cues, on the other hand, can be applied to specific anatomical locations having higher concentration of mechanoreceptors thus have high level of tactile acuity, such as thighs and wrists (Raghuvanshi et al., 2025), while it might serve to distract the learner doing a task (Patelaki et al., 2023b). Again audio cues can also contribute to cognitive load if they are presented in a confusing or overwhelming manner, such as not using a metronome [steady rhythm produced by a regular, timed beat to maintain a consistent tempo; (Lee et al., 2022)] during a task. Furthermore, cognitive load could be heavily influenced by a learner's individual learning preferences that can vary with learners being either visual, auditory, and/or tactile learners (Pashler et al., 2008). A mismatch between the cue modality and a learner's preference can increase extraneous cognitive load, as the learner must devote additional cognitive effort to process information in a less-than-optimal format. To summarize, cues not properly chosen can add to one's cognitive load hindering the learning process instead of facilitating the learning outcomes.

2.3 *Technologies to Assess Cognitive Load*

The conventional learning platforms often focus on one's task performance metrics, such as test scores as means to evaluate learning. However, these often neglect the other critical part of the learning evaluation process which is the underlying cognitive processes that can also influence one's performance in the skill learning (Gkintoni et al., 2025; Pawar et al., 2017). One of the possible reasons might be that the estimation of the underlying cognitive processes is often challenging. In fact, such estimation often requires one to use technological platforms to access the implicit physiological measures that can be used to estimate one's cognitive load (Gkintoni et al., 2025). However, with technological progress, harnessing the subtle physiological signals, such as gaze fixation on a stimulus, brain signals, etc. in real-time is now a reality.

Specifically, one's eye movement can be captured using Eye-gaze trackers which is a powerful non-invasive modality for understanding a learner's visual attention. Tapping into one's eye movement data is important for getting estimates of one's cognitive load given that eyes are "window to one's mind" (König et al., 2016). The movement of the eyes are controlled by attention networks within the brain with research showing that such attention networks are influenced by cognitive processes (Posner & Petersen, 1990). Data on the eye movement captured by Eye-gaze trackers can be processed to extract various gaze-related indices such as fixation duration, saccades, pupil dilation, etc. which have been shown to be strong biomarkers of one's cognitive load (Ekin et al., 2025; Kosachenko et al., 2023; Rodemer et al., 2023), like, long fixation duration on a region of interest can indicate higher cognitive processing. Again, rapid eye movements might suggest a learner is searching for information (Ekin et al., 2025), etc. Pupil dilation is also a robust physiological marker that has been shown to correlate with cognitive effort (Rodemer et al., 2023) during a task.

Again, one's brain activation can be quantified by processing data captured by an EEG device. This offers direct measure of one's brain activation with high temporal resolution which in turn can be mapped to the cognitive load experienced by a learner. The brain activation can be realized by processing the EEG signals belonging to different frequency bands, such as alpha band (8 to 13 Hz), and theta band (3 to 7 Hz), etc. that have been shown to be related to one's working memory load, and attention (Tan et al., 2024; Kosachenko et al., 2023). Researchers have reported that one's working memory overload corresponds to increased activity in alpha wave activity, which can be captured by tapping the EEG signal from the Frontal region of the brain (Kosachenko et al., 2023).

The implications on the Eye-gaze and the brain activation under cases of cognitive load for healthy elderly and those with neurological disorders when being involved in a skill learning scenario might convey differentiated observations. In short, multi-modal data analysis in learning scenarios wherein one can analyze both eye-gaze and EEG signals of such individuals along with monitoring one's task performance can offer a comprehensive view on one's task-specific and cue-specific cognitive load along with performance ability. This information can be valuable for the learner himself / herself to get estimates of his / her cognitive abilities on the one hand, and clinical inputs regarding the choice of cues (that can be task-specific) that can help guide clinical decision-making by the caregiver or the trainer or the nurse to tune learning paradigms on the other hand with the overall aim being improving learning outcomes.

Though physiology-based biomarkers can be used to estimate one's cognitive load, yet, one needs to remember the ethical concerns related to individualized biomarkers. This is because one's physiological data is intimate/personal, which can raise critical ethical and privacy concerns. To protect against such concerns, one needs to collect informed consent from the individual before collecting one's physiological data followed by maintaining strict data governance while designating individuals with unique identification numbers rather than publishing individual specific information, such as name. Also, care needs to be taken to preserve such information on identification in a confidential and restricted repository so as to ensure protection of the individual against misuse of information.

3. Architectural Framework Design while Integrating Multi-modal Data Acquisition

This section outlines the conceptual architecture for a data-driven learning platform that uses multi-modal physiological data acquisition to adaptively generate context-specific cues to foster improved learning.

3.1 *Functional Requirements of the Architecture*

Building from the literature review, several key functional requirements can be identified. First of all, the system architecture will allow one to acquire real-time data from multiple physiological streams (e.g., eye-gaze tracking and EEG) synchronized with the learner's task execution. To enable real-time adaptive cueing and data acquisition, the data processing pipeline will operate with minimal latency and must be time-synchronized to ensure a seamless and responsive user experience. Secondly, the architecture will enable use of statistical analysis models to process the raw physiological data and infer the cognitive load experienced by a learner. This platform architecture will include a "*strategy generator*" that fuses performance data with the estimated cognitive load to dynamically select and deliver individualized cues that optimize learning without causing cognitive overload. Thirdly, the architecture must be modular to seamlessly integrate with existing technology-enhanced learning platforms, like LAReflecT, allowing for the presentation of cues and the collection of performance data. These functional requirements are necessary for the system to provide reports and visualizations of cognitive load and performance that can be useful to both the learner and the trainer thereby facilitating deeper understanding of the learning process.

3.2 *Overview of System Architecture*

The multi-modal-sensitive technology-enhanced learning system architecture (*Fig. 1*) is designed with the aim to build a multi-modal learning platform that delivers individualized cues by integrating both the learner's performance and the cognitive load experienced by the learner (as estimated from the physiology-based biomarkers). The cue-specific physiological data will be captured using EEG (namely Starstim 8; Caravati et al., 2024) and eye-gaze tracking (namely Tobii 4C; Mallas et al., 2023) modules.

These data streams will be pre-processed, synchronized, and sent to a *Cognitive Estimator* to quantify cognitive load based on various indices like pupil diameter, fixation duration, alpha power, etc. This cognitive load measure is combined with traditional performance metrics, such as task scores, within the *Strategy Generator* to create a learner-specific adaptive strategy to send specific task parameters (namely the Task ID and Cue ID) to the *Learning Task Controller*. In turn, the *Learning Task Controller* chooses the task (corresponding to the Task ID from a task repository) along with appropriate cue modality (namely tactile, visual, auditory based on the Cue ID). This closed-loop process ensures that cue selection is dynamically tailored to facilitate effective skill learning. The architecture is compatible with platforms like LAReflecT, supporting integration of cognitive load estimation data and logistics sharing, performance tracking, and report presentation.

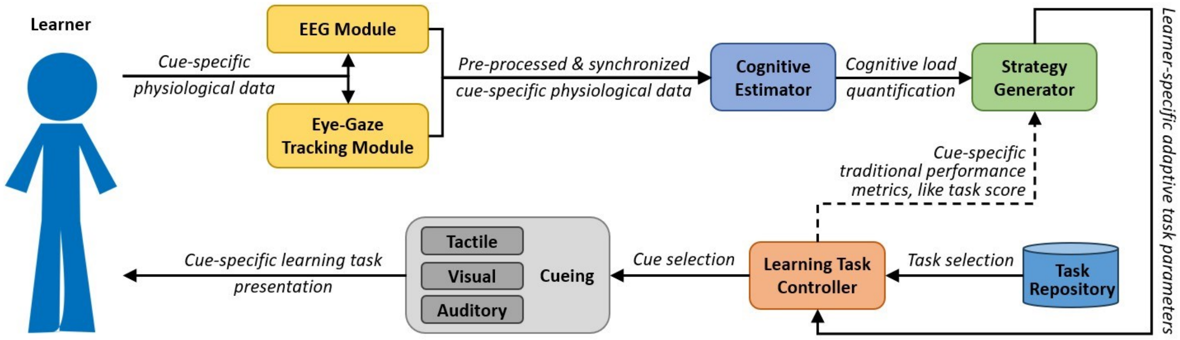

Figure 1. Conceptual Architecture of the Multi-modal-sensitive Technology-enhanced Learning System.

3.3 *Data and Analysis Models*

The system will use several types of models to function effectively. The data processing pipeline is shown in Figure *1*. First, gaze-based cognitive load indicators like, pupil dilation (changes in pupil size indicating cognitive effort), blink rate (frequency of eye blinks), fixation dispersion (variability in fixation locations), etc., will be computed by processing gaze data acquired using the eye-gaze tracking module. This will be achieved by cleaning the raw data through interpolation or exclusion of invalid samples (blinks), and then identifying fixations using dispersion or velocity based algorithms, etc. Alongside, identifying rapid movements exceeding velocity threshold for saccade detection, which includes saccade-based metrics like, saccade amplitude (distance of eye movement), saccade velocity (speed of eye movement), saccade rate (frequency of saccadic movements) will also be computed. Finally, the fixation-based gaze metrics and saccade-based gaze metrics will be used as gaze-based biomarkers of cognitive load. This will be inspired by the previous work of our research group in India wherein we have shown the potential of gaze-sensitive digitized platform to estimate one's cognitive load from gaze-related indices (Ekin et al., 2025; Kosachenko et al., 2023; Rodemer et al., 2023).

Concurrently, EEG data will be processed through a standard signal-processing pipeline. This involves several steps like, artifact removal to filter out noise from sources like eye movements and muscle activity; bandpass filtering to isolate specific frequency ranges of interest; and then spectral analysis, such as a Fast Fourier Transform (FFT), to quantify the power of different neural frequency bands, such as, theta (3-7 Hz), which is associated with working memory and cognitive control, and alpha (8-12 Hz), which is inversely related to attention and cognitive effort. The theta/alpha ratio in specific brain regions (e.g., frontal and parietal lobes) is a robust indicator of cognitive load (Tan et al., 2024; Kosachenko et al., 2023). These EEG-based features will be used as biomarkers of cognitive load.

Once processed, the gaze and physiological features (i.e., the biomarkers) will be fused to train and run a cognitive load estimation model. This model will focus on picking up the relative changes in the task-specific biomarkers with respect to baseline metrics in an individualized manner (thereby taking care after the inter-person variability) to offer an output as an estimate of the learner's cognitive load. This, together with performance scores, will be fed into the *Strategy Generator* (*Figure 2*) that will adapt the delivery of the type of cue to the learner, using either predefined rules (such as a state-machine representation) or a learning-based policy to optimize learning outcomes.

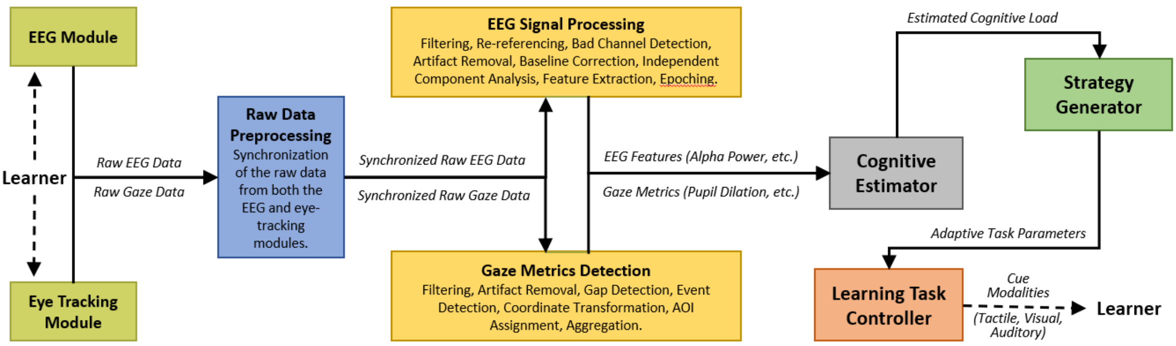

Figure 2. Data flow diagram of the multi-modal-sensitive technology-enhanced learning system.

4. Discussion and Future steps

4.1 *Significance of the Research*

The architecture presented here is significant because it provides a blueprint for moving beyond traditional performance-based learning and creating truly personalized and cognitively-aware learning environments that can optimize the learning experience and improve learning outcomes in an individualized manner. This system emphasises on multi-modal physiological data streams capable of delivering EEG-related and gaze-related data at high temporal resolution to infer the cognitive load experienced by a learner. The system offers a more holistic and accurate understanding of the learning process and the learner. The ability to distinguish between performance issues caused by a lack of knowledge versus those caused by cognitive overload allows for more precise and effective interventions.

4.2 *Challenges and Limitations*

Implementing this architecture presents several technical challenges. The real-time synchronization of heterogeneous data streams from sensors operating at different sampling rates demands a robust, low-latency data acquisition and processing pipeline. Processing computationally-intensive physiological signals while ensuring data quality is another major hurdle (Jamal et al., 2023; Cheng et al., 2020)]. The accuracy of cognitive load estimation models can be constrained by the variability of physiological signals across learning contexts, as well as by non-technical factors such as language barriers. For instance, when one learner group consists of Japanese learners with varied language proficiency compared to another learner group, which comprises Indian learners. Though our proposed multi-modal-sensitive technology-enhanced learning system is neither presently a working prototype nor have undergone empirical validation, yet our proposed architecture can serve as a foundational building block to developing such learning systems that can facilitate effective learning.

4.3 *Future Steps*

In future, we will implement the architecture in an empirical study to quantify learning benefits, such as faster skill acquisition, improved knowledge retention, and reduced cognitive overload compared to traditional performance-based cueing systems. Here the focus will be on the development of the data acquisition and processing layers. This will involve creating a functional system for synchronizing and fusing eye-gaze and EEG data. Also, we will develop learning models and refine statistical models for cognitive load estimation. We plan to explore the possibility of using simple state-machine representation to more complex ones to implement the strategy generator suggesting adaptive variation in task difficulty and also use various cue types. Finally, the prototype will be integrated into an existing learning platform, like LAReflecT, to conduct a pilot study. This study will validate the system's ability to accurately assess cognitive load and demonstrate whether its adaptive cueing strategy leads to measurable improvements in learning outcomes.

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