An Embedded Framework for EEG-Based Neurophysiological Data Acquisition to Support ADHD Monitoring

Julian Andres Salazar Parias

Universidad Nacional de Colombia
Facultad de ingeniera y arquitectura
Departamento de ingeniera eléctrica, electrónica y computación
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Marco Integrado para la Adquisición de Datos Neurofisiológicos Basados en EEG para Apoyar la Monitorización del TDAH

Julian Andres Salazar Parias

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Director(a):
M.Sc. Bernardo Andrés Cardona Noreña
Codirector(a):
Ph.D. Andrés Marino Álvarez Meza

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Declaración

Me permito afirmar que he realizado esta tesis de manera autónoma y con la única ayuda de los medios permitidos. Todos los pasajes que se han tomado de manera textual o figurativa de textos publicados y no publicados, los he reconocido en el presente trabajo. Ninguna parte del presente trabajo se ha empleado en ningún otro tipo de tesis.

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Julian Andres Salazar Parias

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1 Preliminaries

1.1 Motivation

Brain–Computer Interfaces (BCI) have emerged as a powerful class of technologies that enable direct communication between the brain and external devices. These systems are increasingly being applied in neurorehabilitation, education, and clinical diagnosis due to their ability to monitor and interpret neural activity in real time [Luo et al., 2022]. BCIs have the potential to revolutionize the way cognitive s tates are assessed and modulated by offering closed-loop interaction mechanisms that adapt to the user's brain dynamics [Lim et al., 2023, Lin and Chang, 2025]. Central to this capability is the choice of neuroimaging modality, which must meet strict criteria in temporal resolution, portability, and cost-effectiveness—especially in applications involving children or naturalistic settings [Li et al., 2025b].

Several neuroimaging techniques have been explored for use in BCI systems, each with distinct advantages and limitations. Functional Magnetic Resonance Imaging (fMRI) offers high spatial resolution and whole-brain coverage, but its cost, immobility, and dependence on specialized facilities make it impractical for real-time interaction or integration with everyday environments [Yang and Wang, 2025]. Magnetoencephalography (MEG) provides excellent spatiotemporal resolution but is similarly constrained by high operational costs and the need for magnetically shielded rooms [Peksa and Mamchur, 2023]. Functional Near-Infrared Spectroscopy (fNIRS), a more portable option, measures cortical hemodynamic responses with moderate spatial resolution and tolerance to movement [Doherty et al., 2023]. However, its low temporal resolution limits its ability to capture fast-changing neural dynamics, such as those required for attentional monitoring or neurofeedback [Chen et al., 2023].

Electroencephalography (EEG), by contrast, emerges as the most suitable modality for BCI applications that demand real-time responsiveness, portability, and affordability [Niso et al., 2023]. EEG records the brain's electrical activity through non-invasive scalp electrodes, offering millisecond-level temporal resolution ideal for tracking rapid cognitive events like attention shifts or inhibitory control. While EEG's spatial resolution is lower compared to fMRI or MEG, advances in signal processing—such as QEEG, functional connectivity analysis, and source localization—have greatly enhanced its ability to extract meaningful neurophysiological markers [Caiado and Ukolov, 2025, Yadav and Maini, 2023, Värbu et al., 2022]. This practical advantage is highlighted when comparing brain imaging modalities along the spectrum of portability and infrastructure requirements (see Figure **1-1**). Moreover, EEG's lightweight hardware, low infrastructure requirements, and compatibility with embedded systems make it an ideal foundation for interactive, portable, and scalable BCI solutions [Cai et al., 2025].

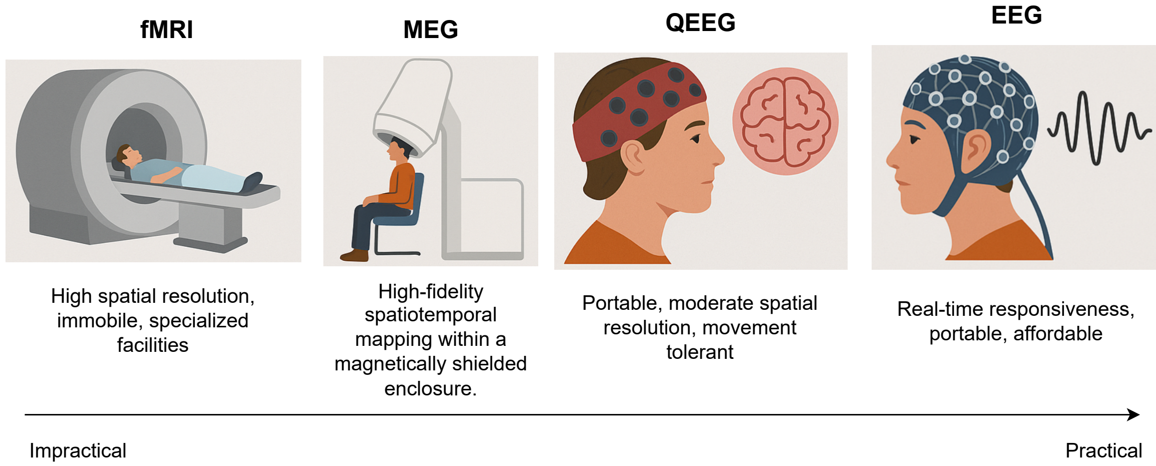

Figure 1-1: Comparison of neuroimaging modalities by spatial resolution, temporal resolution, and cost. EEG stands out for its affordability, portability, and millisecond-level responsiveness.

Building upon these practical advantages, EEG-based BCI systems have been widely adopted across a diverse range of non-clinical domains. In human-computer interaction and entertainment, for instance, motor imagery paradigms allow users to control digital interfaces or external devices simply by visualizing specific physical movements [Gao et al., 2022]. Similarly, in the emerging field of neuromarketing, EEG is utilized to gauge consumer engagement and emotional valence in real-time, providing objective neurophysiological metrics that bypass the biases of traditional behavioral self-reporting [Byrne et al., 2022]. Furthermore, visual experiments leveraging steady-state visually evoked potentials (SSVEPs) and other event-related potentials demonstrate EEG's capacity to create robust communication pipelines and monitor spatial attention [Chen et al., 2022]. These broad applications highlight the versatility of EEG in decoding cognitive and sensory processes in everyday environments, seamlessly paving the way for more specialized, targeted interventions [Tait et al., 2025].

One of the most compelling clinical applications of EEG-based BCI is in the assessment and intervention of neurodevelopmental disorders such as Attention Deficit Hyperactivity Disorder (ADHD). ADHD affects approximately 10 % of children in Colombia [Salari et al., 2023, Pineda et al., 2003] and is characterized by persistent symptoms of inattention, hyperactivity, and impulsivity that interfere with academic performance, social relationships, and emotional regulation. Conventional diagnostic practices rely heavily on behavioral questionnaires and clinical observation, which, while informative, are inherently subjective and susceptible to bias [Raiker et al., 2017]. In this context, EEG offers a valuable alternative by enabling the objective measurement of neural correlates linked to attention and impulse control. Well-established EEG biomarkers such as elevated theta/beta ratios and altered event-related potentials (e.g., P300) have been extensively validated in the ADHD literature, making EEG a scientifically robust and clinically relevant tool for real-time cognitive monitoring and neurofeedback interventions [Tan et al., 2025].

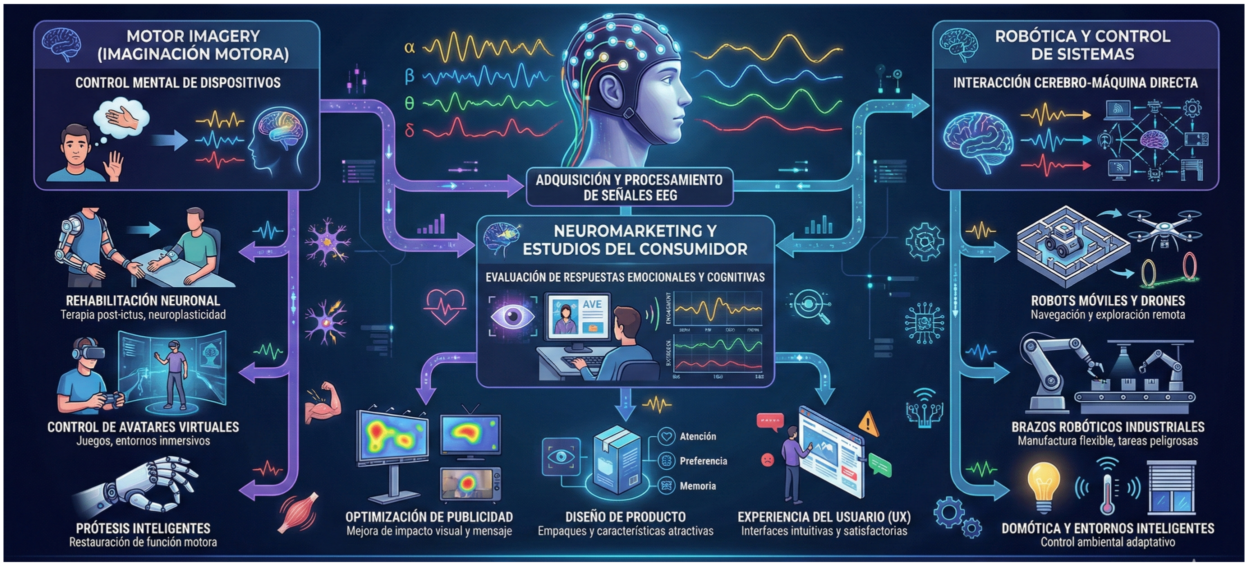

Figure 1-2: Applications of EEG-based BCIs in different domains.

Serious games are digital environments designed not solely for entertainment, but to fulfill educational, therapeutic, or cognitive objectives [Damaševičius et al., 2023]. In the context of neurodevelopmental disorders such as ADHD, they have become increasingly relevant as tools for both cognitive assessment and intervention [Patiño et al., 2025]. Their engaging and adaptive nature allows them to target specific executive functions—like attention, inhibition, and working memory—while maintaining high user motivation, particularly among children [Rodríguez Timaná et al., 2024]. To achieve this, two principal paradigms guide their design [De Luca et al., 2024]. The first is the task-based paradigm, which integrates classical neuropsychological tasks—such as the Go/No-Go, n-back, or Stroop test—into interactive game mechanics, allowing for the precise measurement of behavioral responses tied to well-established cognitive models [Fang et al., 2025]. The second is the neurofeedback paradigm, in which the game dynamically responds to real-time EEG signals, offering auditory or visual feedback based on the user's brain state. This paradigm supports operant conditioning mechanisms, encouraging users to self-regulate neural activity linked to attentional control and inhibition [Firouzabadi et al., 2022].

These design paradigms are intricately aligned with four core cognitive models critical to ADHD pathology: attention, working memory, inhibition, and planning (see Figure **1-3**). Games targeting the attentional model aim to improve sustained and selective attention, often requiring players to maintain focus amid distractions or shifting stimuli [Chen et al., 2024]. Working memory is typically trained through tasks that require the temporary storage and manipulation of information, such as remembering sequences or updating mental representations. The inhibition model involves suppressing prepotent responses or resisting distractions—commonly implemented through fast-paced decision-making challenges or impulse control mechanics [Takahashi et al., 2024, Breitling-Ziegler et al., 2020]. Finally, the planning model emphasizes goal-directed behavior, encouraging users to sequence actions, solve multi-step problems, or anticipate future outcomes [Lorini et al., 2022]. By aligning game mechanics with these cognitive models, serious games become powerful tools not only for engagement but for targeted neurocognitive intervention.

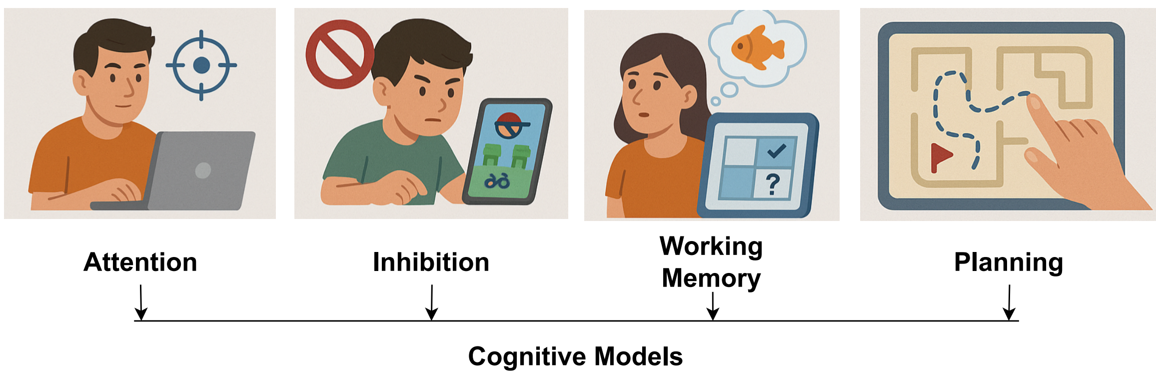

Figure 1-3: Core cognitive models targeted by serious games in ADHD interventions: attention, working memory, inhibition, and planning. Each model maps to a specific set of game dynamics and EEG markers.

When these targeted interventions are integrated with BCI technology, they demonstrate substantial therapeutic benefits by reinforcing executive function, improving behavioral outcomes, and reducing symptom severity through active attention training [Doulou et al., 2025]. By utilizing active BCIs, in which users intentionally modulate their focus to influence the outcome of the game, these systems have been shown to strengthen cognitive control and promote long-term neuroplastic changes directly relevant to ADHD pathology [Cervantes et al., 2023]. Furthermore, these integrated platforms enable adaptive feedback, allowing interventions to dynamically adjust to each child's specific neurocognitive profile. Ultimately, combining robust cognitive models with real-time, objective EEG feedback makes serious games uniquely compatible with BCIs, providing a highly personalized framework for interactive cognitive modulation.

Recent developments in portable EEG hardware have expanded the applicability of BCIs for ADHD beyond clinical settings, enabling real-time monitoring and feedback in homes, classrooms, and th erapeutic environments. Low-cost, wireless EEG headsets—equipped with dry electrodes and embedded microcontrollers—have been successfully integrated into neurofeedback systems and serious games designed for children [Xu and Zhong, 2018]. These platforms allow for real-time signal acquisition and onboard processing, supporting closed-loop interventions without reliance on external computers. Thanks to ARM-based processors and system-on-chip (SoC) designs, it is now possible to run lightweight machine learning models directly on the device for real-time EEG classification [Wang et al., 2020]. Moreover, custom head-mounted EEG systems have shown reliable tracking of the theta/beta ratio, a key biomarker for ADHD, during interactive tasks [Larocco et al., 2020].

The push to bring these portable, AI-driven interventions out of the clinic is heavily supported by the rapid expansion of the digital health sector. As of 2024, the global telehealth and telemedicine market surpassed $123 billion, reflecting a permanent shift toward decentralized care and remote patient monitoring [Grand View Research, 2024]. To support this transition, the global embedded systems market reached over $112 billion in 2024, driven by an immense demand for compact, energy-efficient Internet of Medical Things (IoMT) devices [Coherent Market Insights, 2024]. Concurrently, the integration of artificial intelligence into healthcare—a market valued at over $13 billion in the U.S. alone in 2024—demonstrates a strong clinical and commercial drive to embed complex diagnostic intelligence directly into everyday environments [Nova One Advisor, 2024]. These economic indicators highlight a clear motivation: there is a profound necessity to translate hospital-grade capabilities into accessible, wearable form factors that operate autonomously.

To successfully deploy these autonomous systems in daily life, research must focus on optimizing hardware and software integration for strict portable constraints [Phiri, 2023]. Operating continuously in non-clinical settings necessitates highly efficient energy and resource use, as wearable devices are bound by severe power and memory limitations. Processing biosignals locally via edge AI reduces latency and power-heavy cloud transmissions, yet it requires highly tailored acquisition algorithms that maximize computational efficiency [Shajari et al., 2023]. Furthermore, capturing a comprehensive physiological profile demands the precise synchronization of biomarkers across distributed sensors [Ramasubramanya et al., 2025]. Ensuring that multi-modal data streams are temporally aligned is an absolute necessity for generating accurate, real-time contextual feedback. By establishing robust methods to efficiently acquire, align, and process these integrated biomarkers on low-power architectures, this research aims to unlock the full therapeutic potential of continuous, closed-loop neurofeedback outside of traditional medical facilities [Li et al., 2023].

To address these evolving requirements for decentralized mental health technology, this research is developed within the framework of the project called "Alianza científica con enfoque comunitario para mitigar brechas de atención y manejo de trastornos mentales relacionados con impulsividad en Colombia" (ACEMATE) (Multimodal system supported by serious games for personalized neurocognitive assessment and intervention in impulsivity disorders associated with ADHD), a collaborative initiative involving the Universidad Nacional de Colombia and the Universidad Tecnológica de Pereira. ACEMATE aims to facilitate both face-to-face and remote interventions across clinical, educational, and community settings. However, realizing this vision of accessible care relies entirely on deploying physical infrastructure that resolves the previously outlined technical bottlenecks—specifically, the need for robust, portable hardware capable of precise biomarker synchronization. Consequently, this thesis proposes the development of MONEEE, a specialized EEG signal acquisition system designed to serve as the hardware enabler for ACEMATE. By ensuring low-latency marker integration and high signal fidelity under strict energy and resource constraints, MONEEE provides the essential technological foundation to power the broader ACEMATE ecosystem, ultimately democratizing access to objective, technology-driven mental health services for children.

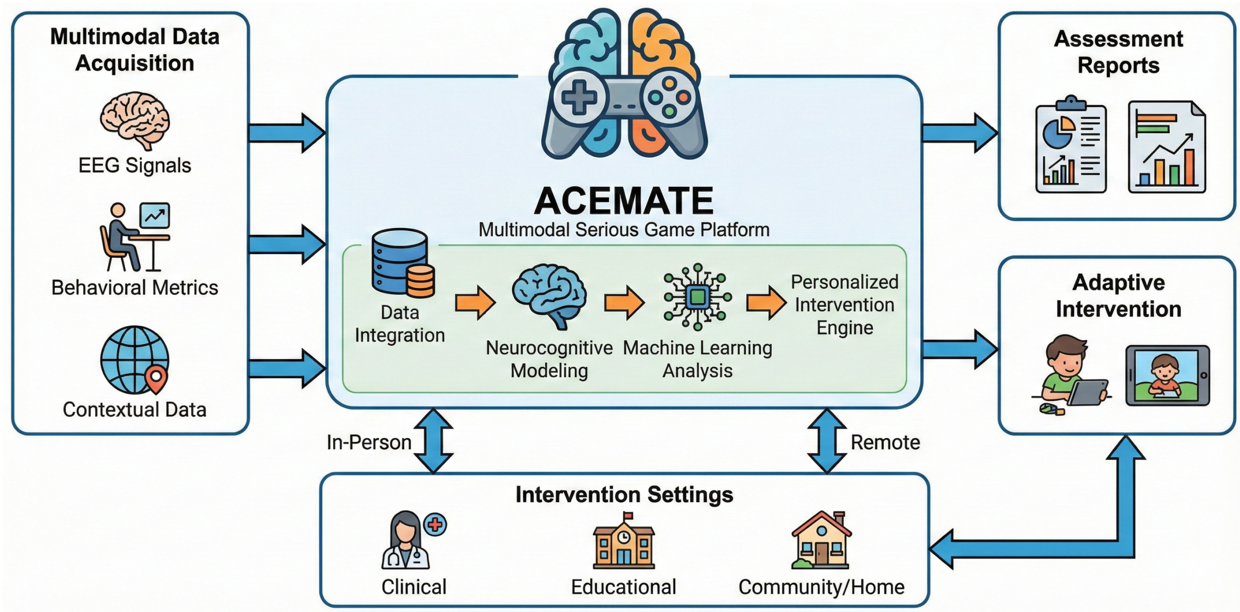

Figure 1-4: Overview of the ACEMATE project.

1.2 Problem statement

While the integration of BCIs and continuous EEG mon itoring within serious games presents a promising avenue for neurocognitive assessment, translating these concepts into functional clinical tools requires a highly robust underlying hardware architecture [Craik et al., 2023]. Fundamentally, the physical acquisition of this neural data begins with an EEG cap fitted with non-invasive sensors designed to detect microvolt-level electrical signals from the cerebral cortex. Because these raw biological signals are inherently weak and highly susceptible to noise, they must be routed to a dedicated acquisition board or a multi-stage card system [Armand Larsen et al., 2024]. This hardware typically consists of an analog front-end—responsible for the high-precision amplification, filtering, and digitization of the signals—and a digital processing unit, such as a microcontroller, for real-time data management and routing [Janapati et al., 2023]. To effectively map the neurocognitive responses elicited by the serious games, this continuous neural data must be contextually locked to specific in-game cognitive stimuli. This vital synchronization is achieved by interfacing the acquisition hardware with the stimulus presentation device, which transmits discrete event markers that map external gameplay milestones directly to the EEG stream [Minissi et al., 2025].

However, the translation of this theoretical promise into clinical reality faces formidable engineering barriers. The efficacy of closed-loop interventions is predicated not on the mere availability of data, but on the fidelity and temporal determinism of that data [Sabio et al., 2024]. Current acquisition architectures, particularly those designed for portability and low cost, are frequently plagued by systemic failures that sever the causal link between neural intention and digital response [Ariza and Pearce, 2022]. This research defines and analyzes two such sequential, critical failures. The foundational challenge stems from severe Signal-to-Noise Ratio (SNR) limitations inherent to embedded architectures [Li et al., 2025a]. In portable EEG devices designed for ADHD monitoring, the physical proximity of high-speed digital processing components inevitably introduces electromagnetic interference. This interference degrades the system's high-precision analog sensing, corrupting the delicate microvolt-level neural signals required before any valid clinical evaluation can even begin [Dobrev and Neycheva, 2022]. Once a reliable physiological signal is secured, a second, equally critical failure emerges: the precise synchronization of biomarkers [Esteban et al., 2026]. Because ADHD neurocognitive assessments rely heavily on time-locked neural responses to specific game events, any temporal variability or unpredictable latency between the digital stimuli and the recorded biological signals fundamentally compromises the diagnostic validity of the data [Kamiński et al., 2026]. The contrast between the theoretical promise of continuous monitoring and the clinical reality is summarized in Figure **1-5**.

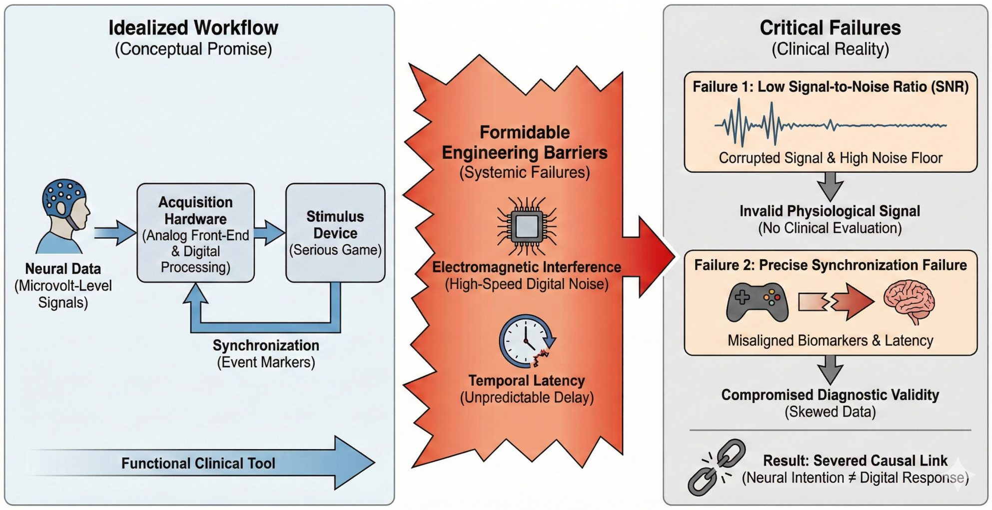

Figure 1-5: The clinical translation problem in neurocognitive assessment systems. The illustration defines the two sequential critical failures that compromise diagnostic validity: the corruption of the analog signal and the temporal misalignment of biomarkers.

1.2.1 SNR limitations in embedded systems and their impact on portable EEG

The physical interface of traditional clinical EEG setups creates a major operational bottleneck for pediatric neurocognitive assessment. Lengthy and restrictive cap placement processes consistently induce restlessness, anxiety, and movement artifacts in children with ADHD [Lim et al., 2023]. If the acquisition hardware cannot be deployed rapidly and comfortably, the resulting setup latencies and prolonged impedance stabilization times severely degrade the SNR [Gorjan et al., 2022]. This physical friction directly compromises the ecological validity and engagement required for a serious game environment, making the rapid deployment of the acquisition cap a critical challenge to overcome [Kaongoen et al., 2023].

Once the physical interface is established, preserving analog signal integrity within a densely populated, mixed-signal embedded system presents a fundamental hardware challenge [Liu et al., 2024]. The close physical proximity of high-speed digital processing units to the analog front-end introduces severe risks of electromagnetic interference and power supply noise coupling [Devi et al., 2022]. If physical board layout and isolation strategies are inadequate, the system's intrinsic background noise will inevitably exceed the baseline input-referred noise thresholds of the acquisition components (typically 1 µVpp) [Rashid et al., 2018]. Overcoming this mixed-signal noise ceiling is essential; failure to do so creates a high noise floor that completely masks the low-amplitude Event-Related Potentials (ERPs) necessary for cognitive assessment [Kim et al., 2022].

Even if analog noise is successfully mitigated, the embedded system's processing hardware faces severe resource constraints when managing continuous, high-frequency electrophysiological data streams. Unoptimized continuous data logging demands substantial computational power and can rapidly induce I/O bottlenecks, RAM saturation, and subsequent thermal throttling [Battaglia et al., 2022]. The immediate consequence of an overburdened CPU or saturated memory footprint is the dropping of crucial data packets and the introduction of variable acquisition latency [Arroba et al., 2024]. This resource exhaustion fundamentally corrupts the integrity and continuity of the EEG data stream itself. Therefore, continuous monitoring of RAM usage and CPU load is critical to ensure the hardware can sustain reliable, uninterrupted data acquisition without buckling under the operational demands [Ajmeria et al., 2022]. As illustrated in Figure **1-6**, the physical friction of traditional cap placement and the subsequent risk of analog signal corruption present immediate hurdles.

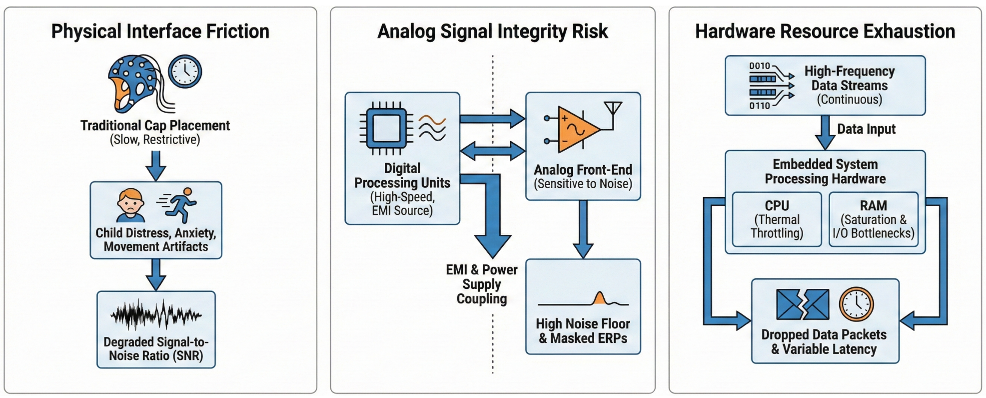

Figure 1-6: Physical, electrical, and computational resource barriers in deploying EEG systems. The illustration highlights operational bottlenecks during patient setup, the risk of SNR degradation due to mixed-signal interference, and embedded system resource exhaustion.

1.2.2 Synchronization and temporal variability in EEG biomarkers for ADHD

The primary challenge in extracting valid neurocognitive assessments lies in the precise temporal synchronization of acquired (EEG) biomarkers with external serious game stimuli [Ahmed et al., 2025]. During interactive sessions, event markers are continuously transmitted from the game interface to the acquisition system. Standard communication protocols, however, introduce inherent, non-deterministic latency driven by transmission overhead, variable polling rates, and operating system scheduling conflicts [Buraimoh et al., 2023]. This unpredictable communication jitter fundamentally skews the temporal alignment between the stimulus presented to the patient and the corresponding neurophysiological response [Larsen et al., 2024]. By conducting rigorous short-term latency bounding tests, this immediate communication delay must be quantified and mitigated to ensure the calculated Event-Related Potentials (ERPs) are temporally accurate and clinically viable [He et al., 2023].

Beyond the immediate delay of single events, maintaining precise synchronization throughout a complete clinical session presents a compounding temporal challenge. Standard pediatric

ADHD evaluations demand sustained, uninterrupted engagement. Continuous execution over these extended periods exposes the acquisition architecture to cumulative temporal errors [Arpaia et al., 2025]. Asynchronous clock drift between the event triggers and the hardware sampling rate, coupled with potential memory buffer saturation and thermal-induced performance fluctuations, introduces progressive instability [Dasenbrock et al., 2022]. This compounding jitter degrades deterministic data throughput, leading to a critical flaw where an ERP captured at the end of a session exhibits a fundamentally different latency profile than one captured at the beginning. Extended stability testing over full-length sessions is therefore imperative to prevent temporal degradation and validate the long-term reliability of the continuous EEG stream [Tran et al., 2026].

In parallel with resolving these mechanical timing issues, valid synchronization relies on the system's proven ability to capture authentic, dynamic electrophysiological phenomena rather than structured noise [Correia et al., 2024]. Before complex ERPs can be reliably synchronized with external events, a foundational physiological baseline test must be conducted. This problem is addressed by detecting spontaneous frequency modulations, specifically the well-documented attenuation of alpha-band activity (8–13 Hz) when a subject transitions from an eyes-closed to an eyes-open state [Isler et al., 2023]. If the signal processing pipeline distorts the bandwidth or lacks the sensitivity to capture these baseline spectral shifts, the recorded data is physiologically invalid [Fló et al., 2022]. Verifying the fundamental ability to resolve these basic frequency changes ensures that the synchronized event markers are anchored to genuine neural activity [Frelih et al., 2025]. Figure **1-7** demonstrates how non-deterministic latency and cumulative temporal drift fundamentally skew the alignment between the game stimulus and the neurophysiological response.

Finally, the temporal precision of the biomarkers must be matched by their spatial and structural integrity, which requires addressing inherent hardware vulnerabilities. High-resolution, multi-channel EEG acquisition creates a strict physical requirement for trace isolation to prevent analog signal bleed. Without meticulous shielding, adjacent channels inevitably suffer from crosstalk, blending distinct spatial brain waves and destroying the topographical accuracy of the recorded data. Furthermore, rendering these continuous data streams can introduce visualization artifacts that masquerade as genuine visual transients or ERPs. By executing rigorous signal isolation and artifact detection tests, these structural issues can be identified and eliminated, ensuring that the precisely synchronized neurocognitive markers are extracted from pristine, uncontaminated data.

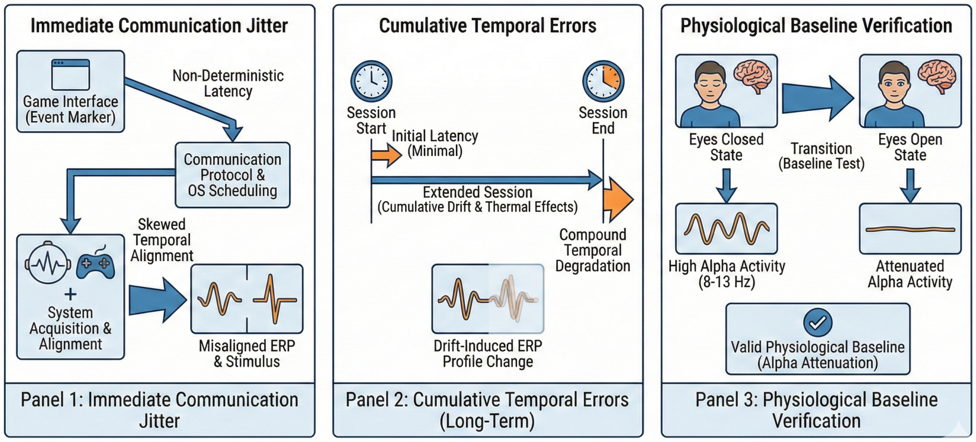

Figure 1-7: Synchronization errors and real-time physiological validation. This figure details the impact of short-term non-deterministic communication jitter, cumulative temporal drift in extended sessions, and physiological baseline verification via alpha-band attenuation.

1.3 Research question

How can a low-latency and low-jitter data synchronization framework be developed and validated to ensure the temporal integrity of multimodal data from embedded EEG systems and dynamic serious game events, while respecting the inherent resource and power constraints of such platforms?

1.4 State of art

In recent years, numerous wireless systems for EEG data acquisition have been developed, with two main approaches standing out: conventional remote monitoring systems and portable smart systems. The former simply digitize the EEG signals and transmit them to a remote unit for processing, usually in a deferred manner [Arpaia et al., 2020]. On the other hand, portable systems preprocess the signals on a local device, such as a microcontroller (MCU), and wirelessly transmit the data using low-power consumption protocols. **1-1** This latter approach is crucial for real-time applications, where low latency is essential.

Marker synchronization in portable EEG acquisition systems [Razavi et al., 2022], particularly in applications combined with serious games [Damaševičius et al., 2023], faces several technical and operational challenges. One of the main issues lies in latency in data transmission protocols. In portable EEG systems, precise synchronization between brain events and interactions in the game is crucial [GomezRomero-Borquez et al., 2024], but inherent limitations of portable acquisition systems, such as latencies in data transfer protocols, can cause temporal mismatches. These latencies primarily stem from bandwidth constraints in wireless transmission and the need to process large volumes of data in real-time [He et al., 2023].

The type of electrode [Liu et al., 2023b] and the number of channels [Abdullah et al., 2022] are determining factors in the quality of the data acquired in portable systems. Although dry electrodes offer greater portability, they tend to generate lower-quality signals due to reduced conductivity, which can complicate precise synchronization with other devices, such as serious games. On the other hand, the use of systems with **low channel density (e.g., 8-16 channels)** [Allouch et al., 2023] is a common strategy in these portable systems to minimize size and improve portability. However, low channel density can affect the spatial resolution of EEG data, limiting the ability to perform accurate analysis of brain patterns. This challenge is reflected in the need to optimize sampling [Zheng et al., 2023] and data transfer protocols [Bayılmış et al., 2022] to ensure that captured signals are transmitted efficiently without significant information loss

The sampling rate is another critical factor, as it directly affects the temporal resolution of EEG signals. The combination of low channel density and insufficient sampling rate can make it difficult to capture fast brain events, such as attention shifts, which are essential in applications like serious games. Furthermore, Signal Front-End Amplifiers (AFE) [Devi et al., 2022] play a key role in signal quality. While low-cost AFEs may be suitable for portable systems, they tend to have limitations in processing capacity, which impacts data synchronization by generating noise and distortions in the EEG signals, especially when connected to mobile devices with lower processing power.

Battery life [Niso et al., 2023] is a significant constraint for portable systems that require long monitoring sessions. EEG systems that operate for several hours often need to optimize their energy consumption, which may involve reducing the sampling rate or channel density, once again impacting data quality and real-time synchronization.

Table 1-1: Acquisition devices used for BCI. The table provides an overview of the different hardware devices, their specifications, and communication protocols.

Hardware BCI	**Empresa**	**Tipo de Electrodo**	**Canales**	**Frecuencia de Muestreo**	**AFE**	**Protocolo y Transferencia**	**Batería**
Cyton + Daisy [OpenBCI, 2024]	OpenBCI	Flexible / Húmedo / Seco	16	250 Hz - 16 kHz	ADS1299	RF / BLE / Wi-Fi	8 h
actiCAP [Products, 2024]	Brain Products GmbH	Flexible / Húmedo / Seco	16	256 Hz - 16 kHz	-	USB	16 h
EPOC X [Emotiv, 2024]	Emotiv	Rígido / Húmedo	14	128 Hz	-	BLE / Bluetooth	6–12 h
Diadem [Bitbrain, 2024]	Bitbrain	Rígido / Seco	12	256 Hz	-	Bluetooth	8 h
g.Nautilus [g.tec, 2024]	g.tec	Flexible	8 / 16 / 32	250 Hz	ADS1299	Propietario	10 h
Plataforma para EEG ambulatorio [Pinho et al., 2014]	-	Activo / Seco	32	250 Hz- -1 kHz	ADS1299	Wi-Fi 802.11 b/g/n	26 h
Sistema para neurofeedback [Totev et al., 2023]	-	Pasivo / Seco	40	250 Hz	ADS1298	RF	-
BEATS [Zou et al., 2022]	-	Flexible / Húmedo	32	4 kHz	ADS1299	Wi-Fi	24 h (cableado)

In the field of brain-computer interfaces (BCIs), several devices have been developed, each with unique features tailored to specific use cases such as clinical research, neurofeedback, or consumer applications. The Cyton + Daisy system by OpenBCI [OpenBCI, 2024] supports up to 16 channels and offers a wide sampling rate range of 250 Hz to 16 kHz, making it suitable for high-resolution EEG acquisition. The device uses flexible, wet, or dry electrodes and incorporates the ADS1299 AFE for high-quality signal conversion. It supports data transfer via RF, Bluetooth Low Energy (BLE), and Wi-Fi, allowing for versatile connectivity. With a battery life of 8 hours, this system is highly adaptable, suitable for both research and practical applications in various environments. Another system, actiCAP [Products, 2024] by Brain Products GmbH, features flexible, wet, or dry electrodes and is capable of recording up to 16 channels with a sampling rate range from 256 Hz to 16 kHz. The actiCAP does not use a dedicated AFE and instead relies on a USB protocol for data transfer. The device provides a robust 16-hour battery life, making it an ideal choice for long-duration experiments and clinical settings that require stable signal acquisition over extended periods. The EPOC X [Emotiv, 2024] by Emotiv is a more compact and consumer-oriented BCI device that uses rigid, wet electrodes and supports 14 channels with a sampling rate of 128 Hz. This device employs Bluetooth Low Energy (BLE) for wireless data transfer, and its battery life ranges from 6 to 12 hours, depending on usage. While its lower sampling rate may limit its use for high-resolution research, the EPOC X remains a popular choice for applications in neurofeedback, cognitive training, and general user interaction. The Diadem [Bitbrain, 2024] system by Bitbrain uses rigid, dry electrodes and supports 12 channels with a sampling rate of 256 Hz. It operates via Bluetooth for data transmission and has a battery life of 8 hours, providing a balance between portability and signal quality. The g.Nautilus [g.tec, 2024] system by g.tec offers great flexibility, supporting configurations with 8, 16, or 32 channels. It operates at a sampling rate of 250 Hz and uses the ADS1299 AFE for high-performance signal acquisition. The system is known for its proprietary data transmission protocol, ensuring reliable connectivity, and its battery lasts up to 10 hours, making it suitable for long-term monitoring and research studies. The BCI system used by [Pinho et al., 2014] employs active, dry electrodes and supports up to 32 channels with a sampling rate range of 250 Hz to 1 kHz. It also incorporates the ADS1299 AFE for analog-to-digital conversion, ensuring high fidelity in signal capture. Data is transferred via Wi-Fi 802.11 b/g/n, enabling flexible and high-speed communication with external devices. The system boasts an impressive 26-hour battery life, making it an excellent option for extended usage in field studies or clinical applications. The BCI system described by [Totev et al., 2023] uses passive, dry electrodes and supports up to 40 channels with a sampling rate of 250 Hz. It incorporates the ADS1298 AFE for high-quality data acquisition and utilizes RF (Radio Frequency) for data transfer. While battery life details are not specified, this device is likely designed for portable, research-focused applications where wireless data transfer is essential for real-time monitoring. Finally, the [Zou et al., 2022] system features 32 flexible, wet electrodes and uses the ADS1299 AFE for high-precision EEG signal acquisition at a sampling rate of 4 kHz. Data is transmitted wirelessly via Wi-Fi, allowing for real-time data monitoring and analysis. The system's battery life is 24 hours when wired, providing extended operation for intensive studies or clinical assessments that require continuous monitoring.

Each of these devices represents a different approach to EEG signal acquisition, offering varying numbers of channels, electrode types, sampling rates, and battery life. While some are optimized for research and clinical use with high sampling rates and extended battery life, others are more suited to consumer applications with lower sampling rates and shorter operational times. The choice of device depends largely on the specific needs of the user, whether for research, clinical monitoring, or personal use in neurofeedback and cognitive training applications.

1.4.1 Unpredictable Latency and Jitter Between Game Events and EEG Recordings

The integration of electroencephalography (EEG) into serious games necessitates a departure from the deterministic timing of traditional psychophysics toward architectures capable of managing the stochastic nature of modern game engines and wireless transmission. In the last years, the resolution of unpredictable latency and jitter has coalesced around a progression of engineering philosophies, moving from software-defined abstraction to hardware-grounded validation, and finally to predictive algorithmic compensation.The dominant engineering philosophy in recent years has been the abstraction of hardware timing differences through Network-Layer Middleware, with the Lab Streaming Layer (LSL) cementing its status as the de facto standard for multimodal synchronization. In their seminal 2024 reference paper, [Kothe et al., 2025] validated the LSL ecosystem's ability to achieve sub-millisecond accuracy by employing a distributed clock discovery protocol similar to NTP, which continuously estimates offsets and drifts between source and recording clocks. This software-centric approach has been pivotal for enabling "zero-configurationresilience in complex setups, allowing disparate devices to synchronize without shared hardware triggers. For instance, [Larsen et al., 2024] applied this framework to the notoriously difficult task of synchronizing EEG with VR-integrated eye-tracking, quantifying a stable hardware offset of 36 ms but noting a persistent stochastic jitter of 5.76 ms inherent to the buffering of consumer-grade peripherals. To mitigate the specific latencies introduced by game engines like Unity, [Niehorster and Nyström, 2025] developed "TittaLSL,.[a] plugin that decouples data transmission from the rendering loop; this allows for end-to-end latencies as low as 3.05 ms, preventing graphical frame drops from corrupting the time-series integrity of the biosignals. This philosophy of software abstraction is further exemplified by the B[Romani et al., 2025], which leverages LSL to scale gamified BCI data collection to consumer hardware, accepting minor precision trade-offs in exchange for massive ecological validity and ease of deployment. However, a counter-philosophy emphasizes Hardware-Ground Truth, arguing that software timestamps are insufficient for clinical-grade validity due to the "motion-to-photon"latency of display drivers. [Ignatious et al., 2023] formalized this rigorous approach with the Çomputation of Latencies in Event-related potential Triggers"(CLET) method, which mandates the use of photodiodes to physically measure the arrival of photons [7]. Their comparative analysis revealed counter-intuitive findings: modern VR headsets often exhibit lower latencies (approx. 82 ms) than standard LED monitors (approx. 122 ms) due to aggressive low-persistence driver optimizations, yet the variance remains high enough to smear high-frequency ERP components. This necessity for hardware validation was statistically reinforced by [Miziara et al., 2025], who compared three synchronization paradigms for TMS-EEG. They demonstrated that direct hardware routing (Paradigm 3) yields a relative timing error of 0.1 %, drastically outperforming the 0.8 % error of software-parallel methods, effectively proving that software middleware introduces a non-negligible noise floor. Consequently, solutions like the TriggerBox and Chronos adapters remain critical for researchers requiring absolute temporal precision, serving as a bridge between the digital game state and the analog amplifier. Furthermore, [Ramlall et al., 2025] extended this hardware rigor to networked environments, utilizing custom synchronization protocols to align dry-electrode EEG with vehicle telemetry in multi-participant driving simulators, ensuring that çollective neurophysiologyïs aligned despite network variance. The third and most emergent philosophy treats latency not as a fixed error to be measured, but as a dynamic variable to be managed via Predictive and Compensatory Algorithms. This approach borrows heavily from edge computing and cloud gaming. [Yi et al., 2025] introduced the ARMA system, which guarantees latency Service Level Objectives (SLOs) in mobile edge computing by dynamically adjusting the complexity of Deep Neural Networks (DNNs) based on real-time network conditions; effectively, the system trades classification complexity for speed when jitter spikes, maintaining the real-time feedback loop required for serious games. Similarly, Microsoft researchers proposed .Ekho"[Hamadanian et al., 2023], a system that embeds inaudible pseudo-noise sequences into game audio to measure and compensate for inter-stream delays in real-time, achieving sub-10ms synchronization across disparate devices. On the neurophysiological side, [Shirinpour et al., 2025] advanced "Bayesian Temporal Prediction"(BTP), which predicts the phase of ongoing neural oscillations to deliver stimuli with "negative latency"—initiating the rendering pipeline milliseconds before the brain enters the desired state. Additionally, [Li et al., 2024] proposed offline stepwise latency correction algorithms that iteratively align single-trial EEG data post-hoc, effectively "de-jittering"the signal mathematically to recover sharp ERP features even from noisy recording environments. Finally, [Liu et al., 2022a] developed the CLAAP model for cloud gaming, which uses time-series forecasting to predict latency spikes before they occur, allowing the game engine to preemptively adjust its state, a technique highly applicable to remote BCI assessments.

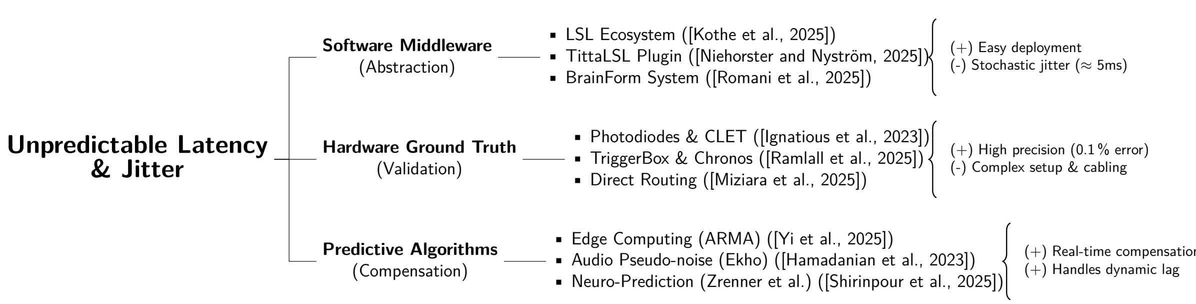

Figure 1-8: Taxonomy of mitigation strategies for unpredictable latency and jitter in multi-modal biomarker synchronization. The diagram categorizes current approaches into software middleware, hardware ground truth validation, and predictive algorithmic compensation.

1.4.2 Resource and Power Constraints in Embedded EEG Platforms

As the MONEEE system targets mobile usage, the engineering challenge shifts to maximizing signal fidelity within the stringent power envelopes of wearable devices. The literature recently addresses this through three synergistic philosophies: reducing data volume via Compressive Sensing, processing data at the edge via TinyML, and optimizing the physical layer via Low-Power ASIC Design.The philosophy of Compressive Sensing (CS) challenges the Nyquist-Shannon theorem, positing that EEG signals can be reconstructed from sparse samples to drastically reduce transmission energy—the primary consumer of battery life in wireless nodes. The state-of-the-art has evolved from simple linear reconstruction to "Deep Compressed Sensing"(CS-EEG). [Lin et al., 2024] demonstrated that integrating CNN-LSTM networks into the reconstruction pipeline allows for compression ratios of up to 70 % while maintaining a Percentage Root-mean-square Difference (PRD) of less than 7 %. This approach offloads the heavy computational reconstruction to the server, keeping the wearable sensor simple. [Kanemoto et al., 2025] implemented these principles in a wireless EEG transmission system that consumes a mere 72 µW, orders of magnitude lower than standard Bluetooth protocols. Further refinement comes from [Zhu et al., 2024], who introduced "Non-local Low-Rank and Cosparse Priors"(NLRC); this technique exploits the high inter-channel correlation of high-density EEG arrays to enhance reconstruction quality without increasing the sampling rate, effectively allowing for denser sensor grids on limited power budgets. Reviews by [Das and Kyal, 2021] further categorize these methods, highlighting that while lossless methods like ECoT ensure integrity, hybrid lossy methods are essential for the high-bandwidth demands of serious gaming. Complementing transmission reduction is the TinyML philosophy: "transmit insights, not data."By processing bio-markers directly on the microcontroller (MCU), these systems eliminate the bandwidth cost of raw data streaming. [Tsakanika et al., 2025] and [Hizem et al., 2025] have pioneered the deployment of complex seizure detection algorithms on resource-constrained ARM Cortex-M and STM32 chips using quantization techniques. By converting 32-bit floating-point weights to 8-bit integers (INT8), they achieved model size reductions of over 50 % (down to 23KB) with negligible loss in accuracy (maintaining >98 % sensitivity). To automate the design of these efficient networks, researchers at [Tragoudaras et al., 2023] applied "Neural Architecture Search"(NAS) specifically for EEG, generating models that fit within kilobytes of SRAM while optimizing for inference latency. This edge-intelligence capability is realized in systems like [Basit et al., 2025], a prosthetic control interface that runs deep learning motor imagery classification entirely on embedded hardware, and STM32-based emotion recognition systems that adapt game mechanics in real-time based on the user's affective state. Comprehensive surveys by the IEEE Internet of Things Journal (2025) confirm that TinyML is shifting the paradigm from cloud-dependent BCI to "self-contained"neuro-wearables [Li et al., 2025a], [Xu et al., 2025]. Finally, the foundational Low-Power ASIC philosophy focuses on optimizing the analog front-end (AFE) to reduce the baseline power consumption of signal acquisition. [Watcharapongvinit et al., 2023] presented a ground-free AFE design consuming only 6.55 µW per channel while maintaining robust noise rejection, critical for ambulatory settings where motion artifacts are prevalent. [Li et al., 2025a] pushed these limits further with a gain-configurable readout circuit achieving an input-referred noise floor of just 0.42 µVpp, ensuring that low-power operation does not compromise the detection of subtle neurocognitive components [Mohamed et al., 2023]. Innovators like CSEM have also introduced çooperative sensor.^{a}rchitectures, where active electrodes are connected via a single unshielded bus, reducing the weight and complexity of the headset cabling [Sriraam et al., 2023]. Furthermore, the shift toward .^{Ev}ent-Driven"processing is gaining traction; [Qaisar, 2023] and other groups have developed hybrid processors that utilize Spiking Neural Networks (SNNs) or Level-Crossing ADCs (LCADC) to process signals only when significant voltage changes occur, mimicking the brain's own energy-efficient sparsity [Liu et al., 2023a]. Recent work by [Liu et al., 2022b] on Ear-EEG AFEs demonstrates that these low-power techniques can be miniaturized into hearable form factors, opening new avenues for unobtrusive serious gaming interfaces. [Musiałek et al., 2024] also demonstrated a low-power sonification algorithm on MCU, proving that complex real-time feedback is possible within a 12mW envelope.

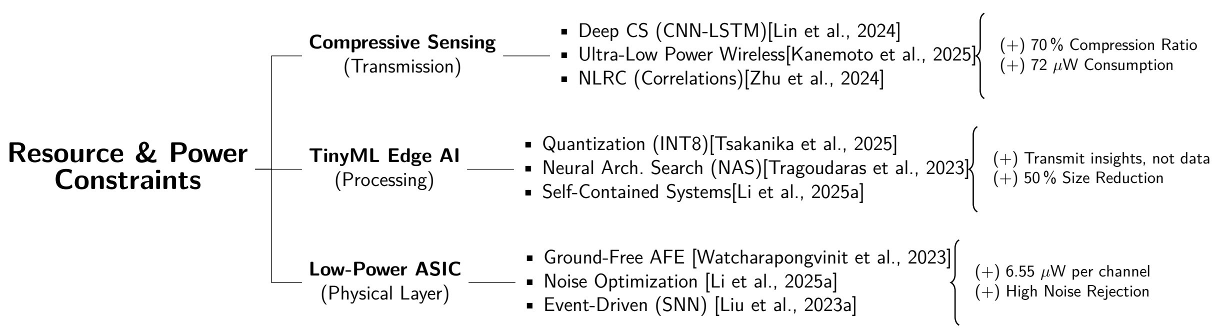

Figure 1-9: Overview of resource and power constraints across transmission, processing, and physical layer approaches.

The review of the state of the art reveals a clear dichotomy in current EEG acquisition architectures between reliable but bulky clinical systems and portable but latency-prone consumer devices; consequently, the most promising alternative for the MONEEE system lies in a wired architecture utilizing high-speed USB serial communication to connect the acquisition unit directly to the host device running the serious game, thereby eliminating the stochastic jitter and bandwidth limitations inherent in wireless transmission protocols. However, existing solutions exhibit significant limitations, as commercial "black-box"systems often restrict access to low-level communication interfaces required for real-time interaction, while standard libraries typically rely on software timestamps that drift from the hardware clock. To address these challenges and strictly validate the proposed system, performance will be defined by the Serial Communication Latency (Δt_{comm}), measured strictly as the time elapsed between the game event generation and the arrival of the data packet at the microcontroller via the dedicated integration library, alongside Synchronization Jitter (σ_{lat}) which must target a standard deviation of < 1 ms over the USB interface to ensure precise event alignment. Furthermore, Signal Fidelity will be assessed via the Percentage Root-mean-square Difference (PRD) to validate data integrity during high-throughput transmission, and Power Efficiency (P_{eff}) will be quantified in μW/channel to ensure that the USB-powered or battery-assisted configuration remains viable for extended sessions, thereby aiming to bridge the gap between clinical precision and gamified usability in the treatment of ADHD.

Table 1-2: Target Performance Specifications for the MONEEE System

Parameter	**State of the Art Gap**	**MONEEE Target**
Architecture	Wireless (High Latency/Jitter)	Wired USB Serial (Deterministic)
Synchronization	Network Middleware (e.g., LSL)	Direct Library Integration
Latency source	Bluetooth Stack + Rendering	USB Polling Rate Only
Validation	External Hardware (Photodiode)	Internal Library Timestamps

1.5 Objectives

1.5.1 General Objective

To design and implement an EEG signal acquisition architecture optimized for applications in educational and clinical settings, focused on latency reduction and precise event synchronization, to improve the objective assessment of cognitive and emotional patterns in children with ADHD.

1.5.2 Specific Objectives

1. Analyze the technical limitations of current EEG acquisition systems, including transmission latencies and low channel density.
2. Develop low-latency algorithms and temporal synchronization strategies to ensure precise alignment between serious game stimuli and EEG responses.
3. Evaluate the proposed architecture in clinical and educational settings, verifying its effectiveness in the diagnosis and treatment of ADHD.

2 Theoretical Framework

The development of the MONEEE system is grounded in the convergence of neurophysiological principles, precision electronic engineering, and computer science. This section systematizes the critical concepts required for the device's implementation, addressing the stochastic nature of biological signals, the low-noise acquisition architecture, and the challenges inherent to temporal synchronization in heterogeneous digital systems.

2.1 Neurophysiology and Event-Related Potentials (ERPs)

Electroencephalography (EEG) constitutes a non-invasive technique for recording cerebral bioelectric activity via transducers arranged on the scalp. While continuous EEG analysis allows for the monitoring of basal brain states—such as wakefulness, sleep, or convulsive pathologies—cognitive neuroscience research requires isolating specific neuronal responses associated with sensory, motor, or cognitive stimuli. These voltage fluctuations, known as Event-Related Potentials (ERPs), represent the synchronized activity of pyramidal neuronal populations in response to information processing.

Within the complex morphology of ERPs, two endogenous components are of particular interest for neurocognitive evaluation and the implementation of serious games in the context of this project. The first is the N200 (or N2) component, a negative deflection that reaches its maximum amplitude between 200 and 350 ms post-stimulus. This component is functionally linked to executive control, specifically in mismatch detection processes and the inhibition of motor responses. The second component, the P300 (or P3b), manifests as a prominent positive deflection with a latency of 300 to 600 ms. Its amplitude is modulated by the allocation of attentional resources and the updating of working memory, being particularly sensitive to stimulus improbability (the *oddball* paradigm). Due to these characteristics, the P300 is consolidated as a robust biomarker for quantifying cognitive load and attentional deficits.

The detection of these components presents a significant challenge in signal processing due to their low signal-to-noise ratio (SNR). ERPs possess typical amplitudes in the range of

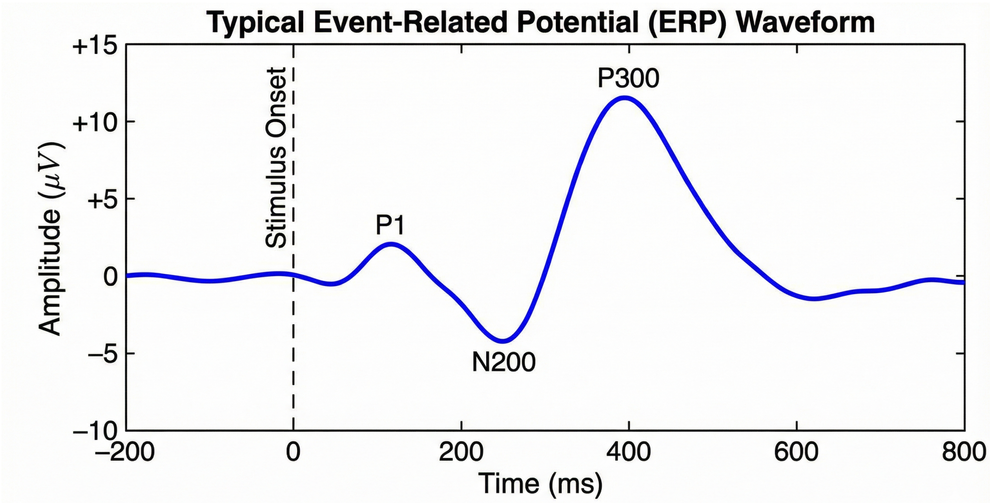

Figure 2-1: Characteristic morphology of an Event-Related Potential (ERP), highlighting exogenous and endogenous components such as the N200 and P300.

$1\mu V$ to $20\mu V$, frequently remaining masked by background EEG activity, the magnitude of which oscillates between $50\mu V$ and $100\mu V$. To extract the signal of interest, the technique of coherent signal averaging is employed. Assuming that background noise is a stochastic process with zero mean and is uncorrelated with the stimulus, by averaging N trials, the noise amplitude decreases in proportion to $1/\sqrt{N}$, while the ERP signal remains constant.

However, the validity of this technique depends strictly on temporal stability. Variability in the synchronization marker's latency, a phenomenon termed *jitter*, introduces systematic errors in the resulting average. Mathematically, if the trigger latency follows a normal distribution with standard deviation σ_t, the averaging process acts as a low-pass filter on the original waveform, attenuating high-frequency components and distorting peak amplitude. A jitter greater than 10 ms ($\sigma_t > 10$ ms) is sufficient to degrade the morphology of the N200 component, compromising the diagnostic utility of the data. Consequently, the MONEEE system must guarantee strict real-time (*hard real-time*) synchronization to preserve the spectral and temporal integrity of the biomarkers.

2.2 Hardware Architecture for Signal Acquisition

The fidelity in the digitization of biopotentials is determined by the topology of the Analog Front-End (AFE). The proposed system integrates the Texas Instruments ADS1299 integrated circuit, an analog-to-digital converter (ADC) designed specifically for biomedical instrumentation, which implements a Delta-Sigma ($\Delta\Sigma$) modulation architecture.

Unlike the Successive Approximation Register (SAR) converters common in general-purpose microcontrollers, the $\Delta\Sigma$ architecture offers superior advantages in terms of dynamic range and noise rejection through two main mechanisms: oversampling and noise shaping. The device samples the input signal at a modulation frequency (f_{mod}) significantly higher than the Nyquist rate, distributing quantization noise power over a wider spectrum. Subsequently, the modulator shifts this noise toward high frequencies, outside the biological band of interest (0–100 Hz), allowing a digital decimation filter to eliminate it effectively while reducing the data rate to the output frequency configured by the user.

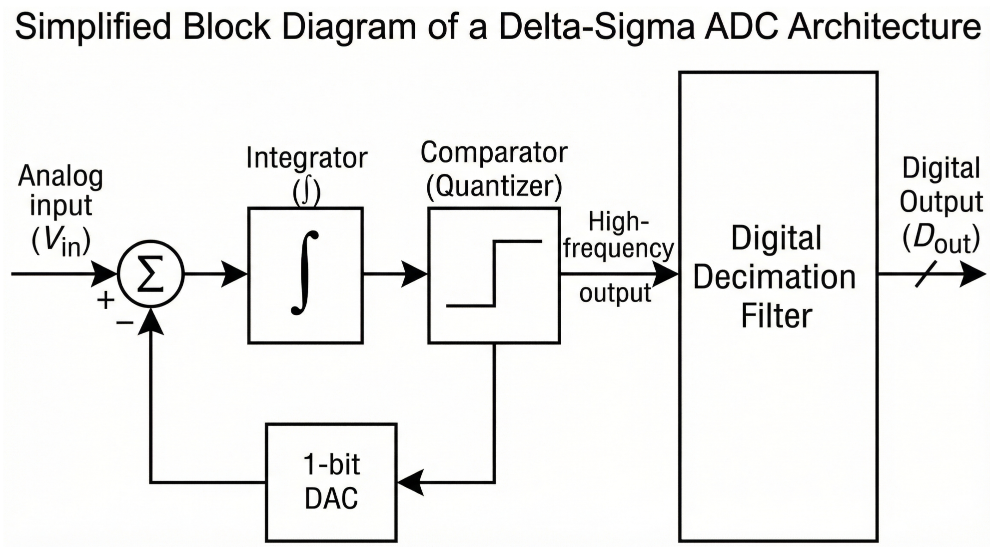

Figure 2-2: Simplified functional scheme of the modulation and filtering stage in a Delta-Sigma architecture ADC.

A critical aspect for functional connectivity and EEG coherence analysis is sampling simultaneity. In traditional multiplexed systems, a single ADC core switches sequentially between channels, introducing a systematic phase delay (t_{skew}) between electrodes. The ADS1299 mitigates this problem by incorporating independent $\Delta\Sigma$ modulators for each of its 8 channels, guaranteeing a virtually null t_{skew} and preserving the real phase relationship between different cortical regions.

To manage data flow without sacrificing temporal determinism, the MONEEE system design adopts a heterogeneous computing architecture that decouples acquisition from high-level processing. This structure is composed of a Microcontroller Unit (MCU), such as the TM4C1294, and a Microprocessor Unit (MPU), based on embedded Linux. The MCU operates under real-time constraints (either on *bare-metal* or with a lightweight RTOS), reacting to ADC hardware interrupts (`DRDY`) on microsecond scales to capture and timestamp samples, preventing FIFO buffer overflows. Meanwhile, the MPU manages computationally intensive and non-deterministic tasks, such as the TCP/IP protocol stack and file system storage. This division of responsibilities isolates bio-signal acquisition from the variable latencies introduced by the Linux kernel scheduler, ensuring data temporal integrity.

2.3 Digital Synchronization Protocols

Precise synchronization between the physiological recording and events generated by the stimulation software (video game) constitutes the central technical challenge of this research. The selection of the synchronization method implies a trade-off between temporal precision, implementation complexity, and intrusion into the user experience. Table **2-1** summarizes the characteristics of the predominant approaches.

Table 2-1: Comparative analysis of synchronization methods for BCI systems.

Method	**Mechanism**	**Precision**	**Implementation**
Optical (Photodiode)	Physical detection of screen luminance changes by an external sensor.	High (< 1 ms)	High (Additional hardware required).
Network (LSL)	Synchronization via local network protocol and software jitter correction.	Medium (< 5 ms)	Low (Software only).
Hardware Trigger (TTL)	Direct electrical signal from Parallel/USB port to the ADC.	Very High (< 1 ms)	Medium (Requires specific interfaces).

There are contrasting approaches to addressing this problem. Optical synchronization, based on photodiodes attached to the monitor, is considered the "gold standard" for validation, as it detects the physical change of pixels, bypassing software, operating system, and GPU rendering latencies. However, its requirement for external hardware limits its viability in massive clinical deployments. As a scalable alternative, the *Lab Streaming Layer* (LSL) protocol offers a middleware solution that unifies disparate data streams by assigning timestamps referenced to a common clock and drift correction algorithms. While LSL simplifies integration, its final accuracy remains dependent on local network stability and the game engine's ability to report the event time accurately.

In the context of the MONEEE system's physical interface, the USB bus introduces non-trivial latency considerations, especially for the transmission of marking commands (*soft-triggers*) from the PC to the amplifier. As a host-controlled bus utilizing polling, data transfer is discretized into frame intervals (1 ms in *Full Speed*) or microframes ($125\mu s$ in *High Speed*). Additionally, the use of the CDC (*Communication Device Class*) to emulate serial ports implies that data traverses the operating system driver stack, where it may be stored in intermediate buffers to optimize global system performance. This behavior introduces variable and unpredictable latencies of several milliseconds between the logical generation of the event in the game and its physical arrival at the USB bus, which is incompatible with the precision requirements for high-frequency ERP component analysis.

To address the latency indeterminacy introduced by the USB stack and OS buffering, the

MONEEE system implements a *hardware-embedded synchronization protocol* that couples synchronization logic directly to the biological sample at the firmware level. Unlike architectures that transmit event markers and EEG data through separate logical channels, MONEEE adopts a specific hexadecimal frame structure where the initial three bytes are strictly reserved for control data, thereby eliminating the need for post-hoc timestamp realignment.

In this encoding scheme, the first byte acts as a binary Event Flag (B_0), explicitly indicating the presence of a synchronization trigger with a value of `1` or a resting state with `0`, while the second byte (B_1) designates the Event Type, carrying the specific code required to classify the nature of the stimulus (e.g., distinguishing between target and standard inputs). This metadata is immediately followed by the third byte (B_2), which serves as a static Start-of-Frame delimiter to identify the beginning of the physiological data payload. By packaging the event markers and the EEG signal within this same atomic transmission unit, the system transforms the synchronization problem into a data parsing task, ensuring that the relative phase relationship is preserved regardless of the jitter introduced by the USB communication or the operating system scheduler.

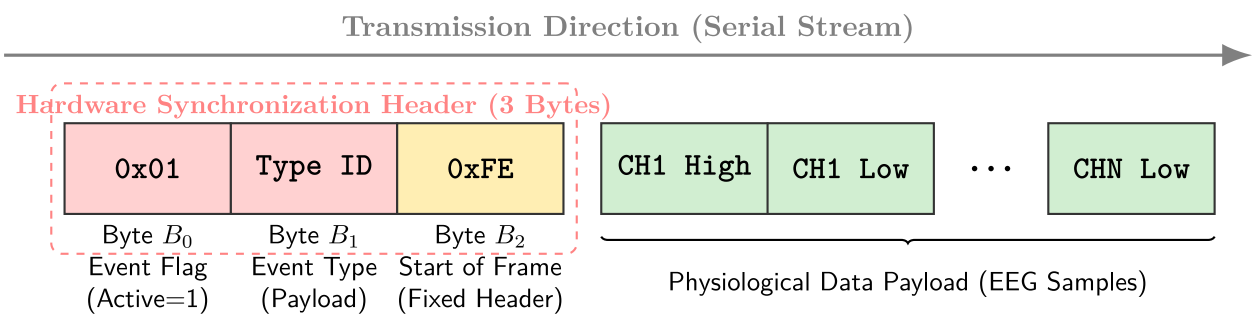

Figure 2-3: Visual representation of the MONEEE serial data transmission frame. The initial three bytes (B_0, B_1, B_2) form a dedicated hardware synchronization prefix attached to every physiological sample, ensuring that event timing is locked to the data stream before USB transmission.

3 Hardware Architecture (The MONEEE System)

The engineering design of the MONEEE system addresses the critical need to capture low-amplitude biopotentials with a high signal-to-noise ratio, while simultaneously guaranteeing low-latency synchronization with external events. To satisfy these requirements, a heterogeneous embedded computing architecture has been implemented, physically decoupling the real-time acquisition domain from the high-level computational domain. This separation allows each subsystem to be optimized for its specific function: signal integrity and determinism for acquisition, and performance and connectivity for processing.

3.1 System Topology and Data Flow

The device operates under an *edge-computing* paradigm, dedicating its resources exclusively to EEG signal management. The architecture establishes a strictly unidirectional data flow from the patient toward the processing unit, designed to minimize transport latency. The signal chain is formally modeled by the following transduction and transmission sequence:

$$\text{Electrodes} \xrightarrow{\text{Analog}} \text{ADS1299} \xrightarrow{\text{SPI}} \text{TM4C1294} \xrightarrow{\text{SPI}} \text{RPi CM4} \tag{3-1}$$

As illustrated in Figure **3-1**, the hardware is structured into three differentiated functional zones: the Analog Front-End (AFE), the Real-Time Core, and the Compute Core. This segmentation is not merely logical but physical, employing isolation barriers to protect the integrity of physiological measurements.

For this project, we have established the MONEEE system as a robust electronic design aligned with acquisition systems in its segment. The designs presented in Figures **3-2**, **3-3**, **3-4**, **3-5**, **3-6**, and **3-7** illustrate our proposal for an EEG signal acquisition board, conceived to significantly improve the capacity of real-time BCI systems, overcoming current challenges and contributing to the advancement of technology in this field.

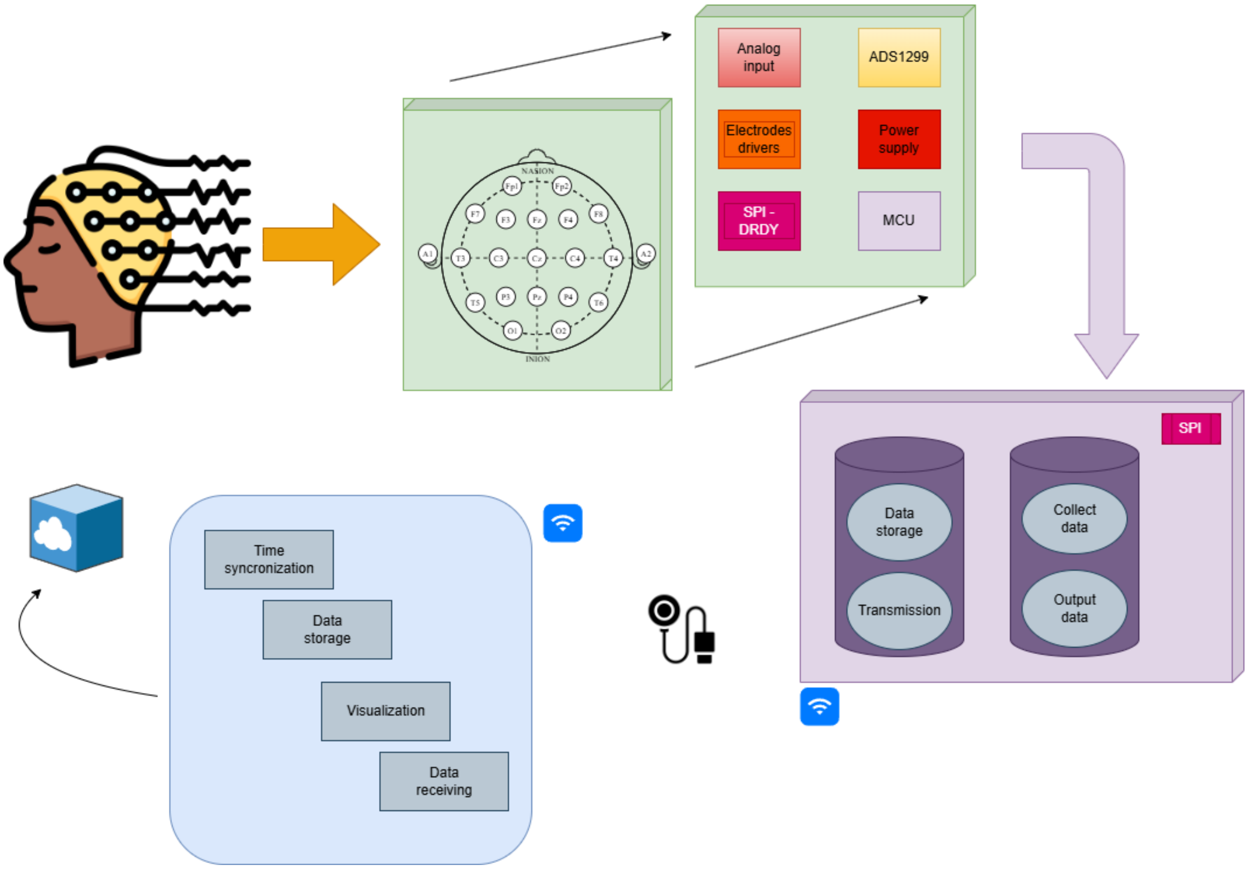

Figure 3-1: Block diagram of the MONEEE architecture, evidencing the segregation between the deterministic acquisition (MCU) and high-level processing (MPU) domains.

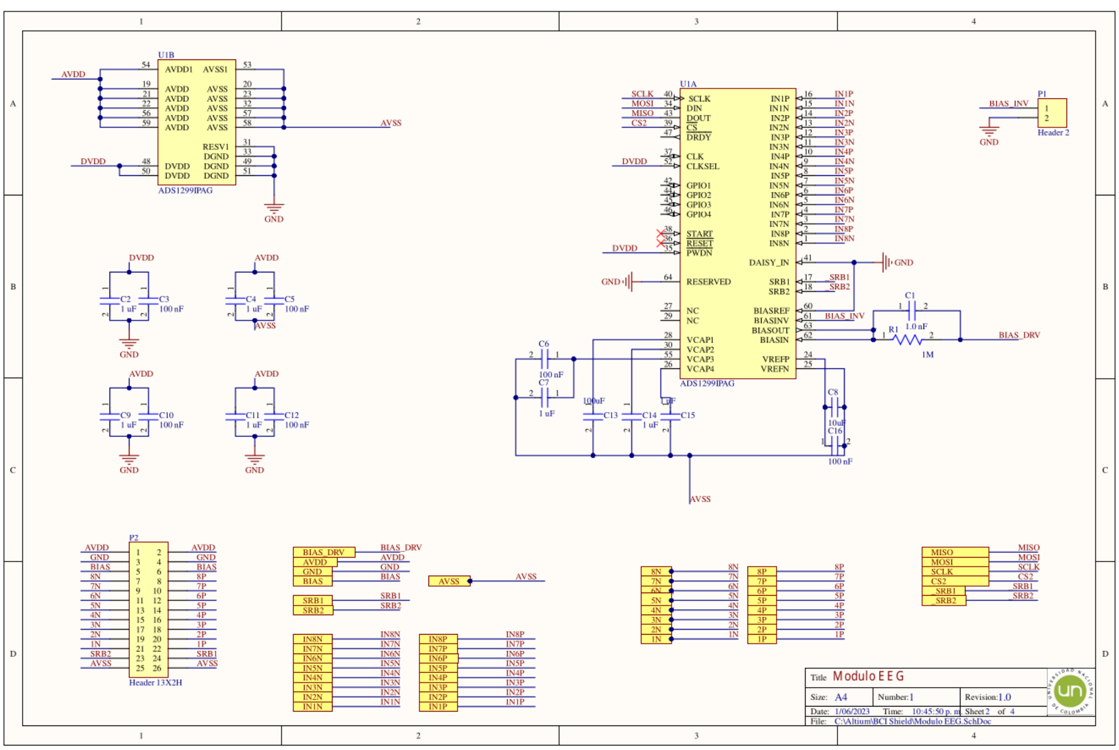

Figure 3-2: Schematic design for the module responsible for acquiring EEG signals.

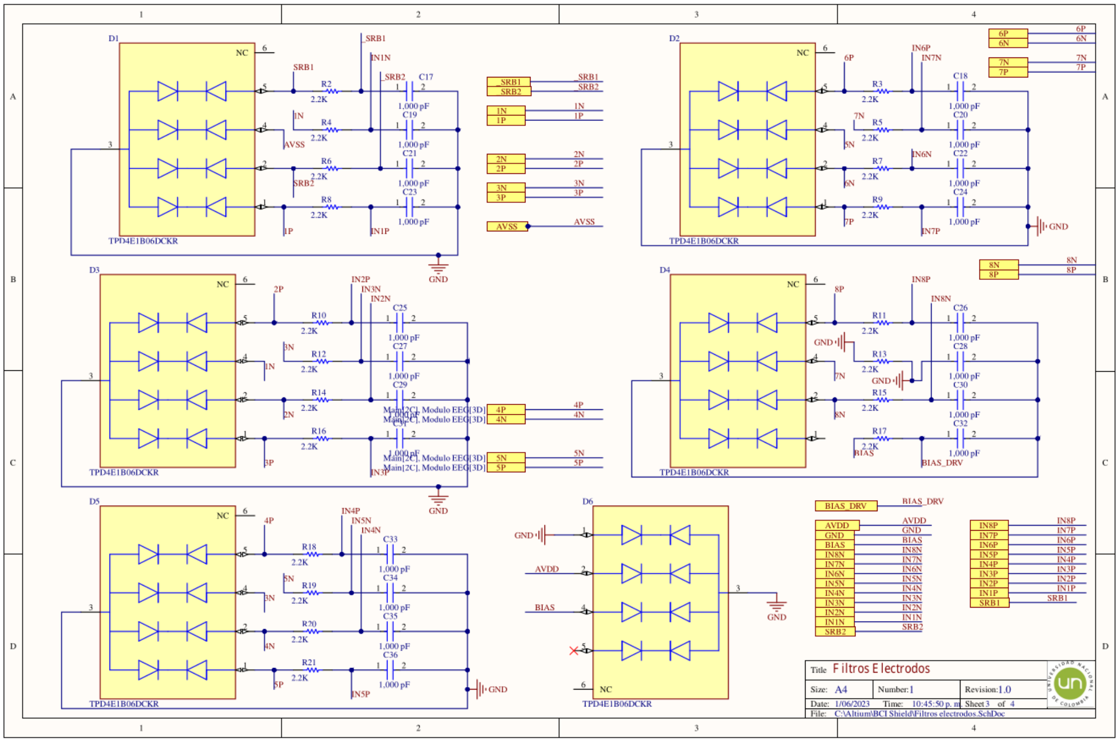

Figure 3-3: Schematic design of coupling filters.

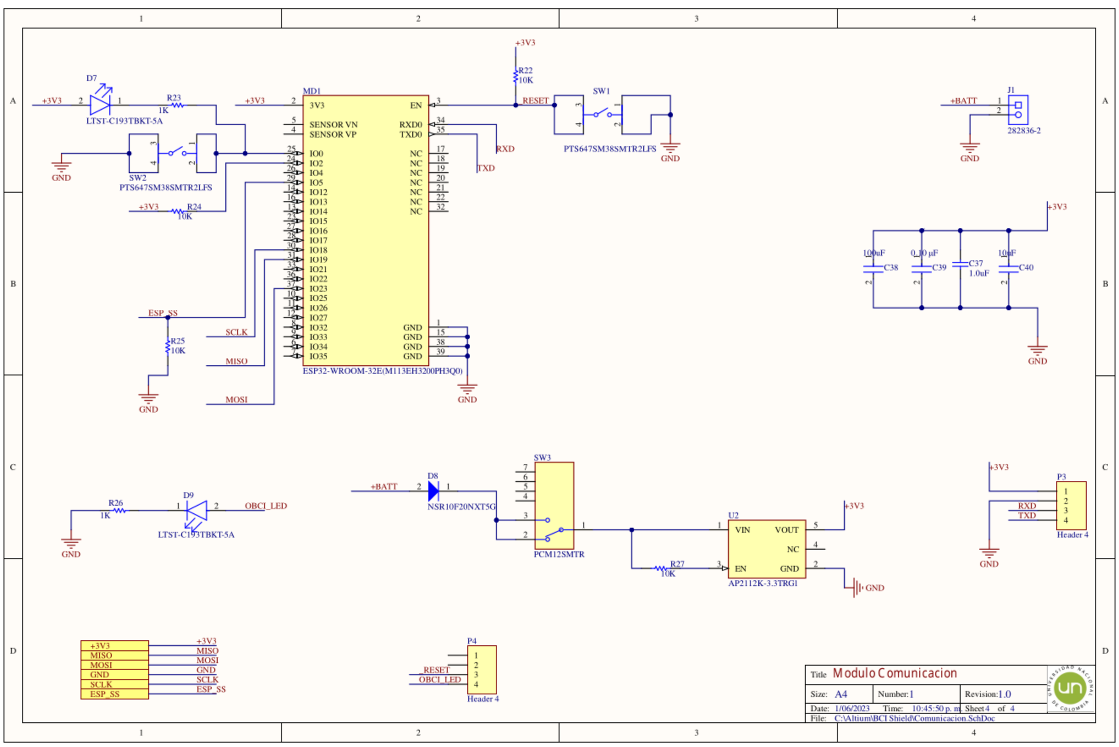

Figure 3-4: Schematic design of the module responsible for communicating the collected data to another device or to the cloud.

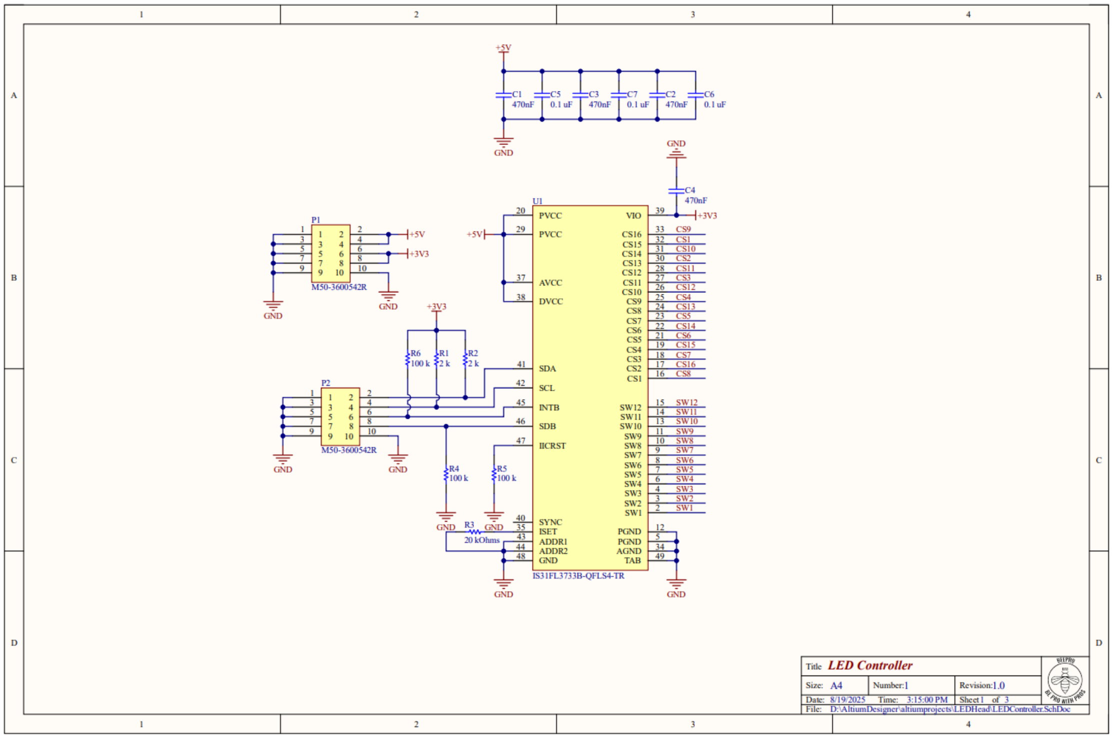

Figure 3-5: Module for impedance visualization of the electrodes.

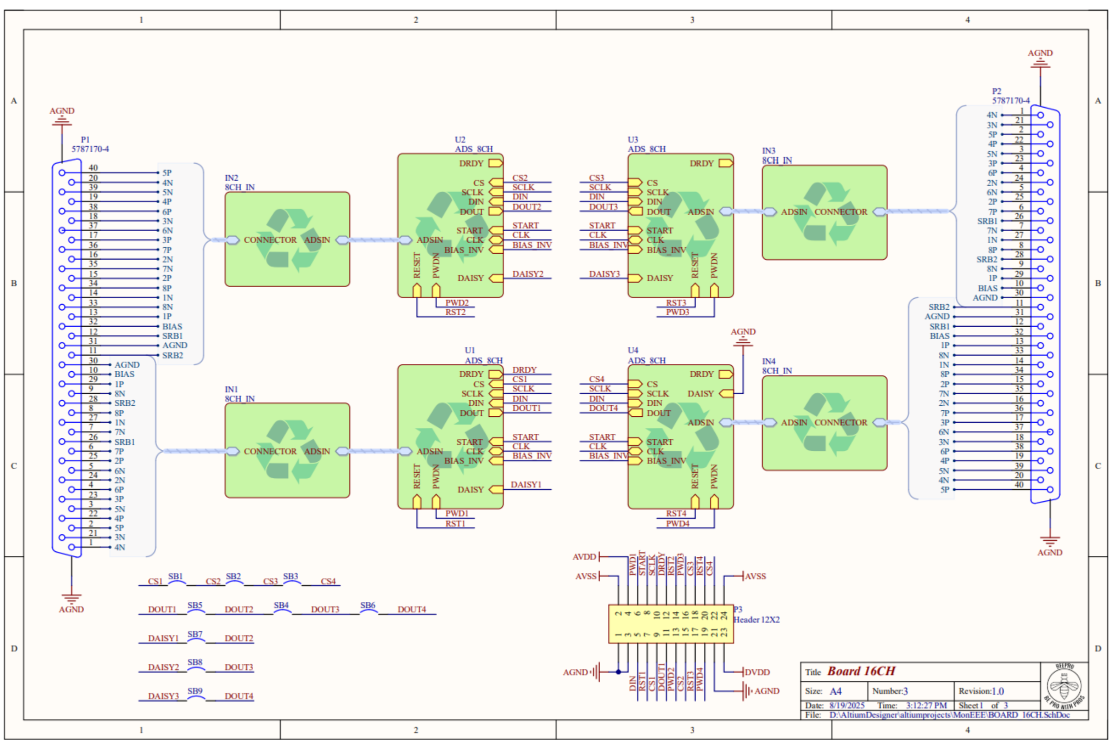

Figure 3-6: Connection between the different ADS1299 acquisition modules.

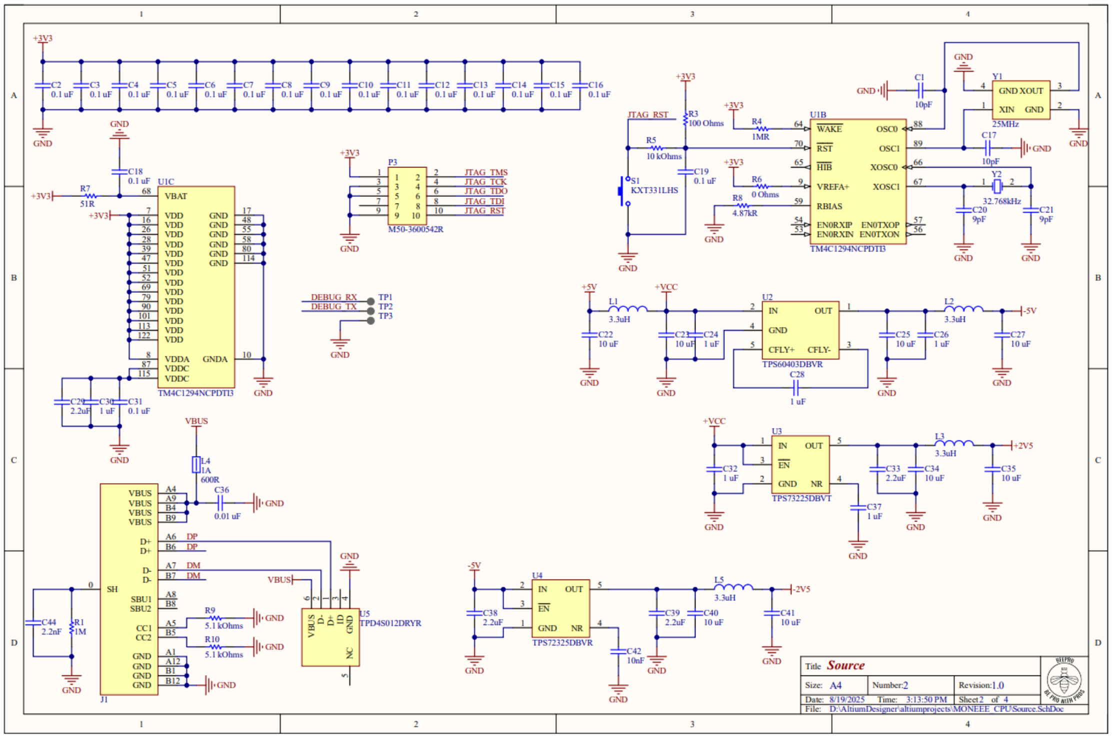

Figure 3-7: Motherboard for microcontroller and microprocessor.

3.2 Analog Front-End (AFE) and Biomedical Interface

The interface between the biological medium and the digital system is realized via the Texas Instruments ADS1299 integrated circuit. This component, a 24-bit analog-to-digital converter (ADC) with 8 simultaneous channels, has been specifically configured to optimize surface electroencephalography capture.

To maximize effective resolution on signals typically oscillating between 10 and $100\mu V$, the internal Programmable Gain Amplifier (PGA) is set to a gain of $24V/V$. Likewise, the sampling rate is fixed at 250 SPS or 500 SPS. This frequency provides a bandwidth that exceeds Nyquist requirements for the spectral components of interest (P300 and N200, generally located below 30 Hz), while allowing for the advantages of oversampling to reduce the noise floor. The input multiplexer is maintained in NORMAL mode for electrode acquisition, preserving the capability to internally switch toward test signals for self-calibration routines.

The suppression of electromagnetic interference, primarily 50/60 Hz mains noise, is managed through an active Driven Right Leg (DRL) topology. Unlike a passive ground reference, the ADS1299's *Bias Drive* circuit monitors the common-mode voltage present at the detection electrodes. This signal is inverted, amplified, and reinjected into the patient's body through the reference electrode. This negative feedback loop actively cancels interference, raising the Common-Mode Rejection Ratio (CMRR) to levels exceeding 110 dB, which is indispensable for unshielded clinical environments.

Finally, signal integrity is ensured through rigorous power management. The AFE is powered by a dedicated Li-Po battery and regulated by a PMIC (Power Management Integrated Circuit). The analog power domain ($AVDD$) is isolated from digital rails via Low-Dropout Regulators (LDOs) with high Power Supply Rejection Ratio (PSRR). This strategy prevents high-frequency switching noise, inherent to CPU operation in the compute module, from capacitively coupling to the amplifier input stages.

3.3 The Digital Core: Heterogeneous Processing

The digital architecture implements a shared responsibility model, distributing the computational load between a real-time microcontroller and an application microprocessor.

The Real-Time Unit, based on the Texas Instruments TM4C1294 (ARM Cortex-M4F), acts as the acquisition system master. Operating on *bare metal* or a lightweight real-time operating system, the TM4C guarantees deterministic behavior. Its primary function is to service the `DRDY` (Data Ready) hardware interrupt from the ADC immediately, ensuring lossless sample capture. Additionally, its Floating Point Unit (FPU) facilitates the application of in-situ digital pre-processing, such as notch filtering or scaling, without compromising interrupt service times. It is at this stage that the hardware *timestamp* is assigned, achieving microsecond precision.

Subsequently, data is transferred to the Compute Unit, constituted by a Raspberry Pi Compute Module 4 (CM4). This module runs a full operating system (Linux) and assumes high-level tasks: mass storage management, execution of the *Lab Streaming Layer* (LSL) gateway, and telemetric transmission via Wi-Fi. The CM4 processes the continuous stream coming from the microcontroller, packaging it into standardized formats for consumption by the serious game software.

Communication between both cores is established via a high-speed serial interface (UART $>$ 921600 baud or SPI). To guarantee patient safety and signal integrity, this digital link includes galvanic isolation (utilizing digital isolators such as the ISO77xx series). This prevents the formation of ground loops between the floating acquisition stage (battery) and any peripheral connected to the electrical grid. The communication protocol employs lightweight binary frames encapsulating the 24-bit data along with their timestamps, protected by a Cyclic Redundancy Check (CRC) to verify transmission integrity.

3.4 Event Synchronization Interface (USB-C)

Synchronization with the stimulation platform (tablet) is physically performed through a USB Type-C port. This port, managed by the system's USB controller, allows for the reception of .$^{\text{ev}}$ent markers"generated by the game software at the precise instant of the stimulus. Given that the connection of commercial devices introduces significant electrical noise—a product of the tablet's internal DC-DC converters—the MONEEE system design incorporates total isolation of the USB bus. The data lines $(D + /D-)$ traverse a specialized isolation integrated circuit (e.g., ADuM3160), effectively breaking galvanic continuity.

To manage the transmission of these synchronization markers from the software side, the system utilizes `MoneLib`, a specialized library designed to bridge the Unity-based game environment with the embedded hardware. This library operates as a native Android plugin (`.aar`), enabling the game engine to communicate directly with the USB Host peripheral of the tablet. The software architecture requires an Android device running version 12 (Snow Cone) or higher with USB-C Host support to properly initialize the communication driver.

The communication protocol is optimized for low latency, encoding game events—such as player interactions or system states—into lightweight hexadecimal values sent via USB. For instance, a player marking an .$^{\text{O}}$"transmits the hexadecimal code `0x00`, while marking an "X"sends `0x01`, and a system restart triggers `0xFF`. To ensure signal integrity and prevent saturation of the USB channel, the protocol enforces a minimum safety interval of 1 millisecond between consecutive event transmissions.

This integration allows the "Serious Game"to act as a precise stimulation trigger. When a user interacts with the game (e.g., touching a cell), the `MoneLibrary.SendUsbData` function is called immediately, dispatching the corresponding integer value to the microcontroller. This event is then captured by the embedded system's USB device peripheral and timestamped, ensuring that the cognitive task (the game) and the physiological recording (the EEG) remain temporally aligned for valid post-hoc analysis.

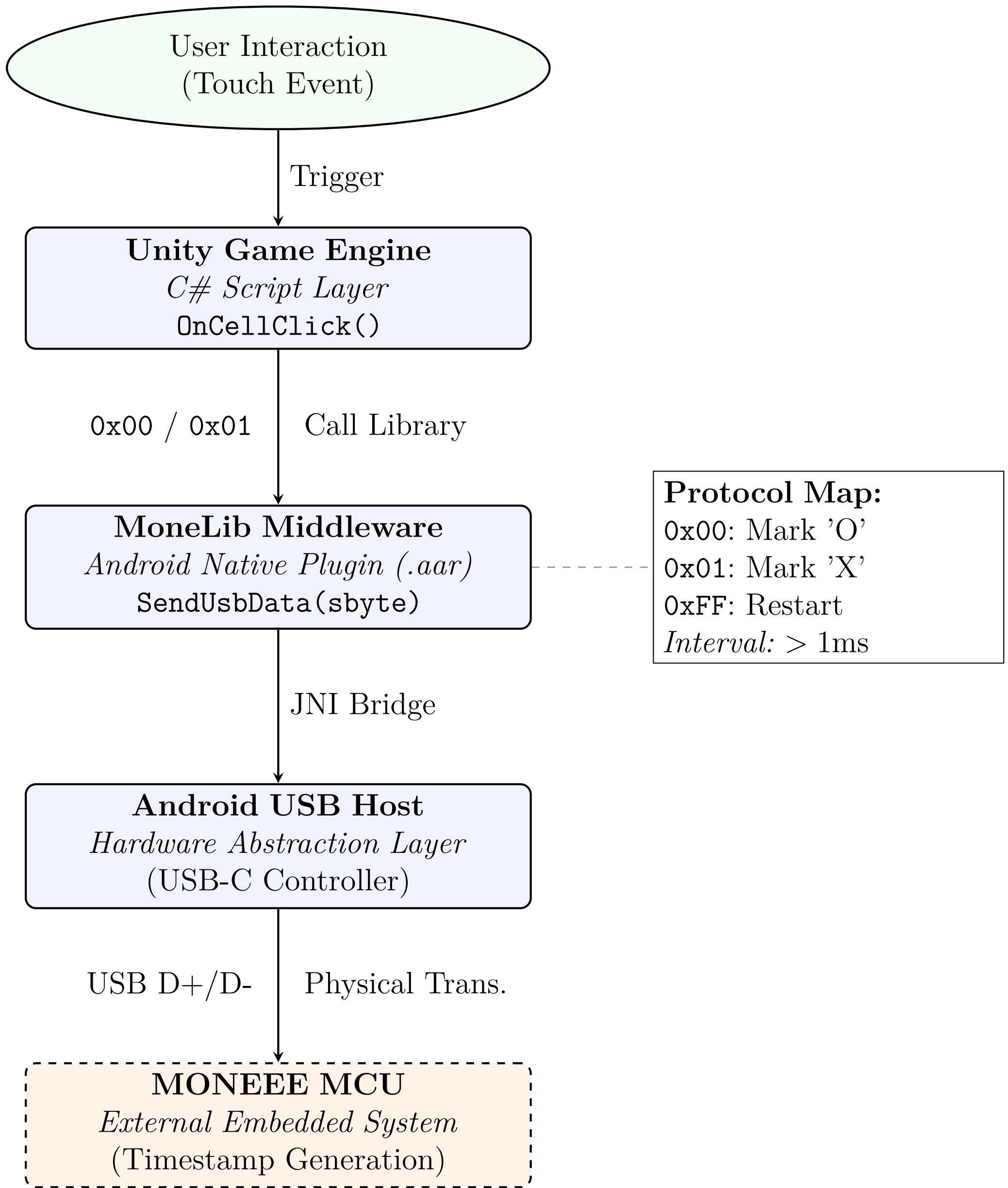

Figure 3-8: Data flow diagram of the Event Synchronization Interface. The high-level interaction within Unity is transduced into a hexadecimal marker by the MoneLib middleware and transmitted via the USB isolation barrier to the MONEEE acquisition core.

4 Firmware Architecture and Temporal Synchronization Strategy

This section delves into the embedded computational logic governing the MONEEE hardware and its interface with the simulation environment. It describes the central methodological contribution of this development: a hardware-level event injection mechanism designed to mitigate the stochastic latency inherent to general-purpose operating systems, thereby achieving precise synchronization between physiological data and game stimuli at the microcontroller (MCU) level.

4.1 Deterministic Firmware Design on the TM4C1294

The firmware resident on the Texas Instruments TM4C1294 microcontroller has been structured under a *bare-metal* paradigm (dispensing with a complex operating system) to guarantee strictly deterministic behavior. The software architecture is event-driven, establishing an execution hierarchy where data acquisition holds maximum priority, subordinating any communication or maintenance tasks.

The synchronization engine depends on the precise management of the `DRDY` (Data Ready) interrupt signal generated by the ADS1299 converter. This signal activates the capture logic at the programmed sampling frequency (e.g., 250 Hz, corresponding to a 4 ms period).

The sequence of operations within the Interrupt Service Routine (ISR) is critical for maintaining the system's phase coherence. Upon detection of the falling edge of the `DRDY` signal, the microcontroller activates the *Chip Select* (`CS`) line of the SPI bus and initiates a Direct Memory Access (DMA) transfer. This mechanism allows for the automatic reading of 24 bytes of data (8 channels of 24 bits plus status bits) without CPU intervention, which is reserved for managing storage in a circular buffer and verifying event flags.

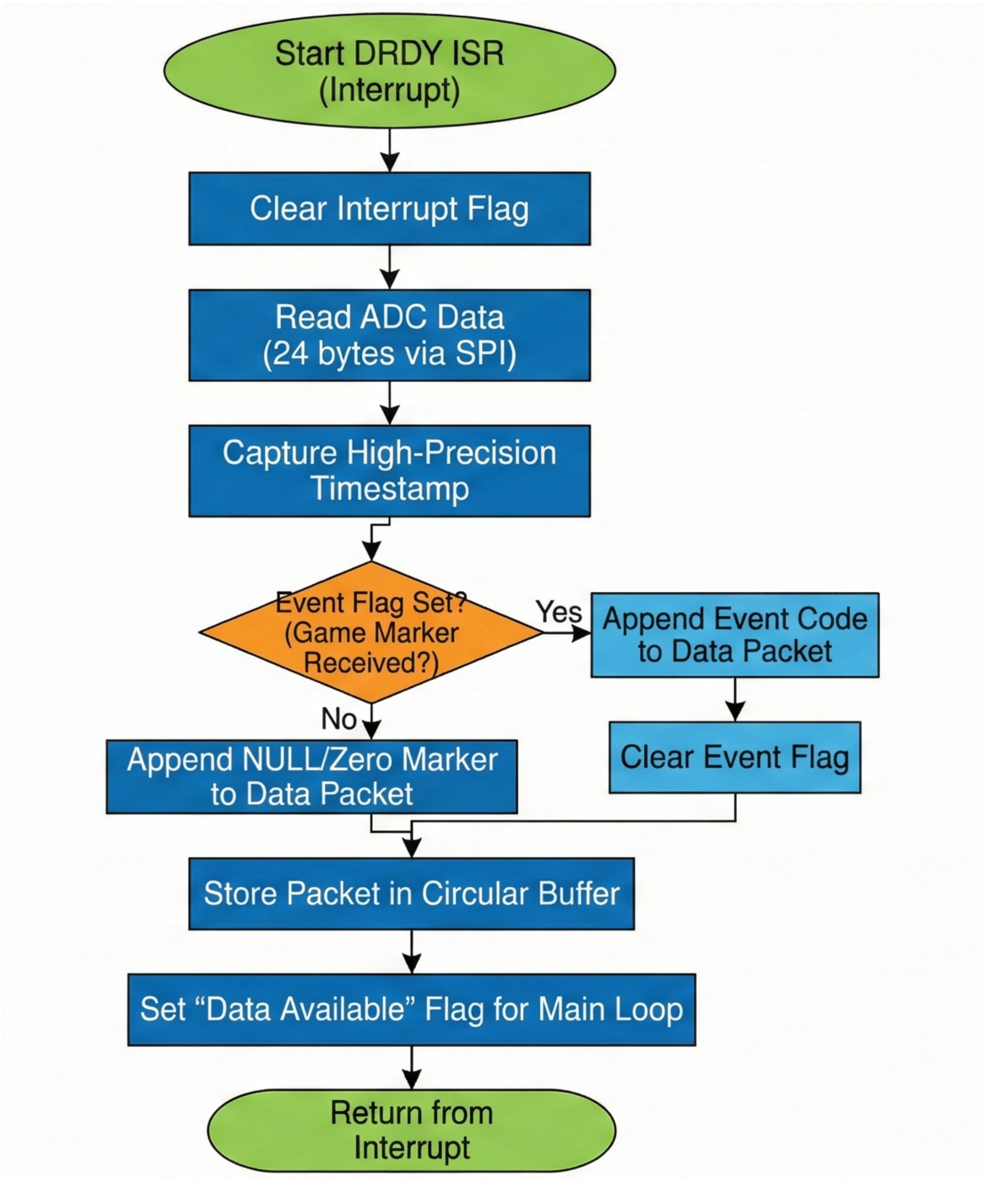

Figure 4-1: Flowchart of the Interrupt Service Routine (ISR) associated with the Data Ready signal (DRDY).

4.1.1 Hardware Event Injection Strategy

To resolve the problem of temporal desynchronization, the system design dispenses with PC or Raspberry Pi clocks for event *timestamping*. Instead, a direct injection strategy into the data frame is implemented.

The operation of this mechanism is based on the immediate reception of commands. When the stimulation software (Game) generates a visual event, it transmits an 8-bit hexadecimal code (e.g., `0x0A`) via the USB-C interface to the TM4C. The arrival of this byte triggers a high-priority interrupt in the MCU, which immediately stores the value in a volatile register named `Current_Event`. During the subsequent ADS1299 sampling cycle (which occurs within an interval of less than 4 ms), the ISR queries this register and concatenates the event code directly to the end of the EEG data packet in progress. In this way, the event marker and the physiological sample become physically linked within the same data structure before being transmitted to the Linux environment. This approach ensures that the relative *jitter* between the stimulus and the biological response is virtually null, bounded only by the temporal resolution of the sampling period.

4.2 Integration Protocol with the Simulation Environment

Interaction with the serious game, developed in the Unity engine, is managed via a custom communication library that acts as an abstraction layer over the tablet's serial API. This library exposes high-level methods, such as `SendMarker(int code)`, which are invoked by the game logic at the exact instant of stimulus rendering.

To guarantee the integrity of commands transmitted over the USB link and prevent the erroneous interpretation of electromagnetic noise as valid events, a robust binary protocol has been defined. The transmission structure consists of 3-byte frames, detailed in Table **4-1**.

Table 4-1: Definition of the Serial Event Transmission Protocol.

Byte 0 (Header)	Byte 1 (Payload)	Byte 2 (Footer)
Start Marker `0xFF`	Event Code `0x00 - 0xFE`	Validation `0xAA`

The protocol uses the byte `0xFF` to signal the start of a transaction, followed by the event identifier (where specific codes denote states such as login, standard stimulus, or *oddball* stimulus). The frame concludes with the byte `0xAA`, used for integrity validation; any sequence that does not respect this structure is immediately discarded by the TM4C firmware, ensuring high noise immunity.

4.3 Processing in the Compute Module (Raspberry Pi CM4)

The Raspberry Pi Compute Module 4 plays the role of an aggregation node and data gateway. While strict synchronization is the responsibility of the microcontroller, the CM4 must process the information flow with sufficient efficiency to prevent communication buffer overflows.

To minimize operating system-induced latency, the Linux kernel on the CM4 has been optimized using the *PREEMPT_RT* patch. This modification transforms Linux into a real-time operating system, allowing execution threads associated with hardware drivers (such as the UART receiver) to preempt standard user-space processes. Additionally, core isolation techniques are employed (*CPU shielding* via the `isolcpus` parameter), dedicating specific processor cores exclusively to data ingestion and freeing them from non-critical interruptions such as Wi-Fi network management or the graphical interface.

Finally, the application software on the CM4, developed in a hybrid Python/C++ environment, ingests the binary packets coming from the TM4C, extracts the injected event markers, and reformats the continuous stream to the Extensible Data Format (XDF) standard. This format, native to the *Lab Streaming Layer* (LSL) middleware, allows multimodal time series to be encapsulated, facilitating the coexistence of EEG samples and discrete event markers in parallel streams with a unified time base, thus optimizing analytical post-processing.

5 Final remarks

5.1 Conclusion and discussion

- This research confirms that the MONEEE system's partitioned design effectively solves the trade-off between signal fidelity and computational power. By physically decoupling the acquisition domain (TM4C1294) from the compute domain (Raspberry Pi CM4), the system preserves signal integrity against digital switching noise. The results demonstrate that handling biopotentials in a deterministic ("bare metal") environment is a critical requirement for achieving the signal-to-noise ratio necessary to reliably detect low-amplitude ERP components, such as the N200 and P300, without the interference typical of complex operating systems.

- The investigation establishes that the proposed hardware injection strategy offers a superior alternative to traditional software-based time-stamping. By physically coupling event markers with EEG samples at the microcontroller level, the system eliminates the variable latency and *jitter* inherent in software layers. This thesis demonstrates that such precise synchronization—bounded strictly by the sampling rate—is a fundamental prerequisite for preventing signal attenuation during the averaging process, thereby ensuring the diagnostic validity and temporal precision of the recorded data.

- The development and validation of the `MoneLib` library represents a significant contribution to the field of neuroinformatics, bridging the gap between custom hardware and the Unity engine. By functioning as a low-latency interface, `MoneLib` enables a precise millisecond-level alignment between user interactions and physiological responses. This innovation not only proves the technical viability of the system but provides a robust methodological framework for conducting cognitive assessments within "serious games,.[en]abling research in scenarios that offer significantly higher ecological validity than static laboratory paradigms.

5.2 Future work

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5.3 Academic contributions

5.3.1 Journal papers

5.3.2 Patents

5.3.3 Software registered

References

[Abdullah et al., 2022] Abdullah, Faye, I., and Islam, M. R. (2022). Eeg channel selection techniques in motor imagery applications: a review and new perspectives. *Bioengineering*, 9(12):726.

[Ahmed et al., 2025] Ahmed, Y., Ferguson-Pell, M., Adams, K., and Ríos Rincón, A. (2025). Eeg-based engagement monitoring in cognitive games. *Sensors*, 25(7):2072.

[Ajmeria et al., 2022] Ajmeria, R., Mondal, M., Banerjee, R., Halder, T., Deb, P. K., Mishra, D., Nayak, P., Misra, S., Pal, S. K., and Chakravarty, D. (2022). A critical survey of eeg-based bci systems for applications in industrial internet of things. *IEEE Communications Surveys & Tutorials*, 25(1):184–212.

[Allouch et al., 2023] Allouch, S., Kabbara, A., Duprez, J., Khalil, M., Modolo, J., and Hassan, M. (2023). Effect of channel density, inverse solutions and connectivity measures on eeg resting-state networks reconstruction: A simulation study. *NeuroImage*, 271:120006.

[Ariza and Pearce, 2022] Ariza, J. Á. and Pearce, J. M. (2022). Low-cost assistive technologies for disabled people using open-source hardware and software: A systematic literature review. *IEEe Access*, 10:124894–124927.

[Armand Larsen et al., 2024] Armand Larsen, S., Klok, L., Lehn-Schiøler, W., Gatej, R., and Beniczky, S. (2024). Low-cost portable eeg device for bridging the diagnostic gap in resource-limited areas. *Epileptic Disorders*, 26(5):694–700.

[Arpaia et al., 2025] Arpaia, P., Esposito, A., Galdieri, F., and Natalizio, A. (2025). Acquisition delay of wireless eeg instruments in time-sensitive applications. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*.

[Arpaia et al., 2020] Arpaia, P., Moccaldi, N., Prevete, R., Sannino, I., and Tedesco, A. (2020). A wearable eeg instrument for real-time frontal asymmetry monitoring in worker stress analysis. *IEEE Transactions on Instrumentation and Measurement*, 69(10):8335–8343.

[Arroba et al., 2024] Arroba, P., Buyya, R., Cárdenas, R., Risco-Martín, J. L., and Moya, J. M. (2024). Sustainable edge computing: Challenges and future directions. *Software: Practice and Experience*, 54(11):2272–2296.

REFERENCES

[Basit et al., 2025] Basit, A., Nawaz, M., Rehman, S., and Shafique, M. (2025). Cognitivearm: Enabling real-time eeg-controlled prosthetic arm using embodied machine learning. In *2025 62nd ACM/IEEE Design Automation Conference (DAC)*, pages 1–7. IEEE.

[Battaglia et al., 2022] Battaglia, F., Gugliandolo, G., Campobello, G., and Donato, N. (2022). Eeg-over-ble: A novel low-power architecture for multi-channel eeg monitoring systems. In *2022 IEEE International Symposium on Measurements & Networking (M&N)*, pages 1–6. IEEE.

[Bayılmış et al., 2022] Bayılmış, C., Ebleme, M. A., Çavuşoğlu, Ü., Küçük, K., and Sevin, A. (2022). A survey on communication protocols and performance evaluations for internet of things. *Digital Communications and Networks*, 8(6):1094–1104.

[Bitbrain, 2024] Bitbrain (2024). Diadem. Accessed: 2024-12-16.

[Breitling-Ziegler et al., 2020] Breitling-Ziegler, C., Tegelbeckers, J., Flechtner, H. H., and Krauel, K. (2020). Economical assessment of working memory and response inhibition in adhd using a combined n-back/nogo paradigm: An erp study. *Frontiers in Human Neuroscience*, 14:322.

[Buraimoh et al., 2023] Buraimoh, E., Ozkan, G., Timilsina, L., Chamarthi, P. K., Papari, B., and Edrington, C. S. (2023). Overview of interface algorithms, interface signals, communication and delay in real-time co-simulation of distributed power systems. *IEEE Access*, 11:103925–103955.

[Byrne et al., 2022] Byrne, A., Bonfiglio, E., Rigby, C., and Edelstyn, N. (2022). A systematic review of the prediction of consumer preference using eeg measures and machine-learning in neuromarketing research. *Brain Informatics*, 9(1):27.

[Cai et al., 2025] Cai, Z., Li, P., Cheng, L., Yuan, D., Li, M., and Li, H. (2025). A high performance heterogeneous hardware architecture for brain computer interface. *Biomedical Engineering Letters*, 15(1):217–227.

[Caiado and Ukolov, 2025] Caiado, F. and Ukolov, A. (2025). The history, current state and future possibilities of the non-invasive brain computer interfaces. *Medicine in Novel Technology and Devices*, 25:100353.

[Cervantes et al., 2023] Cervantes, J.-A., López, S., Cervantes, S., Hernández, A., and Duarte, H. (2023). Social robots and brain–computer interface video games for dealing with attention deficit hyperactivity disorder: A systematic review. *Brain Sciences*, 13(8):1172.

[Chen et al., 2024] Chen, A., Hao, S., Han, Y., Fang, Y., and Miao, Y. (2024). Exploring the effects of different bci-based attention training games on the brain: A functional near-infrared spectroscopy study. *Neuroscience Letters*, 818:137567.

[Chen et al., 2023] Chen, J., Xia, Y., Zhou, X., Vidal Rosas, E., Thomas, A., Loureiro, R., Cooper, R. J., Carlson, T., and Zhao, H. (2023). fnirs-eeg bcis for motor rehabilitation: a review. *Bioengineering*, 10(12):1393.

[Chen et al., 2022] Chen, X., Liu, B., Wang, Y., and Gao, X. (2022). A spectrally-dense encoding method for designing a high-speed ssvep-bci with 120 stimuli. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 30:2764–2772.

[Coherent Market Insights, 2024] Coherent Market Insights (2024). Embedded computing market size to worth US$ 174.38 billion by 2031.

[Correia et al., 2024] Correia, G., Crosse, M. J., and Lopez Valdes, A. (2024). Brain wearables: validation toolkit for ear-level eeg sensors. *Sensors*, 24(4):1226.

[Craik et al., 2023] Craik, A., González-España, J. J., Alamir, A., Edquilang, D., Wong, S., Sánchez Rodríguez, L., Feng, J., Francisco, G. E., and Contreras-Vidal, J. L. (2023). Design and validation of a low-cost mobile eeg-based brain–computer interface. *Sensors*, 23(13):5930.

[Damaševičius et al., 2023] Damaševičius, R., Maskeliūnas, R., and Blažauskas, T. (2023). Serious games and gamification in healthcare: a meta-review. *Information*, 14(2):105.

[Das and Kyal, 2021] Das, S. and Kyal, C. (2021). Efficient multichannel eeg compression by optimal tensor truncation. *Biomedical Signal Processing and Control*, 68:102749.

[Dasenbrock et al., 2022] Dasenbrock, S., Blum, S., Maanen, P., Debener, S., Hohmann, V., and Kayser, H. (2022). Synchronization of ear-eeg and audio streams in a portable research hearing device. *Frontiers in Neuroscience*, 16:904003.

[De Luca et al., 2024] De Luca, V., Schena, A., Covino, A., et al. (2024). Serious games for the treatment of children with adhd: The bravo project. *Information Systems Frontiers*.

[Devi et al., 2022] Devi, S., Guha, K., Baishnab, K. L., Iannacci, J., and Krishnaswamy, N. (2022). Survey on various architectures of preamplifiers for electroencephalogram (eeg) signal acquisition. *Microsystem Technologies*, 28(4):995–1009.

[Dobrev and Neycheva, 2022] Dobrev, D. P. and Neycheva, T. D. (2022). High-quality biopotential acquisition without a reference electrode: power-line interference reduction by adaptive impedance balancing in a mixed analog–digital design. *Medical & Biological Engineering & Computing*, 60(6):1801–1814.

[Doherty et al., 2023] Doherty, E. J., Spencer, C. A., Burnison, J., Čeko, M., Chin, J., Eloy, L., Haring, K., Kim, P., Pittman, D., Powers, S., Pugh, S. L., Roumis, D., Stephens, J. A., Yeh, T., and Hirshfield, L. (2023). Interdisciplinary views of fnirs: Current advancements, equity challenges, and an agenda for future needs of a diverse fnirs research community. *Frontiers in Integrative Neuroscience*, 17:1059679.

[Doulou et al., 2025] Doulou, A., Pergantis, P., Drigas, A., and Skianis, C. (2025). Managing adhd symptoms in children through the use of various technology-driven serious games: A systematic review. *Multimodal Technologies and Interaction*, 9(1):8.

[Emotiv, 2024] Emotiv (2024). Epoc x. Accessed: 2024-12-16.

[Esteban et al., 2026] Esteban, F. J., Vargas, E., Langa, J. A., and Soler-Toscano, F. (2026). Synchronization, information, and brain dynamics in consciousness research. *Applied Sciences*, 16(2):1056.

[Fang et al., 2025] Fang, H., Fang, C., Che, Y., Peng, X., Zhang, X., and Lin, D. (2025). Reward feedback mechanism in virtual reality serious games in interventions for children with attention deficits: Pre- and posttest experimental control group study. *JMIR Serious Games*, 13:e67338.

[Firouzabadi et al., 2022] Firouzabadi, F. D., Ramezanpour, S., Firouzabadi, M. D., Yousem, I. J., Puts, N. A. J., and Yousem, D. M. (2022). Neuroimaging in attention-deficit/hyperactivity disorder: Recent advances. *American Journal of Roentgenology*, 218(2):321–332. PMID: 34406053.

[Fló et al., 2022] Fló, A., Gennari, G., Benjamin, L., and Dehaene-Lambertz, G. (2022). Automated pipeline for infants continuous eeg (apice): A flexible pipeline for developmental cognitive studies. *Developmental Cognitive Neuroscience*, 54:101077.

[Frelih et al., 2025] Frelih, T., Matkovič, A., Mlinarič, T., Bon, J., and Repovš, G. (2025). Modulation of aperiodic eeg activity provides sensitive index of cognitive state changes during working memory task. *eLife*, 13:RP101071.

[Gao et al., 2022] Gao, C., Xia, M., Zhang, Z., Han, Y., and Gu, Y. (2022). *Improving the brain-computer interface learning process with gamification in motor imagery: A review*. IntechOpen.

[GomezRomero-Borquez et al., 2024] GomezRomero-Borquez, J., Del-Valle-Soto, C., Del-Puerto-Flores, J. A., Castillo-Soria, F. R., and Maciel-Barboza, F. (2024). Implications for serious game design: Quantification of cognitive stimulation in virtual reality puzzle games through msc and spen eeg analysis. *Electronics*, 13(11):2017.

[Gorjan et al., 2022] Gorjan, D., Gramann, K., De Pauw, K., and Marusic, U. (2022). Removal of movement-induced eeg artifacts: current state of the art and guidelines. *Journal of neural engineering*, 19(1):011004.

[Grand View Research, 2024] Grand View Research (2024). Telehealth market size, share & trends analysis report by product, by delivery mode, by disease area, by end-use, by region, and segment forecasts, 2025 - 2030. Accessed: 2026-02-19.

[g.tec, 2024] g.tec (2024). g.nautilus pro flexible. Accessed: 2024-12-16.

[Hamadanian et al., 2023] Hamadanian, P., Gallatin, D., Alizadeh, M., and Chintalapudi, K. (2023). Ekho: Synchronizing cloud gaming media across multiple endpoints. In *Proceedings of the ACM SIGCOMM 2023 Conference*, pages 533–549.

[He et al., 2023] He, C., Chen, Y.-Y., Phang, C.-R., Stevenson, C., Chen, I.-P., Jung, T.-P., and Ko, L.-W. (2023). Diversity and suitability of the state-of-the-art wearable and wireless eeg systems review. *IEEE Journal of Biomedical and Health Informatics*, 27(8):3830–3843.

[Hizem et al., 2025] Hizem, M., Aoueileyine, M. O.-E., Belhaouari, S. B., El Omri, A., and Bouallegue, R. (2025). Sustainable e-health: Energy-efficient tiny ai for epileptic seizure detection via eeg. *Biomedical Engineering and Computational Biology*, 16:11795972241283101.

[Ignatious et al., 2023] Ignatious, E., Azam, S., Jonkman, M., and De Boer, F. (2023). Frequency and time domain analysis of eeg based auditory evoked potentials to detect binaural hearing in noise. *Journal of Clinical Medicine*, 12(13):4487.

[Isler et al., 2023] Isler, J. R., Pini, N., Lucchini, M., Shuffrey, L. C., Morales, S., Bowers, M. E., and Fifer, W. P. (2023). Longitudinal characterization of eeg power spectra during eyes open and eyes closed conditions in children. *Psychophysiology*, 60(1):e14158.

[Janapati et al., 2023] Janapati, R., Dalal, V., and Sengupta, R. (2023). Advances in modern eeg-bci signal processing: A review. *Materials Today: Proceedings*, 80:2563–2566.

[Kamiński et al., 2026] Kamiński, S., Byra, M., Szczepanski, J., and Pregowska, A. (2026). Complexity-based eeg biomarkers for early diagnosis of adhd. *International Journal of Psychophysiology*, page 113333.

[Kanemoto et al., 2025] Kanemoto, D., Takimoto, E., and Hirose, T. (2025). Development of low-power and high-accuracy wireless eeg transmission system using compressed sensing with an eeg basis. In *2025 IEEE International Symposium on Circuits and Systems (ISCAS)*, pages 1–5. IEEE.

[Kaongoen et al., 2023] Kaongoen, N., Choi, J., Choi, J. W., Kwon, H., Hwang, C., Hwang, G., Kim, B. H., and Jo, S. (2023). The future of wearable eeg: A review of ear-eeg technology and its applications. *Journal of neural engineering*, 20(5):051002.

[Kim et al., 2022] Kim, M., Yoo, S., and Kim, C. (2022). Miniaturization for wearable eeg systems: recording hardware and data processing. *Biomedical Engineering Letters*, 12(3):239–250.

[Kothe et al., 2025] Kothe, C., Shirazi, S. Y., Stenner, T., Medine, D., Boulay, C., Grivich, M. I., Artoni, F., Mullen, T., Delorme, A., and Makeig, S. (2025). The lab streaming layer for synchronized multimodal recording. *Imaging Neuroscience*, 3:IMAG–a.

[Larocco et al., 2020] Larocco, J., Le, M., and Paeng, D.-G. (2020). A systemic review of available low-cost eeg headsets used for drowsiness detection. *Frontiers in Neuroinformatics*, 14.

[Larsen et al., 2024] Larsen, O. F., Tresselt, W. G., Lorenz, E. A., Holt, T., Sandstrak, G., Hansen, T. I., Su, X., and Holt, A. (2024). A method for synchronized use of eeg and eye tracking in fully immersive vr. *Frontiers in Human Neuroscience*, 18:1347974.

[Li et al., 2025a] Li, B., Wang, Z., and Tang, X. (2025a). High-precision adc design techniques in isscc 2025. *Journal of Semiconductors*, 46(7):070204–1.

[Li et al., 2025b] Li, J., Chen, G., Li, G., Xiao, L., Jia, R., and Zhang, K. (2025b). Flexible brain electronic sensors advance wearable brain-computer interface. *npj Biomedical Innovations*, 2(1):24.

[Li et al., 2023] Li, J., Quintin, E., Wang, H., McDonald, B. E., Farrell, T. R., Huang, X., and Clancy, E. A. (2023). Application-layer time synchronization and data alignment method for multichannel biosignal sensors using ble protocol. *Sensors*, 23(8):3954.

[Li et al., 2024] Li, Y., Sommer, W., Tian, L., and Zhou, C. (2024). Assessing the influence of latency variability on eeg classifiers-a case study of face repetition priming. *Cognitive Neurodynamics*, 18(6):4055–4069.

[Lim et al., 2023] Lim, C., Soh, C., Lim, S., et al. (2023). Home-based brain–computer interface attention training program for attention deficit hyperactivity disorder: a feasibility trial. *Child and Adolescent Psychiatry and Mental Health*, 17:15.

[Lin and Chang, 2025] Lin, J. and Chang, W. (2025). Effectiveness of serious games as digital therapeutics for enhancing the abilities of children with attention-deficit/hyperactivity disorder (adhd): Systematic literature review. *JMIR Serious Games*, 13:e60937.

[Lin et al., 2024] Lin, S., Wang, Z., Wang, Y., and Liu, J. (2024). Cs-eeg: A deep compressed sensing approach for single-channel eeg reconstruction. In *2024 3rd International Conference on Health Big Data and Intelligent Healthcare (ICHIH)*, pages 195–198. IEEE.

[Liu et al., 2024] Liu, H., Zhu, Z., Wang, Z., Zhao, X., Xu, T., Zhou, T., Wu, C., Pignaton De Freitas, E., and Hu, H. (2024). Design and implementation of a scalable and high-throughput eeg acquisition and analysis system. *Moore and More*, 1(1):14.

[Liu et al., 2023a] Liu, J., Fan, J., Zhong, Z., Qiu, H., Xiao, J., Zhou, Y., Zhu, Z., Dai, G., Wang, N., Liu, Q., et al. (2023a). An ultra-low power reconfigurable biomedical ai processor with adaptive learning for versatile wearable intelligent health monitoring. *IEEE transactions on biomedical circuits and systems*, 17(5):952–967.

[Liu et al., 2023b] Liu, Q., Yang, L., Zhang, Z., Yang, H., Zhang, Y., and Wu, J. (2023b). The feature, performance, and prospect of advanced electrodes for electroencephalogram. *Biosensors*, 13(1):101.

[Liu et al., 2022a] Liu, S., Xu, X., and Claypool, M. (2022a). A survey and taxonomy of latency compensation techniques for network computer games. *ACM Computing Surveys (CSUR)*, 54(11s):1–34.

[Liu et al., 2022b] Liu, Z., Kong, J., Qu, M., Zhao, G., and Zhang, C. (2022b). Progress in data acquisition of wearable sensors. *Biosensors*, 12(10).

[Lorini et al., 2022] Lorini, E., Sabouret, N., Ravenet, B., Davila, J. L. F., and Clavel, C. (2022). Cognitive planning in motivational interviewing. In *Proceedings of the 14th International Conference on Agents and Artificial Intelligence (ICAART 2022)*, pages 1–11, Online, Portugal. INSTICC: Institute for Systems and Technologies of Information, Control and Communication.

[Luo et al., 2022] Luo, J., Xue, N., and Chen, J. (2022). A review: research progress of neural probes for brain research and brain–computer interface. *Biosensors*, 12(12):1167.

[Minissi et al., 2025] Minissi, M. E., Garcia, C., Trillo, A., and Alcañiz, M. (2025). The role of social and neural synchrony in enhancing learning and collaboration in vr serious games: A two-study protocol. In *International Conference on Extended Reality*, pages 465–474. Springer.

[Miziara et al., 2025] Miziara, I. M., Fallon, N., Marshall, A., and Lakany, H. (2025). A comparative study to assess synchronisation methods for combined simultaneous eeg and tms acquisition. *Scientific reports*, 15(1):12816.

[Mohamed et al., 2023] Mohamed, M., Mohamed, N., and Kim, J. G. (2023). Advancements in wearable eeg technology for improved home-based sleep monitoring and assessment: A review. *Biosensors*, 13(12):1019.

[Musiałek et al., 2024] Musiałek, F., Szabra, D., and Wojtas, J. (2024). Time-efficient snr optimization of wms-based gas sensor using a genetic algorithm. *Sensors*, 24(6).

[Niehorster and Nyström, 2025] Niehorster, D. C. and Nyström, M. (2025). Tittalsl: A toolbox for creating networked eye-tracking experiments in python and matlab with tobii eye trackers. *Behavior Research Methods*, 57(7):190.

[Niso et al., 2023] Niso, G., Romero, E., Moreau, J. T., Araujo, A., and Krol, L. R. (2023). Wireless eeg: A survey of systems and studies. *NeuroImage*, 269:119774.

[Nova One Advisor, 2024] Nova One Advisor (2024). U.s. artificial intelligence in healthcare market size and trends 2024 to 2034.

[OpenBCI, 2024] OpenBCI (2024). Cyton daisy biosensing boards (16-channel). Accessed: 2024-12-16.

[Patiño et al., 2025] Patiño, J., Vega, I., Becerra, M. A., Duque-Grisales, E., and Jimenez, L. (2025). Integration between serious games and eeg signals: A systematic review. *Applied Sciences*, 15(4):1946.

[Peksa and Mamchur, 2023] Peksa, J. and Mamchur, D. (2023). State-of-the-art on brain-computer interface technology. *Sensors*, 23(13):6001.

[Phiri, 2023] Phiri, T. (2023). Adaptive and autonomous systems in advanced computing: A future of self-optimizing technologies. *Journal of Advanced Computing Systems*, 3(5):1–12.

[Pineda et al., 2003] Pineda, D. A., Lopera, F., Palacio, J. D., Ramirez, D., and Henao, G. C. (2003). Prevalence estimations of attention-deficit/hyperactivity disorder: differential diagnoses and comorbidities in a colombian sample. *International Journal of Neuroscience*, 113(1):49–71.

[Pinho et al., 2014] Pinho, F., Correia, J. H., Sousa, N. J., Cerqueira, J. J., and Dias, N. (2014). Wireless and wearable eeg acquisition platform for ambulatory monitoring. In *2014 IEEE 3nd International Conference on Serious Games and Applications for Health (SeGAH)*, pages 1–7. IEEE.

[Products, 2024] Products, B. (2024). Acticap. Accessed: 2024-12-16.

[Qaisar, 2023] Qaisar, S. M. (2023). Adaptive rate eeg processing and machine learning-based efficient recognition of epilepsy. In *Advanced Methods in Biomedical Signal Processing and Analysis*, pages 341–373. Elsevier.

[Raiker et al., 2017] Raiker, J. S., Freeman, A. J., Perez-Algorta, G., Frazier, T. W., Findling, R. L., and Youngstrom, E. A. (2017). Accuracy of achenbach scales in the screening of attention-deficit/hyperactivity disorder in a community mental health clinic. *Journal of the American Academy of Child & Adolescent Psychiatry*, 56(5):401–409.

[Ramasubramanya et al., 2025] Ramasubramanya, A., Singh, P., Kumar, A., Lin, K. C., Prasad, S., and Muthukumar, S. (2025). A wearable biosensing platform for continuous monitoring of inflammatory and metabolic biomarkers for real-time health tracking and personalized care. *Bioengineering & Translational Medicine*, page e70104.

[Ramlall et al., 2025] Ramlall, P., Jones, E., and Roy, S. (2025). Development of a networked multi-participant driving simulator with synchronized eeg and telemetry for traffic research. *Systems*, 13(7):564.

[Rashid et al., 2018] Rashid, U., Niazi, I. K., Signal, N., and Taylor, D. (2018). An eeg experimental study evaluating the performance of texas instruments ads1299. *Sensors*, 18(11):3721.

[Razavi et al., 2022] Razavi, M., Janfaza, V., Yamauchi, T., Leontyev, A., Longmire-Monford, S., and Orr, J. (2022). Opensync: an open-source platform for synchronizing multiple measures in neuroscience experiments. *Journal of neuroscience methods*, 369:109458.

[Rodríguez Timaná et al., 2024] Rodríguez Timaná, L., Castillo García, J., Bastos Filho, T., Ocampo González, A., Hincapié Monsalve, N., and Valencia Jimenez, N. (2024). Use of serious games in interventions of executive functions in neurodiverse children: Systematic review. *JMIR Serious Games*, 12:e59053.

[Romani et al., 2025] Romani, M., Zanoni, D., Farella, E., and Turchet, L. (2025). Brainform: a serious game for bci training and data collection. *arXiv preprint arXiv:2510.10169*.

[Sabio et al., 2024] Sabio, J., Williams, N. S., McArthur, G. M., and Badcock, N. A. (2024). A scoping review on the use of consumer-grade eeg devices for research. *Plos one*, 19(3):e0291186.

[Salari et al., 2023] Salari, N., Ghasemi, H., Abdoli, N., Rahmani, A., Shiri, M. H., Hashemian, A. H., Akbari, H., and Mohammadi, M. (2023). The global prevalence of adhd in children and adolescents: a systematic review and meta-analysis. *Italian journal of pediatrics*, 49(1):48.

[Shajari et al., 2023] Shajari, S., Kuruvinashetti, K., Komeili, A., and Sundararaj, U. (2023). The emergence of ai-based wearable sensors for digital health technology: a review. *Sensors*, 23(23):9498.

[Shirinpour et al., 2025] Shirinpour, S., Alekseichuk, I., Güth, M. R., Haigh, Z., Wischnewski, M., and Opitz, A. (2025). Bayesian temporal prediction: A robust algorithm for real-time eeg phase-dependent brain stimulation. *IEEE Transactions on Biomedical Engineering*.

[Sriraam et al., 2023] Sriraam, N., Srinivasulu, A., and Prakash, V. (2023). A low-cost, low-power flexible single-lead ecg textile sensor for continuous monitoring of cardiac signals. *IEEE Sensors Journal*, 23(17):20189–20198.

[Tait et al., 2025] Tait, P. J., Timm, E. C., O'Keefe, J., Watermeyer, T., Vitorio, R., Morris, R., and Stuart, S. (2025). Mobi: Mobile brain/body imaging to understand walking and balance. In *Locomotion and Posture in Older Adults: The Role of Aging and Movement Disorders*, pages 15–38. Springer Nature Switzerland, Cham.

[Takahashi et al., 2024] Takahashi, N., Ono, T., Omori, Y., Iizumi, M., Kato, H., Kasuno, S., and Tsuchiya, K. J. (2024). Assessment of executive functions using a 3d-video game in children and adolescents with adhd. *Frontiers in Psychiatry*, 15:1407703.

[Tan et al., 2025] Tan, C., Zhou, H., Zheng, A., Yang, M., Li, C., Yang, T., and Zhang, J. (2025). P300 event-related potentials as diagnostic biomarkers for attention deficit hyperactivity disorder in children. *Frontiers in Psychiatry*, 16:1590850.

[Totev et al., 2023] Totev, T., Taskov, T., and Dushanova, J. (2023). A wireless eeg system for neurofeedback training. *Applied Sciences*, 13(1):96.

[Tragoudaras et al., 2023] Tragoudaras, A., Antoniadis, C., and Massoud, Y. (2023). Tinyml for eeg decoding on microcontrollers. In *2023 IEEE International Symposium on Circuits and Systems (ISCAS)*, pages 1–5. IEEE.

[Tran et al., 2026] Tran, X. T., Vo, T. N., Vu, S. T., Tran, T. T., Nguyen, M. D., Do, T., and Lin, C. T. (2026). Inter-and intra-subject variability in eeg: A systematic survey.

[Tsakanika et al., 2025] Tsakanika, E., Tsoukas, V., Kakarountas, A., and Kokkinos, V. (2025). High accuracy of epileptic seizure detection using tiny machine learning technology for implantable closed-loop neurostimulation systems. *BioMedInformatics*, 5(1):14.

[Värbu et al., 2022] Värbu, K., Muhammad, N., and Muhammad, Y. (2022). Past, present, and future of eeg-based bci applications. *Sensors (Basel)*, 22(9):3331.

[Wang et al., 2020] Wang, X., Hersche, M., Tomekce, B., Kaya, B., Magno, M., and Benini, L. (2020). An accurate eegnet-based motor-imagery brain–computer interface for low-power edge computing. In *2020 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*. IEEE.

[Watcharapongvinit et al., 2023] Watcharapongvinit, K., Yongpanich, I., and Wattanapanitch, W. (2023). Design of a low-power ground-free analog front end for ecg acquisition. *IEEE Transactions on Biomedical Circuits and Systems*, 17(2):299–311.

[Xu et al., 2025] Xu, J., Qu, T., Pan, Q., Li, Y., Liu, L., Li, Y., Zhou, J., Yao, C., and Hong, Z. (2025). Analog front-end circuit techniques for wearable exg, bioz, and ppg signal acquisition: A review. *IEEE Open Journal of the Solid-State Circuits Society*.

[Xu and Zhong, 2018] Xu, J. and Zhong, B. (2018). Review on portable eeg technology in educational research. *Computers in Human Behavior*, 81:340–349.

[Yadav and Maini, 2023] Yadav, H. and Maini, S. (2023). Electroencephalogram based brain-computer interface: Applications, challenges, and opportunities. *Multimedia Tools and Applications*, 82:47003–47047.

[Yang and Wang, 2025] Yang, L. and Wang, Z. (2025). Applications and advances of combined fmri-fnirs techniques in brain functional research. *Frontiers in Neurology*, 16:1542075.

[Yi et al., 2025] Yi, J., Lee, G., Jeong, M., Shin, S., Kim, D., and Lee, Y. (2025). Towards end-to-end latency guarantee in mec live video analytics with app-ran mutual awareness. In *Proceedings of the 23rd Annual International Conference on Mobile Systems, Applications and Services*, pages 402–416.

[Zheng et al., 2023] Zheng, J., Li, Y., Zhai, Y., Zhang, N., Yu, H., Tang, C., Yan, Z., Luo, E., and Xie, K. (2023). Effects of sampling rate on multiscale entropy of electroencephalogram time series. *Biocybernetics and Biomedical Engineering*, 43(1):233–245.

[Zhu et al., 2024] Zhu, J., Feng, L., and Wang, C. (2024). Compressive sensing of multichannel electroencephalogram signals based on nonlocal low-rank and cosparse priors. *Mathematical and Computational Applications*, 29(6):115.

[Zou et al., 2022] Zou, B., Zheng, Y., Shen, M., Luo, Y., Li, L., and Zhang, L. (2022). Beats: An open-source, high-precision, multi-channel eeg acquisition tool system. *IEEE Transactions on Biomedical Circuits and Systems*, 16(6):1287–1298.