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Fusing Physiological Signals to Build a Cognitive Screening Architecture and Adaptive Learning Environment in the Metaverse

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Abstract: Cognitive health plays a vital role in one’s quality of life across the lifespan, particularly in the elderly, where cognitive decline can be more prominent. Conventional screening methods, e.g., Addenbrooke’s Cognitive Examination, Montreal Cognitive Assessment, etc., though effective, are time-consuming and resource-intensive. Recent advances highlight the potential of integrating physiological signals as biomarkers for rapid, language-agnostic assessment of cognitive health. This concept paper proposes an architecture that fuses eye-tracking and Heart Rate Variability within the LA-ReflecT platform that can then be utilized for cognitive screening and learning. A two-phase implementation plan is proposed to develop and validate a cognitive screening platform integrated with physiological biomarkers and further use the inputs to tailor learning tasks in the metaverse for improved skill learning. This approach has the potential to support cognitive skill maintenance and enhance skill learning outcomes through adaptive, data-driven methods.

Keywords: Adaptive learning, gaze-tracking, heart rate variability, cognitive load, metaverse

1. Introduction

Cognition is often quoted as a spectrum of mental processes required for complex and simple responses to the environment (Bayne et al., 2019). Cognition plays an important role in one’s day-to-day life, influencing the activities of individuals of all ages. Intact cognitive health is linked to reduced risk of dementia and delayed onset of neurodegenerative diseases. Cognition-stimulating activities like problem-solving, memory exercises, and social interactions can help preserve cognitive function, prevent decline, and maintain mental acuity and independence in later years of life (Stites et al., 2018; Pan et al., 2015). Although some degree of cognitive decline is a normal part of aging (Harada et al., 2013), it is often overlooked because it is perceived as an inevitable consequence of growing older. This leads to one's cognitive health getting ignored, leading to more severe consequences in the future. Cognitive decline in the elderly population can be due to various reasons, and one of the prevalent reasons is stroke, with literature suggesting that around 40-70% of stroke survivors experience some form of cognitive impairment (Huang et al., 2023). The conventional ways of screening cognitive health involve pen-and-paper based tools like Addenbrooke's Cognitive Examination (ACE III), Montreal Cognitive Assessment (MoCA), etc. (Matías-Guiu et al., 2017). Though powerful, such pen-and-paper based screening requires long administration time, availability of trained resources, etc. (John et al., 2017). Such limitations can be overcome using technology-aided solutions. To address this situation, digital screening tools are in use in recent years (Inamoto et al., 2023) (Privitera et al.,2024). These tools are mostly aimed at using digital stimuli, followed by AI-based predictive modelling for screening based on the inputs. But the question lies in whether making the stimulus digital or adding the technology

as a complementary tool to clinicians makes the screening process useful. In recent years, new horizons have emerged in the field of screening where physiological signals (e.g., looking pattern, Heart Rate Variability (HRV), etc.) have been reported as potent for cognitive screening. Eye movements provide a unique window into one's underlying cognitive processes, and eye-tracking enables assessments that are language-agnostic, an important advantage when working with individuals with speech and language disorders (e.g., Aphasia), elderly individuals, or those with limited literacy (Wedel et al., 2023). Again, HRV is an exceptional marker for stress while giving insights into one's cognitive load (Luque-Casado et al.,2016; McDuff et al.,2014) during task performance, jeopardizing learning outcomes.
The present concept paper aims to fuse physiological signals with a digital platform to build a cognitive screening architecture that can be used to enhance the learning delivered through an adaptive metaverse environment. Based on the cognitive health, this environment will adaptively offer tasks in an individualized manner while tapping into the underlying relationship between cognitive health screening and adaptive learning. In fact, cognitive screening identifies an individual's cognitive strengths and weaknesses which will be fed into adaptive metaverse learning environment that will tailor content delivery, pacing, and complexity in an individualized manner. This is possible with platforms e.g., LA-ReflecT, which are potent to engage users interacting with digital stimuli in a structured, gamified, and adaptive manner, while capturing meaningful behavioral data of the user coupled with an ability to track both engagement and performance in real-time (Majumdar et al., 2023; Majumdar et al.,2025). Such platforms, originally aimed at learning, can be repurposed or adapted for cognitive screening, followed by skill learning. Therefore, based on the above evidence, we present an architecture to integrate Eye-Tracking and HRV followed by fetching the information into LA-ReflecT Platform, making it a multimodal assessment tool that not only evaluates cognitive performance but also captures subtle physiological and attentional markers (Phase I henceforth*).* Such amalgamation within an accessible metaverse could facilitate accurate, rapid, and unbiased screening. Results of the screening assessments can be subsequently used to improve the cognitive status of individuals through different learning activities offered adaptively using the LA-ReflecT Platform *(*Phase II henceforth*).*

2. Literature Review

Understanding the foundations of multimodal, technology-enabled cognitive screening requires a brief synthesis of three complementary domains of our concept paper: eye-tracking, HRV, and metaverse-based learning environments.

2.1 Eye-tracking and Its Use in the Context of Prescreening and Skill Learning

Eye-tracking has emerged as a non-invasive approach for detecting one's cognitive status, giving a glimpse of the dynamic relationship between visual attention and brain function. Literature suggests that metrics like Fixation points, Fixation Duration, pupillary dilation, etc., are highly informative of cognitive processes, including attention, memory, and executive function (Skaramagkas et al., 2021; Eckstein et al., 2017) making gaze-related features indicative of one's core cognitive functions, while serving as powerful, real-time markers of cognitive load while executing various tasks with relevance to task performance that are quantifiers of one's skill learning, e.g. as the brain processes complex information, longer Fixation Duration and increased pupil dilation are consistently associated with higher levels of cognitive effort (Negi & Mitra, 2020).

2.2 Heart Rate Variability and Its Utility in the Context of Prescreening and Skill Learning

HRV can be considered a reliable physiological indicator of our nervous system activities and, by extension, states such as stress, cognitive load, and engagement. The HRV can be found to be distinctly differentiated between stressed and relaxed situations (Shaffer & Ginsberg, 2017), with HRV increasing with an increase in cognitive task demands as perceived by the learner. With regard to the applicability of HRV as a metric of one's learning, the HRV has been shown to differentiate engaged from disengaged learners (Luque-Casado et al.,2016). Researchers have shown that individuals with sustained high Heart Rate (coupled with reduced variability) throughout the active learning process demonstrate retention of information and self-reported engagement (Latino et al.,2025).

2.3 Metaverse and Its Utility as an Adaptive Learning Platform

As per the literature, the Metaverse is a multi-layer interactive environment through extended reality (Peukert et al.,2024). The metaverse offers immersive, controllable environments that can standardize stimulus delivery while capturing rich behavioral traces, making it a strong vehicle for cognitive screening and training workflows (Tan et al.,2024). The capabilities of the metaverse align perfectly with our proposed architecture that seeks to fuse biomarkers derived from eye-tracking and HRV to infer one's cognitive load during a task and, in turn, suggest tasks for skill learning within an individualized and adaptive framework. For the presented metaverse-driven screening and training workflow, the LA-ReflecT serves as a platform that delivers standardized, gamified tasks while logging fine-grained learner interactions for analytics and adaptation.

3. System Architecture and Implementation Plan

3.1 Overview of the System Architecture

A bird's-eye view of the system architecture with the structural outline, data flow, integration of hardware and software modules, is presented in *Figure 1.* There are four sub-modules within this architecture implementated in two phases (as described later in 3.2).

3.1.1 Eye-tracking Sub-Module

This module consists of a research-grade, commercially available Tobii 4C (Tobii, 2025) Eye Tracker, which will be used to track one's eye movement in real-time. The data logged in the back-end will be processed to compute various gaze-related features like Fixations (points and duration), pupillary dilation, Saccades, etc. These features will serve as the key to understanding one's cognitive status, as evidenced by the literature. The data captured using the eye-tracker will be used twofold: first, it will be helpful in estimating the cognition of the individual using it (Phase I*),* and secondly, it will help guide the choice of activities in an adaptive and individualized manner *(*Phase II*)* aimed to promote effective learning.

3.1.2 Heart Rate Monitoring Sub-Module

This module consists of a Heart Rate Monitoring device (BioPac MP150) sensor (BIOPAC Systems, Inc., 2016), which allows quantification of HRV based on the data captured using the Photoplethysmogram (PPG) sensor connected in wireless mode. This sensor unit facilitates the collection of raw PPG values, which can be further processed to compute HRV, which can serve as stress biomarkers to understand the type of tasks that cause cognitive load in an individualized manner (Phase I). For Phase II, this data will be used to guide the design of learning activities.

3.1.3 Cognitive Task Sub-Module

The Cognitive Task sub-module will be used to present various activities related to *(i) Acoustic and Language Processing, (ii) Mathematical and Logical Processing, and (iii) Visual Processing***,** which are often reported in literature as challenging for the elderly and those with speech disorders (Rasmus & Błachnio, 2021). The *Acoustic and Language Processing tasks* will require one to comprehend system-generated audio inputs. The *Mathematical and Logical Processing tasks* will require one to use sequential and logical reasoning for task execution. Again, the *Visual Processing tasks* will need one to do picture-text matching with the text involving the phonetic aspects of the words (but without any audio inputs). One's performance in such tasks, along with individualized cognitive states captured using the biomarkers, will be part of Phase I. For Phase II, the LA-ReflecT interface will be used to selectively present tasks of varying challenges as labelled during Phase I, with an ultimate aim to foster improved skill learning.

3.1.4 Multimodal Data Synthesis Sub-Module

The LA-ReflecT will be the central unit for data orchestration and feedback where it will be used as the Task Interface for delivering the digital stimuli while establishing communication between the different sub-modules used in Phase I and Phase II. We will utilize its inherent capabilities of providing standardized logging and dashboards while offering learning tasks. The platform ensures privacy and trust where data being captured is stored with strict data governance while designating individuals with unique identification numbers rather than publishing individual-specific information. Also, such information on identification will be preserved in a confidential and restricted repository to ensure protection of the individual against misuse of information.

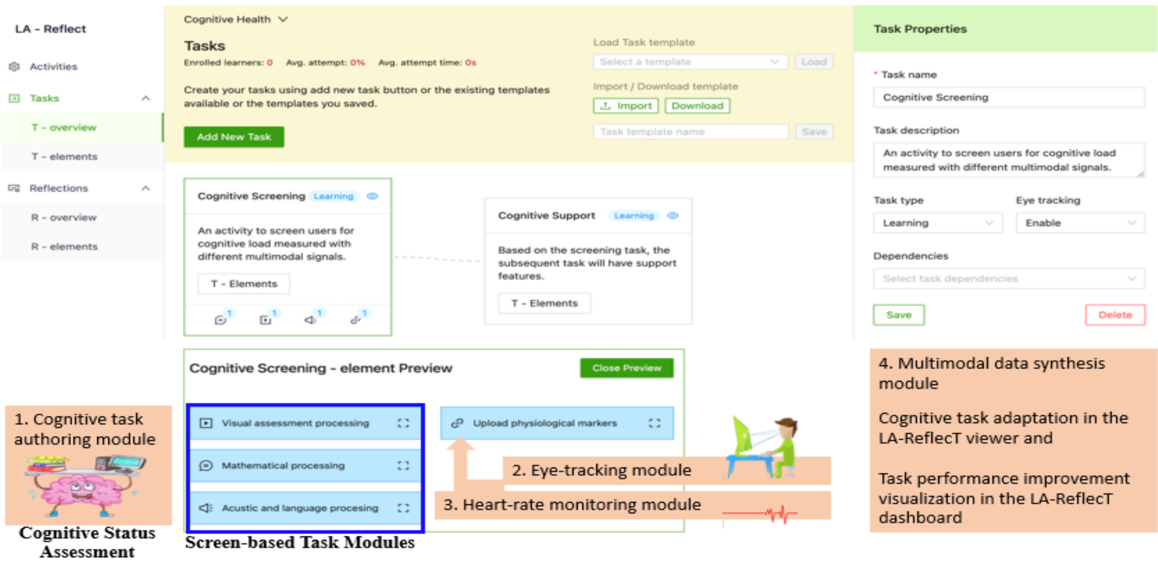

Figure 1. Overview of the system architecture.

3.2 Implementation Plan

The implementation plan for *Phases I and II* can be visualized as follows

3.2.1 Phase I – Developing a Multimodal Cognitive Screening Functionalities

The goal will be to evaluate one's cognitive status of in terms of physiological and attentional biomarkers. To achieve this, the data from the Integrated Eye-Tracking and Heart Rate Variability (HRV) sub-modules, fetched as biomarkers and task-based information (such as performance), will be fed to the LA-ReflecT platform, where, based on further computation, one's cognition will be decided as Low, Medium, or High (*Figure 2*). The outcome would offer a holistic assessment of an individual's cognitive health while overcoming the limitations of using pen-and-paper-based or only performance-based screening. The screening in the metaverse can follow earlier approaches of quantifying Eye-Tracking (Rane et al., 2023) and

HRV (Kuriakose et al., 2012) in cognitive health and stress determination.

3.2.2 Phase II – Enhancement of Adaptive Learning in the Metaverse

The goal will be to improve an individual's cognitive status through learning based on inputs from Phase I. To achieve this, we will use the results of the screening tasks (divided into Low, Mid, and High Level) as shown in *Figure 2*, to offer learning activities mapped with the cognition level through the LA-ReflecT platform. The platform will provide an adaptive, gamified, and metaverse-based environment to engage users, resulting in strengthened skill learning. For example, let us consider a task requiring sequential logical reasoning in which one needs to arrange items on a table in a particular order. For a learner with cognitive deficits (output of Phase I), the metaverse-based environment will offer easier sequences to handle (Phase II). Upon improvement in cognitive ability, the environment will adaptively increase the task difficulty while challenging the learner. The LA-ReflecT platform will be explored to foster such adaptive learning in individuals.

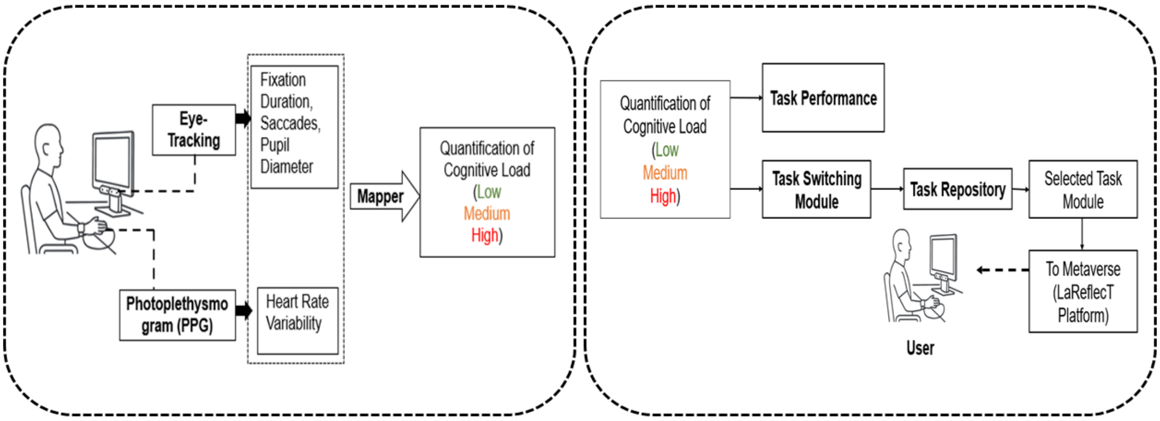

Figure 2. Implementation of Phase I and Phase II of the proposed system.

4. Discussion and Future Steps

In this paper, we present the architectural framework for fusing multimodal physiological signals in a metaverse environment to guide the choice of tasks based on one's (a) task-specific cognitive load and (b) performance in a task while presenting tasks in an individualized and adaptive manner within the metaverse environment so as to foster effective skill learning in the elderly. The Phase I focuses on multimodal cognitive screening in terms of physiological markers combined with digitized tasks that are relevant to the elderly, those with language disorders, or with limited literacy. Subsequently, Phase II of the work aims to achieve improved skill learning through an adaptive metaverse environment (LA-ReflecT platform). In this Phase, assessments achieved as a part of Phase I, will be embedded in an immersive environment utilizing the LA-ReflecT platform with standardized stimulus delivery for facilitating learning. Although our proposed architecture has not undergone empirical validation, yet this can serve as a foundational building block in developing a physiology-sensitive adaptive learning metaverse environment.

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References

Bayne, T., Brainard, D., Byrne, R. W., Chittka, L., Clayton, N., Heyes, C., … Webb, B. (2019). What is cognition? Current Biology, 29(13), R608–R615.
Eckstein, M. K., Guerra-Carrillo, B., Singley, A. T. M., & Bunge, S. A. (2017). Beyond eye gaze: What else can eye-tracking reveal about cognition and cognitive development? Developmental Cognitive Neuroscience, 25, 69–91.
Harada, C. N., Love, M. C. N., & Triebel, K. (2013). Normal cognitive aging. Clinics in Geriatric Medicine, 29(4), 737–752.
Huang, Y., Wang, Q., Zou, P., He, G, Zeng, Y., & Yang, J. (2023). Prevalence and factors influencing cognitive impairment among the older adult stroke survivors: A cross-sectional study. Frontiers in Public Health, 11, 1254126.
Inamoto, Y., Mukaino, M., Imaeda, S., Sawada, M., Satoji, K., Nagai, A., … Otaka, Y. (2023). A tablet-based aphasia assessment system “STELA”: Feasibility and validation study. JMIR Formative Research, 7(1), e42219.
John, A. A., Javali, M., Mahale, R., Mehta, A., Acharya, P. T., & Srinivasa, R. (2017). Clinical impression and Western Aphasia Battery classification of aphasia in acute ischemic stroke: Is there a discrepancy? Journal of Neurosciences in Rural Practice, 8(1), 74–79.
Kuriakose, S., Sarkar, N., & Lahiri, U. (2012, December). A step towards an intelligent human–computer interaction: Physiology-based affect-recognizer. In 2012 4th International Conference on Intelligent Human Computer Interaction (IHCI) (pp. 1–6). IEEE.
Latino, F., Tafuri, D., & Tafuri, F. (2025). Academic self-pressure and physiological responses in adolescents: A pilot experimental study on the moderating role of an escape room–based physical activity intervention on cognitive and academic outcomes. International Journal of Environmental Research and Public Health, 22(6), 948.
Luque-Casado, A., Perales, J. C., Cárdenas, D., & Sanabria, D. (2016). Heart Rate variability and cognitive processing: The autonomic response to task demands. Biological Psychology, 113, 83–90.
Majumdar, R., Liang, C., Ocheja, P., & Li, H. (2025, May). A cooperative learning framework with joint attention and interaction data in the LA-ReflecT platform. In Proceedings of the 2025 Symposium on Eye Tracking Research and Applications (pp. 1–3).
Majumdar, R., Prasad, P., Kadam, K., Gatare, K., & Warriem, J. M. (2023, August). LA-ReflecT: A platform facilitating micro-learning and its multimodal learning analytics. In European Conference on Technology Enhanced Learning (pp. 731–735). Springer Nature Switzerland.
Matías-Guiu, J. A., Valles-Salgado, M., Rognoni, T., Hamre-Gil, F., Moreno-Ramos, T., & Matías-Guiu, J. A. (2017). Comparative diagnostic accuracy of the ACE-III, MIS, MMSE, MoCA, and RUDAS for screening of Alzheimer disease [Supplementary material]. https://doi.org/10.6084/m9.figshare.4822960
McDuff, D., Gontarek, S., & Picard, R. (2014, August). Remote measurement of cognitive stress via Heart Rate variability. In 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 2957–2960). IEEE.
Negi, S., & Mitra, R. (2020). Fixation duration and the learning process: An eye tracking study with subtitled videos. Journal of Eye Movement Research, 13(6), 10–16910.
Pan, C. W., Wang, X., Ma, Q., Sun, H. P., Xu, Y., & Wang, P. (2015). Cognitive dysfunction and health-related quality of life among older Chinese. Scientific Reports, 5(1), 17301.
Peukert, C., Qahri-Saremi, H., Schultze, U., Thatcher, J. B., Cheung, C. M., Frenzel-Piasentin, A., ... & Turel, O. (2024). Metaverse: A real change or just another research area? Electronic Markets, 34(1), 32.
Privitera, A. J., Ng, S. H. S., Kong, A. P. H., & Weekes, B. S. (2024). AI and aphasia in the digital age: A critical review. Brain Sciences, 14(4), 383.
Rane, D., Dash, D. P., Dutt, A., Dutta, A., Das, A., & Lahiri, U. (2023). Distinctive visual tasks for characterizing mild cognitive impairment and dementia using oculomotor behavior. Frontiers in Aging Neuroscience, 15, 1125651.
Rasmus, A., & Błachnio, A. (2021). Auditory processing disorders in elderly persons vs. linguistic and emotional prosody. International Journal of Environmental Research and Public Health, 18(12), 6427.
Shaffer, F., & Ginsberg, J. P. (2017). An overview of Heart Rate variability metrics and norms. Frontiers in Public Health, 5, 258.
Skaramagkas, V., Giannakakis, G., Ktistakis, E., Manousos, D., Karatzanis, I., Tachos, N. S., … Tsiknakis, M. (2021). Review of eye tracking metrics involved in emotional and cognitive processes. IEEE Reviews in Biomedical Engineering, 16, 260–277.
Stites, S. D., Harkins, K., Rubright, J. D., & Karlawish, J. (2018). Relationships between cognitive complaints and quality of life in older adults with mild cognitive impairment, mild Alzheimer disease dementia, and normal cognition. Alzheimer Disease & Associated Disorders, 32(4), 276–283.
Tan, N. C., Lim, J. E., Sultana, R., Quah, J. H. M., & Wong, W. T. (2024). A virtual reality cognitive screening tool based on the six cognitive domains. Alzheimer’s & Dementia: Diagnosis, Assessment & Disease Monitoring, 16(4), e70030.
Wedel, M., Pieters, R., & van der Lans, R. (2023). Modeling eye movements during decision making: A review. Psychometrika, 88(2), 697–729.