Low-Latency EEG Marker Integration in Serious Games for Neurocognitive Assessment

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"The concern for man and his destiny must always be the primary interest of any technical effort. Never forget this between your diagrams and equations"

Albert Einstein

"Believe you can, and you are halfway there."

Theodore Roosevelt

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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1 Preliminaries

1.1 Motivation

Brain–Computer Interfaces (BCIs) 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. BCIs have the potential to revolutionize the way cognitive states are assessed and modulated by offering closed-loop interaction mechanisms that adapt to the user's brain dynamics [*Lim et al.*, 2023, *Lin & 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.

Several neuroimaging techniques have been explored for use in Brain–Computer Interface (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 & Wang*, 2025]. Magnetoencephalography (MEG) provides excellent spatiotemporal resolution but is similarly constrained by high operational costs and the need for magnetically shielded rooms [*Peksa & 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.

Electroencephalography (EEG), by contrast, emerges as the most suitable modality for BCI applications that demand real-time responsiveness, portability, and affordability. 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 & Ukolov*, 2025, *Yadav & Maini*, 2023, *Värbu et al.*, 2022]. 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.

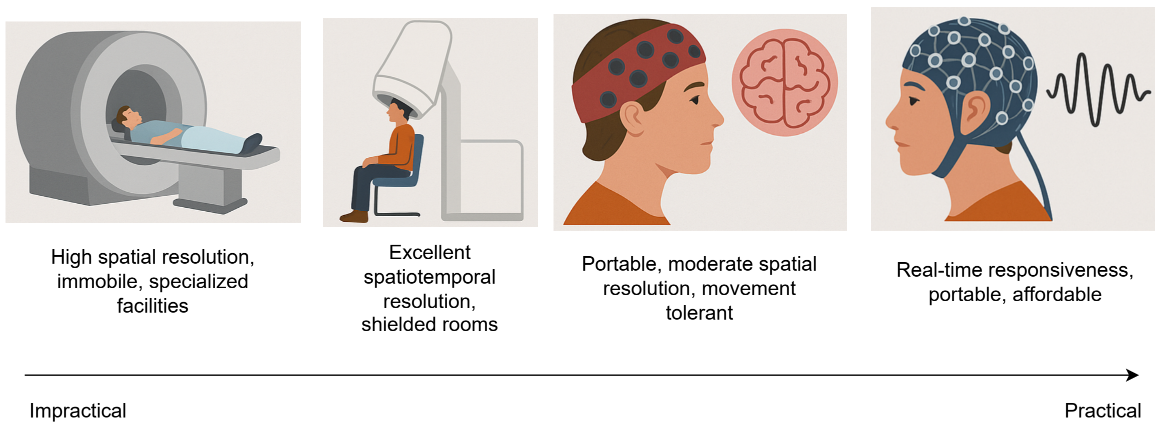

Figure 1-1: Comparison of neuroimaging modalities by spatial resolution, temporal resolution, and cost. EEG stands out for its affordability, portability, and millisecond-level responsiveness.

One of the most compelling clinical applications of EEG-based BCIs 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.

Serious games are digital environments designed not solely for entertainment, but to fulfill educational, therapeutic, or cognitive objectives. 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]. These features make serious games particularly compatible with EEG-based BCIs for interactive cognitive modulation.

Serious games designed for ADHD not only provide engaging environments for cognitive stimulation, but also serve as structured frameworks for assessing and training specific executive functions. Two principal paradigms guide the design of these games. 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. This allows 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 paradigms are often aligned with four core cognitive models critical to ADHD pathology: attention, working memory, inhibition, and planning. 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, particularly when combined with EEG-based BCIs that provide objective feedback on brain performance in real time.

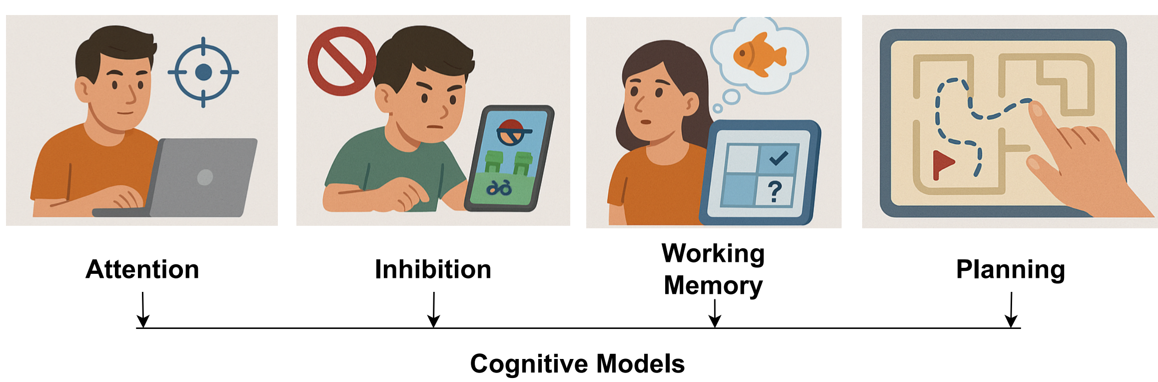

Figure 1-2: Core cognitive models targeted by serious games in ADHD interventions: attention, working memory, inhibition, and planning. Each model maps to a specific set of game dynamics and EEG markers.

Serious games integrated with BCI technology have demonstrated therapeutic benefits by reinforcing executive function, improving behavioral outcomes, and reducing symptom severity through active attention training and neurofeedback mechanisms [*Doulou et al.*, 2025]. Active BCIs, in which users intentionally modulate their focus to influence the outcome of the game, have been shown to strengthen cognitive control and promote long-term neuroplastic changes relevant to ADHD pathology [*Cervantes et al.*, 2023]. These platforms also enable adaptive feedback, allowing interventions to dynamically adjust to each child's neurocognitive profile.

However, the effectiveness of such systems depends on precise temporal synchronization between game-generated stimuli and EEG signals. Detecting event-related potentials (such as the P300 wave) or dynamic oscillations in the theta and beta frequency bands during attentional tasks requires sub-millisecond timing accuracy [*Wikström et al.*, 2022, *Sandstrak*, 2024]. Without rigorous synchronization—typically achieved via TTL triggers or low-latency USB/Wi-Fi communication—EEG signal interpretation is susceptible to noise, jitter, and event misclassification [*Iwama et al.*, 2023]. This challenge is particularly critical in real-time therapeutic environments where accurate feedback is essential.

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 therapeutic 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 & 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].

Altogether, these technological advances offer a promising foundation for rethinking ADHD diagnosis and intervention—especially in child populations. Nevertheless, critical technical challenges remain, particularly the synchronization of cognitive stimuli with neurophysiological responses in embedded systems. This challenge motivates the present research, which aims to design and implement a portable EEG acquisition and analysis system with precise synchronization to game events, enabling objective, real-time support for cognitive stimulation and diagnostic processes in children with ADHD.

1.2 Problem statement

The design and implementation of serious games synchronized with neurophysiological signals such as electroencephalography (EEG) presents a critical challenge, especially when targeting cognitive stimulation and diagnostic support in pediatric populations with Attention Deficit Hyperactivity Disorder (ADHD). The scientific validity of such applications is fundamentally dependent on the precise temporal synchronization of at least two disparate data streams: the high-temporal-resolution physiological data from the EEG system and the context-dependent event data generated by the serious game. A core technical obstacle lies in achieving this precise synchronization, a requirement that is essential for both the accuracy of event-related potential (ERP) measurements and the effectiveness of real-time interventions.1 This thesis addresses two primary facets of this challenge: the temporal inaccuracies introduced by system-level operations and the physical limitations of the hardware itself.

1.2.1 Unpredictable Latency and Jitter Between Game Events and EEG Recordings

The primary technical issue in synchronizing EEG data with serious game events is the presence of unpredictable latency and jitter. Latency is the delay between an event's physical occurrence (e.g., a stimulus appearing on screen) and its corresponding timestamp being recorded in the data stream. A more pernicious issue is jitter, defined as the statistical variability in that latency over time. While a constant latency might be correctable in post-processing, jitter introduces random, unpredictable timing errors that cannot be easily removed after data acquisition. This issue is caused by several interrelated factors: buffering delays in data pipelines, the non-deterministic scheduling of non-real-time operating systems, variability in communication protocols (such as USB, Bluetooth, or the Lab Streaming Layer), and asynchronous execution within game engines like Unity. These conditions lead to a lack of temporal precision, where the timestamp of an in-game event does not accurately align with the corresponding entry in the EEG data stream. This misalignment significantly compromises the quality of neurophysiological analysis. ERP components such as the P300 and N200, which are commonly used to evaluate attentional processes in ADHD, depend on millisecond-level synchronization between stimulus onset and neural response. When event markers are not precisely aligned due to jitter, the resulting ERP waveform becomes temporally "smeared,çausing a reduction in both amplitude and interpretability, which degrades the signal-to-noise ratio and threatens diagnostic reliability. This is particularly critical in pediatric populations where subtle attentional deficits are being assessed. Furthermore, in real-time systems like neurofeedback applications, where immediate feedback is essential for operant conditioning, even minor delays can disrupt the feedback loop. If the user receives auditory or visual feedback that no longer corresponds precisely to their brain state, the therapeutic effectiveness is reduced, potentially leading to user disengagement or ineffective training outcomes. The temporal precision required is demanding; some brain-computer interface (BCI) paradigms require accuracy within ± 2 milliseconds, yet jitter introduced by a game's graphical rendering at 50 frames per second can be as high as 20 milliseconds. Recent studies have quantified these challenges. For example, Larsen et al. (2024) found that even in systems optimized with Unity and LSL, event marker delays averaged 36 milliseconds with a jitter of 5 to 6 milliseconds—well above the acceptable margin for many ERP analyses. Additionally, Brain Products (2024) reports that embedded platforms lacking efficient buffering and timestamping can exhibit latencies up to 100 milliseconds, particularly under high computational load. These delays, caused by a lack of dedicated real-time scheduling and protocol optimization, result in a substantial loss of synchronization fidelity, ultimately undermining both research validity and clinical utility.

1.2.2 Resource and power constraints in embedded EEG platforms

The second major issue stems from the computational and energy limitations of embedded and wearable EEG systems. Designed to be mobile and unobtrusive, these systems often operate on limited battery power, constrained CPU cycles, and reduced memory.11 These constraints are exacerbated when the system must simultaneously support real-time data acquisition, multichannel EEG streaming, and high-frequency event marker registration. Conventional EEG setups that rely on centralized data processing can also lead to high energy consumption and increased data transmission latency.12 These limitations make it difficult to implement low-latency communication and high-resolution timestamping. Wireless data transmission, in particular, is very power-intensive.13 Protocols such as Bluetooth and Wi-Fi—commonly used in portable EEG systems—can introduce packet retransmissions, buffering delays, and inconsistent delivery times that worsen synchronization accuracy.5 The consequences are significant. System designers are forced to lower EEG sampling rates, simplify marker handling, or accept increased delays—all of which reduce the reliability of the collected data and the interactivity of the game.14 For example, a review of wearable EEG systems found that wireless devices consistently showed worse timing stability and synchronization performance compared to wired configurations, especially when embedded resources were under heavy computational load. Brain Products (2024) corroborates these findings, warning that system performance degrades as channel count and sampling rate increase—conditions commonly required in clinical-grade EEG systems.5 This creates a fundamental trade-off: increasing signal fidelity and temporal resolution compromises system portability, while optimizing for mobility sacrifices diagnostic precision. Therefore, a critical gap exists in establishing a robust methodology to reliably synchronize multimodal data streams from EEG systems and dynamic serious games with quantifiable, millisecond-level precision, while also operating within the power and resource constraints of embedded platforms. This thesis addresses the problem of ensuring the temporal integrity of these data streams to enable scientifically valid analysis of neuro-cognitive processes during gameplay.

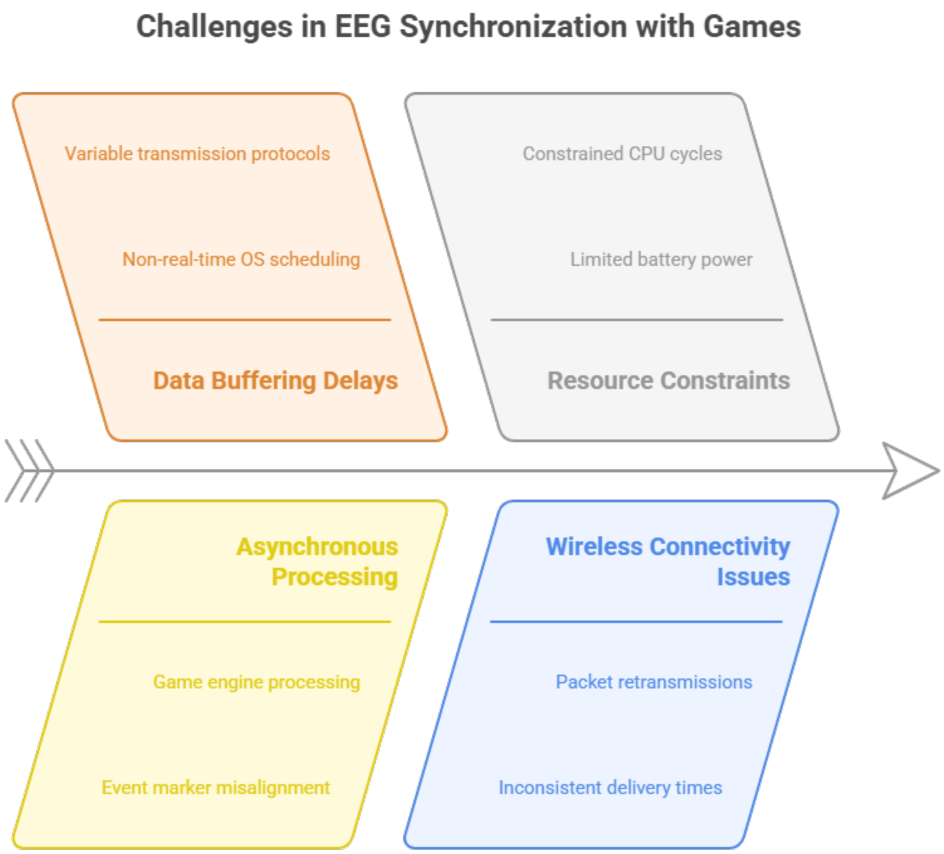

Figure 1-3: Challenges in EEG systems and serious games for ADHD evaluation.

1.3 Investigation 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 Objectives

1.4.1 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.

1.4.2 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.

1.5 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.*, 2023] 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.

2 Theoretical Framework

This chapter establishes the scientific and engineering foundations required to develop the MONEEE system. It addresses the physiological nature of the signals being measured, the electronic principles of high-precision acquisition, and the computational challenges of synchronizing disparate digital systems.

2.1 Neurophysiology & Event-Related Potentials (ERPs)

Electroencephalography (EEG) measures the electrical activity of the brain via electrodes placed on the scalp. While continuous EEG provides information about the state of the brain (e.g., sleep stages, seizure activity), cognitive neuroscience often focuses on the brain's response to specific sensory, cognitive, or motor events. These time-locked responses are known as Event-Related Potentials (ERPs).

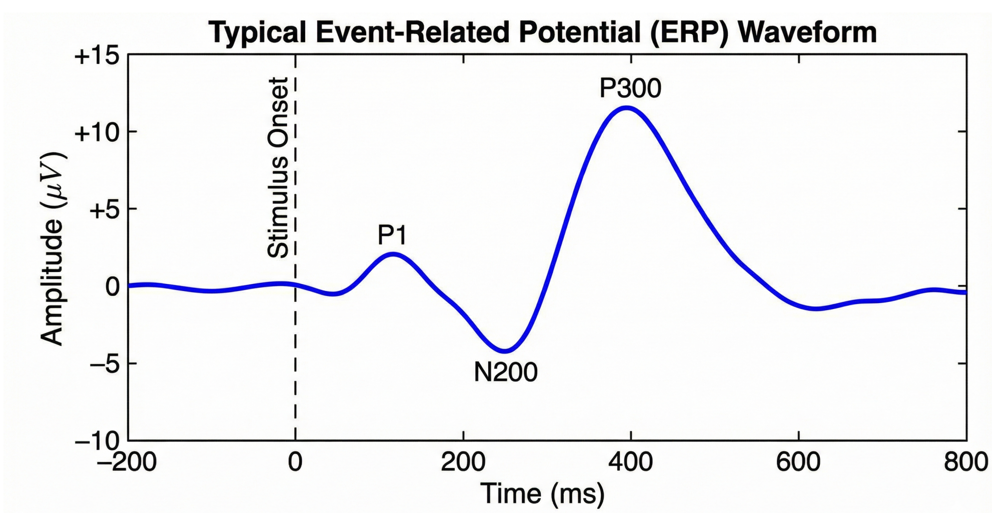

Figure 2-1: Typical waveform of an Event-Related Potential showing P300 and N200 components.

2.1.1 The P300 and N200 Components

ERPs are small voltage fluctuations (typically $1\mu V$ to $20\mu V$) embedded within the larger background EEG noise ($50\mu V$ to $100\mu V$). Two components are particularly relevant for neurocognitive assessment and serious games:

- **The N200 (N2):** A negative deflection peaking approximately 200–350 ms after stimulus onset. It is primarily associated with executive control functions, specifically mismatch detection (when a stimulus deviates from expectation) and response inhibition.

- **The P300 (P3b):** A large positive deflection peaking 300–600 ms post-stimulus. The P300 reflects processes related to context updating and the allocation of attentional resources. Its amplitude is often proportional to the improbability of the target stimulus (the 'oddball' effect), making it a robust metric for assessing attention and cognitive workload in ADHD patients.

2.1.2 The Necessity of Millisecond-Level Precision

Because ERPs are much smaller than background brain activity, they cannot be reliably identified in a single trial. Instead, researchers use *Signal Averaging*. By averaging N time-locked trials, the background noise (assumed to be random with a mean of zero) decreases by a factor of $\sqrt{N}$, while the time-locked ERP signal remains constant.

However, this technique relies on the assumption of temporal stability. If the synchronization marker (the 'trigger' indicating when the game event occurred) has variable latency—known as *jitter*—the averaging process will 'smear' the ERP peaks. Mathematically, if the latency follows a Gaussian distribution with standard deviation σ_t, the averaged signal is effectively low-pass filtered. A jitter of just $\sigma_t > 10$ ms can significantly attenuate high-frequency components of the N200, rendering the diagnostic data invalid. Therefore, the MONEEE system requires hard-real-time synchronization capabilities.

2.2 Signal Acquisition Hardware

The fidelity of the EEG data depends heavily on the analog-front-end architecture. The MONEEE system utilizes the Texas Instruments ADS1299, a specialized Analog-to-Digital Converter (ADC) for biopotential measurements.

2.2.1 Delta-Sigma ($\Delta\Sigma$) Analog-to-Digital Converters

Unlike Successive Approximation Register (SAR) ADCs often found in general-purpose microcontrollers, the ADS1299 is a Delta-Sigma modulator. This architecture is chosen for its superior noise performance and dynamic range.

1. **Oversampling:** The ADC samples the input at a frequency (f_{mod}) much higher than the Nyquist rate. This spreads the quantization noise over a wider bandwidth.
2. **Noise Shaping:** The modulator pushes the quantization noise into higher frequencies, away from the biological signal band (0–100 Hz).
3. **Digital Filtering:** A subsequent digital decimation filter removes the high-frequency noise and reduces the data rate to the user-selected output (e.g., 250 SPS or 500 SPS).

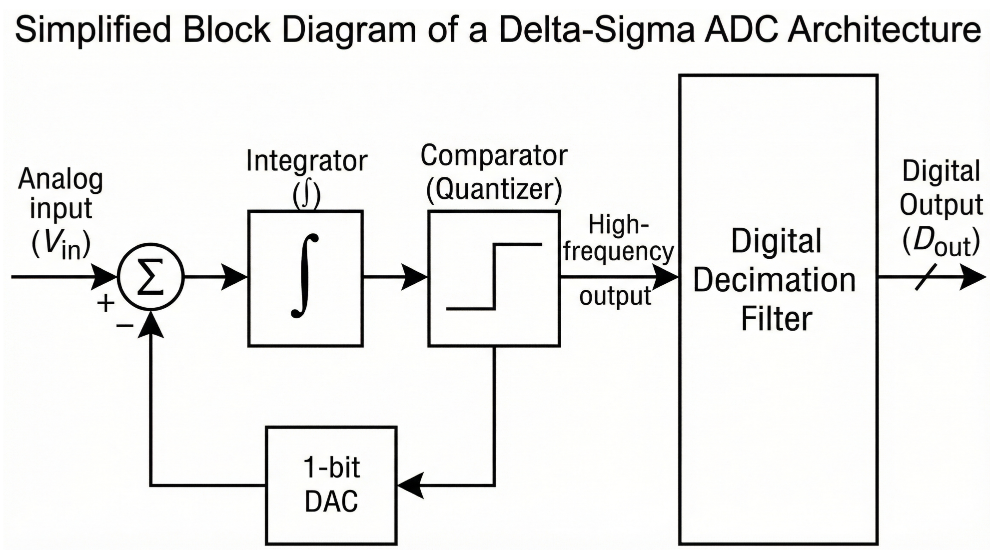

Figure 2-2: Simplified block diagram of a Delta-Sigma ADC architecture.

Simultaneous Sampling

A critical feature of the ADS1299 is its ability to sample all 8 channels simultaneously. In multiplexed architectures, a single ADC switches between channels sequentially, introducing a phase delay between electrodes (t_{skew}). For EEG connectivity analysis (coherence), t_{skew} must be zero. The ADS1299 achieves this by dedicating a separate $\Delta\Sigma$ modulator to every channel.

2.2.2 Heterogeneous Embedded Systems: MCU vs. MPU

To balance signal integrity with data throughput, modern acquisition systems often employ a heterogeneous architecture, combining a Microcontroller Unit (MCU) and a Microprocessor Unit (MPU).

- **The MCU (e.g., TM4C1294):** Acts as the hard real-time controller. It operates "bare metal.ºr with a Real-Time Operating System (RTOS). Its primary role is **determinism**. When the ADC indicates data is ready (via a `DRDY` hardware interrupt), the MCU must capture it within microseconds to prevent FIFO overflows. It is responsible for timestamping the incoming data precisely when it arrives.

- **The MPU (e.g., Raspberry Pi Compute Module):** Runs a rich Operating System like Linux. It handles high-throughput tasks such as network stacks (TCP/IP), file storage, and complex drivers. However, standard Linux is non-deterministic; the kernel scheduler may preempt a task for 10–20 ms to handle background processes.

- **The Synergy:** In the MONEEE architecture, the MCU guarantees the timing of the acquisition, effectively isolating the sensitive bio-signals from the non-deterministic jitter of the Linux-based MPU.

2.3 Digital Synchronization Protocols

Synchronizing the EEG data (recorded by hardware) with the game events (generated by software) is the principal challenge of this thesis. Several methods exist, each with trade-offs regarding latency and intrusiveness.

Table 2-1: Comparison of Synchronization Methods

Method	**Mechanism**	**Precision**	**Implementation**
Optical (Photodiode)	Hardware sensor detects pixel changes on screen.	High (< 1 ms)	High (External hardware required).
Network (LSL)	Time-sync via NTP-like protocols over LAN.	Medium (< 5 ms)	Low (Software only).
Hardware Trigger (TTL)	Parallel port or USB-to-TTL directly to ADC.	Very High (< 1 ms)	Medium (Legacy ports or dongles).

2.3.1 Optical vs. Network Synchronization

Optical (Ground Truth): Placing a photodiode on the monitor to detect the exact moment a visual stimulus appears. This bypasses all operating system and GPU rendering delays. It is often used as the "gold standard"to validate other methods but is impractical for widespread clinical deployment due to the hardware setup required.

Lab Streaming Layer (LSL): A network-based middleware that handles time-series data. It synchronizes streams by mapping local machine timestamps to a common clock, performing jitter correction. While effective, it relies on the quality of the local network and the accuracy of the software timestamps generated by the game engine.

2.3.2 USB Latency Characteristics

The MONEEE system utilizes USB for communication between the MCU and the MPU/Host. Understanding USB latency is vital for "soft-triggers"(commands sent from the PC to the amplifier).

- **Polling Intervals:** USB is a host-controlled bus. The host polls the device for data.
  - *Full Speed (USB 2.0):* Frame time is 1 ms. Data is transferred only once per frame.
  - *High Speed:* Microframe time is $125\mu s$.
- **CDC Class Overhead:** The Communication Device Class (CDC) emulates a serial port. While convenient for development, the OS driver stack buffers data to improve throughput, often at the cost of latency. A command sent by the game engine may sit in the OS output buffer for several milliseconds before being placed on the USB bus (Start-of-Frame), creating variable delays inconsistent with ERP analysis requirements.

3 Hardware Architecture (The MONEEE System)

This chapter details the engineering design of the MONEEE system. The architecture is designed to address the specific requirement of low-latency synchronization between game events and physiological signals. The system is built upon a heterogeneous embedded platform that physically separates the real-time acquisition domain from the high-level computational domain.

3.1 System Overview & Block Diagram

The MONEEE system operates as a dedicated edge-computing device for EEG acquisition. The data flow is strictly unidirectional for physiological signals, designed to minimize latency and maximizing signal integrity. The high-level signal chain is defined as follows:

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

The architecture is divided into three primary zones: the *Analog Front-End*, the *Real-Time Core*, and the *Compute Core*.

3.2 Analog Front-End (AFE)

The Analog Front-End is the interface between the biological medium and the digital system. It is built around the Texas Instruments ADS1299, an 8-channel, 24-bit delta-sigma ADC designed specifically for biopotential measurements.

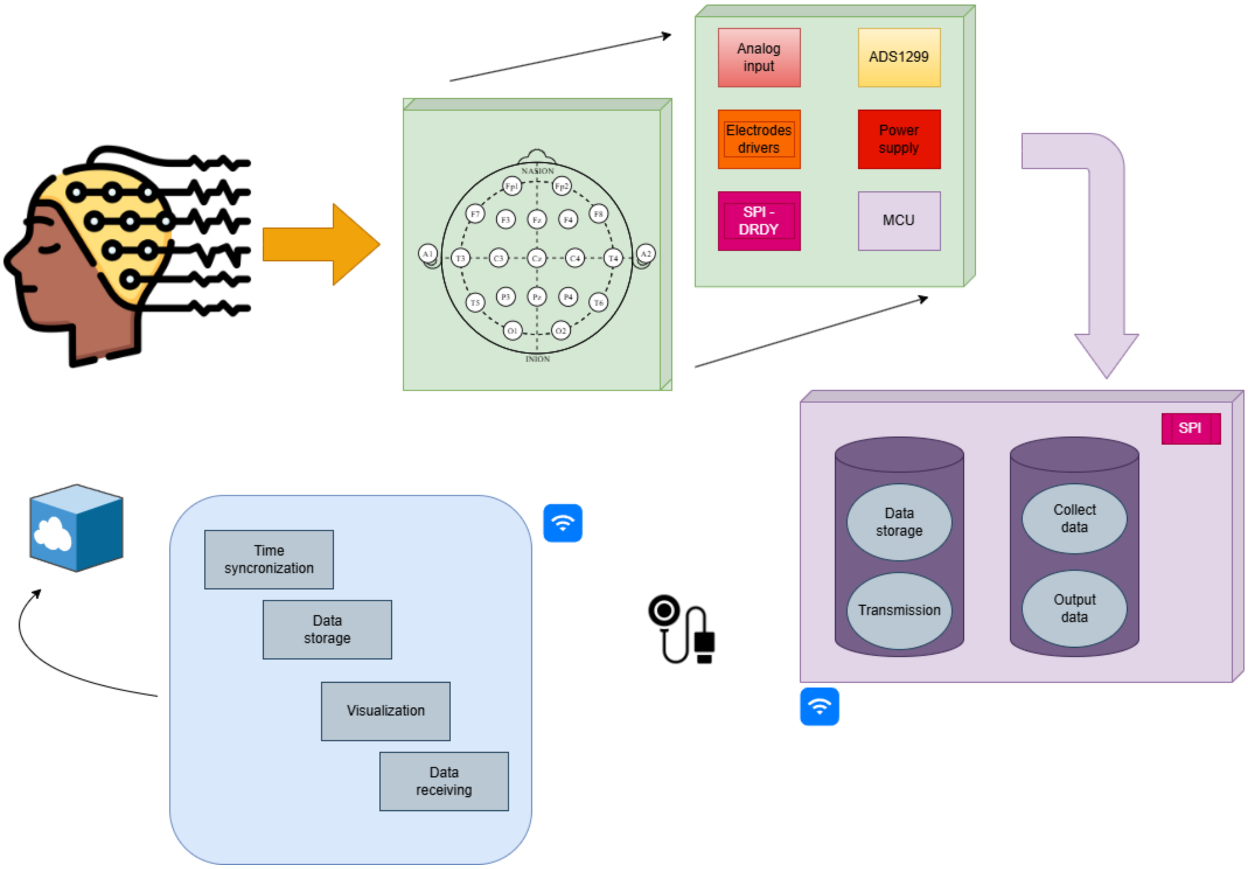

Figure 3-1: High-level block diagram of the MONEEE system showing the separation between the acquisition (MCU) and compute (MPU) domains.

3.2.1 Configuration of the ADS1299

The ADS1299 is configured to operate in a low-noise, high-gain mode suitable for scalp EEG. The key configuration parameters implemented in the register settings are:

- **Gain:** Programmable Gain Amplifier (PGA) set to $24V/V$ to maximize the dynamic range for small EEG signals $(10 - 100\mu V)$.
- **Data Rate:** Configured for 250 SPS (Samples Per Second) or 500 SPS, providing a bandwidth sufficient for capturing the P300 and N200 components (typically < 30 Hz) while allowing for oversampling benefits.
- **Input Multiplexer:** Set to `NORMAL` electrode input, with options to switch to internal test signals for calibration.

3.2.2 Bias Drive Implementation (Driven Right Leg)

To reject common-mode noise (such as 50/60 Hz mains interference), the system utilizes a Driven Right Leg (DRL) circuit, referred to as the *Bias Drive* in the ADS1299 architecture. Instead of a passive ground, the DRL circuit measures the common-mode voltage on the sensing electrodes, inverts it, amplifies it, and drives it back into the body through a reference electrode. This negative feedback loop actively cancels interference, significantly improving the Common Mode Rejection Ratio (CMRR) to typically > 110 dB.

3.2.3 Power Supply Isolation

Safety and noise performance dictate the power architecture. The AFE is powered by a dedicated Li-Po battery managed by a PMIC (Power Management IC). Crucially, the analog power domain ($AVDD$) is isolated from the noisy digital domains of the Raspberry Pi using Low-Dropout Regulators (LDOs) with high Power Supply Rejection Ratio (PSRR). This ensures that the high-frequency switching noise from the Compute Module's CPU rails does not couple into the sensitive EEG measurements.

3.3 The Digital Core (The Split-Architecture)

The digital processing load is distributed between a microcontroller and a microprocessor, leveraging the strengths of each.

3.3.1 Real-Time Unit (TI TM4C1294)

The Texas Instruments TM4C1294 (ARM Cortex-M4F) serves as the hard real-time controller.

- **Role:** It acts as the SPI Master for the ADS1299. Its primary responsibility is to service the `DRDY` (Data Ready) interrupt from the ADC immediately upon assertion, ensuring zero sample loss.
- **Floating-Point Unit (FPU):** The hardware FPU allows for real-time application of basic digital filters (e.g., notch filters for line noise) or scaling factors before data transmission, without stalling the interrupt service routines.

- **Determinism:** Unlike the Linux-based CM4, the TM4C code runs on bare metal (or a lightweight RTOS), guaranteeing that the timestamp applied to each incoming data packet is accurate to within microseconds.

3.3.2 Compute Unit (Raspberry Pi CM4)

The Raspberry Pi Compute Module 4 acts as the system's "Host."

- **Role:** It manages high-bandwidth data storage (to eMMC or SD card), runs the Lab Streaming Layer (LSL) gateway, and handles network transmission via Wi-Fi.
- **Throughput:** The CM4 processes the incoming stream from the TM4C, formats it into LSL chunks, and broadcasts it to the serious game running on the tablet or local network.

3.3.3 Inter-Processor Communication

Data is transferred from the TM4C1294 to the RPi CM4 via a high-speed serial interface.

- **Physical Layer:** A high-speed UART connection (baud rate > 921600) or SPI is utilized. To prevent ground loops between the battery-powered AFE and the potentially mains-connected tablet (if charging), this link is galvanically isolated using digital isolators (e.g., ISO77xx series).
- **Protocol:** A lightweight binary packet protocol is defined, wrapping the 24-bit EEG data and the 32-bit hardware timestamp into a frame with a cyclic redundancy check (CRC) to ensure data integrity during transmission.

3.4 The Event Interface (USB-C)

The physical interface for the serious game tablet is a USB Type-C connector.

3.4.1 Hardware Implementation

The USB-C port is configured as a downstream facing port (or device mode depending on the tablet role) using a USB Controller integrated into the TM4C or CM4 carrier board. This port handles the reception of .^{ev}ent markers"sent by the game.

3.4.2 Signal Conditioning and Isolation

Connecting a commercial tablet via USB introduces significant noise risks. The tablet's internal DC-DC converters can inject noise into the USB ground line. To mitigate this, the MONEEE system employs full USB isolation. The data lines ($D + /D-$) pass through a specialized USB isolator IC (e.g., ADuM3160 or similar), effectively breaking the galvanic path. This ensures that the çlean"ground of the EEG sensors remains floating relative to the "dirty"ground of the tablet, preserving the signal-to-noise ratio required for detecting the ERPs.

4 Firmware and Synchronization Strategy

This chapter details the software logic embedded within the MONEEE hardware and the serious game interface. It describes the core contribution of this work: a hardware-level event injection mechanism that eliminates operating system latency by synchronizing physiological data with game events at the Microcontroller (MCU) level.

4.1 TM4C1294 Firmware Design

The firmware running on the Texas Instruments TM4C1294 is designed as a 'Bare Metal' application (or utilizing a minimal RTOS scheduler) to guarantee deterministic execution. The architecture is event-driven, prioritizing data acquisition over all other tasks.

4.1.1 Interrupt Service Routines (ISR)

The synchronization engine relies on the precise handling of the ADS1299 `DRDY` (Data Ready) signal. The ADS1299 pulls the `DRDY` pin low at the programmed sample rate (e.g., 250 Hz, every 4 ms).

The ISR sequence is critical for maintaining phase coherency:

1. **Trigger:** The GPIO interrupt triggers on the falling edge of `DRDY`.
2. **Capture:** The MCU asserts the SPI Chip Select (`CS`) and initiates a Direct Memory Access (DMA) transfer to read 24 bytes of data (8 channels $\times$ 24 bits + status bits).
3. **Buffering:** The raw data is moved to a circular buffer. Crucially, the ISR checks a global `Event_Flag` variable before closing the packet.

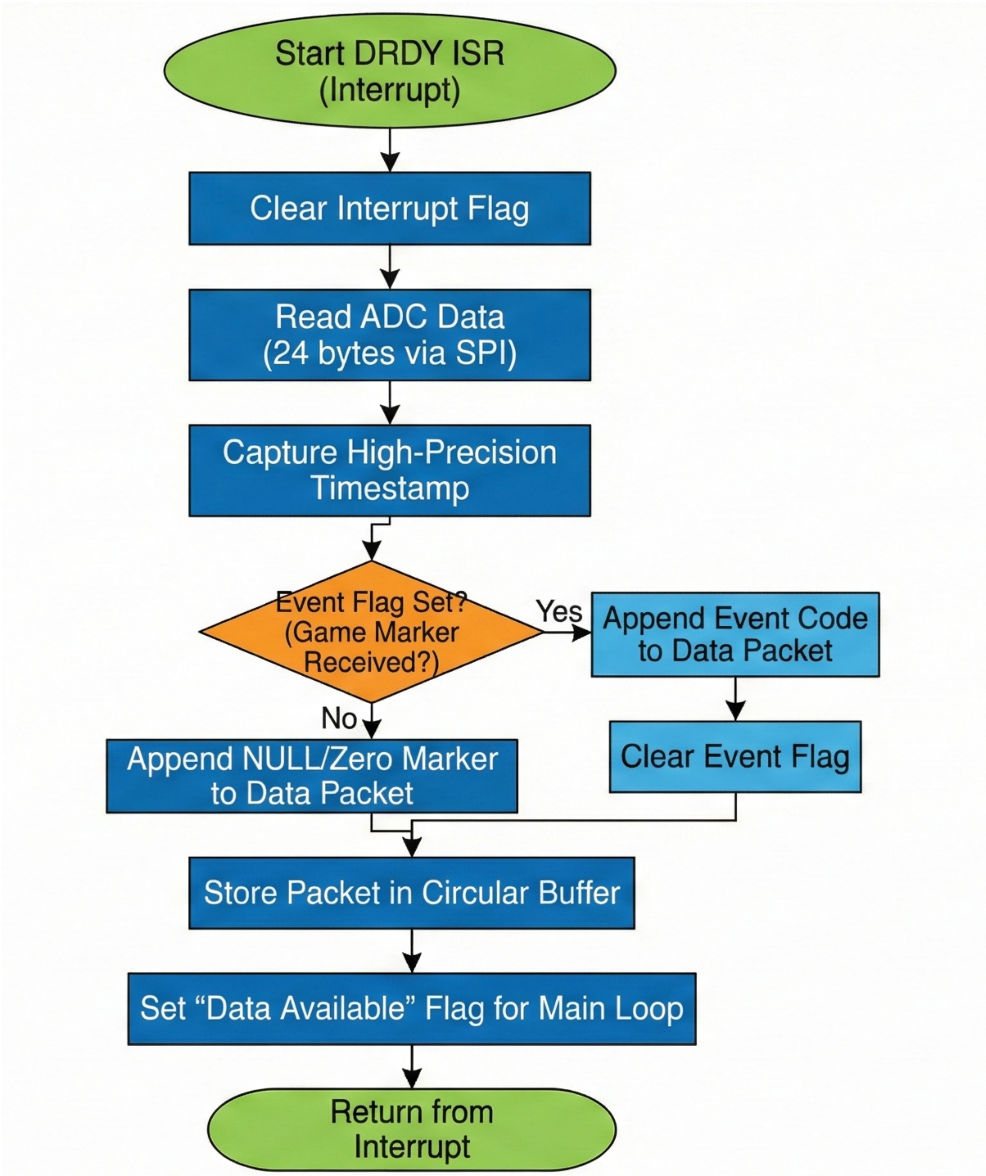

Figure 4-1: Flowchart of the Data Ready (DRDY) Interrupt Service Routine.

4.1.2 The "Timestamping" Engine

To solve the synchronization problem, the system does not rely on the PC or RPi clock to timestamp events. Instead, it uses a **Hardware Injection Strategy**.

- **Mechanism:** When the Tablet (Game) generates a stimulus, it sends a specific 8-bit Hex Code (e.g., `0x0A` for 'Target Appears') via the USB-C interface to the TM4C.
- **Injection:** This USB reception triggers a high-priority interrupt on the TM4C. The received byte is immediately stored in a volatile `Current_Event` register.

- **Synchronization:** During the *next* immediate ADS1299 sample cycle (within < 4 ms), the ISR reads this `Current_Event` register. It appends the Hex Code directly to the tail of the current EEG data packet.
- **Result:** The event marker and the EEG sample are physically bound together in the same data frame before they ever reach the non-deterministic Linux environment. This ensures that the relative jitter between the marker and the signal is effectively zero (bounded only by the sampling period).

4.2 Serious Game Integration

For the serious game (developed in Unity), a custom communication library was developed to interface with the MONEEE hardware.

4.2.1 Communication Library

The library acts as a wrapper around the tablet's serial API. It exposes simple functions such as `SendMarker(int code)` that the game logic calls at the exact frame a visual stimulus is rendered.

4.2.2 Protocol Definition

To ensure command integrity over the USB link, a lightweight binary protocol is defined. The tablet sends events using the following 3-byte structure:

Table 4-1: Serial Event Protocol Structure

Byte 0	**Byte 1**	**Byte 2**
Start Marker	Event Code	End Marker
`0xFF`	`0x00 - 0xFE`	`0xAA`

- **Start Byte (`0xFF`):** Signals the beginning of a command.
- **Event Code:** The specific identifier for the game event (e.g., `0x01` = Game Start, `0x02` = Game Over, `0x10` = Standard Stimulus, `0x20` = Deviant Stimulus/Oddball).
- **End Byte (`0xAA`):** Used to validate the packet. If the TM4C receives `0xFF` followed by a code but no `0xAA`, the packet is discarded as noise.

4.3 Raspberry Pi CM4 Software

The Raspberry Pi Compute Module 4 acts as the data aggregator and gateway. While the hard synchronization is handled by the TM4C, the RPi must process data efficiently to prevent buffer overflows.

4.3.1 Linux Kernel Configuration

To minimize process switching latency, the Linux kernel on the CM4 is optimized:

- **PREEMPT_RT Patch:** The kernel is patched with `PREEMPT_RT`, turning Linux into a real-time operating system. This allows high-priority driver threads (like the UART receiver) to preempt standard processes, ensuring that the data stream from the TM4C is read smoothly from the serial buffer.
- **CPU Isolation:** Specific CPU cores are isolated (using `isolcpus` boot parameters) to dedicate them solely to data ingestion, keeping them free from GUI or Wi-Fi interrupt overhead.

4.3.2 Data Formatting (XDF)

The RPi software (written in Python/C++) ingests the raw binary packets from the TM4C. It parses the injected event markers and reformats the stream into the **Extensible Data Format (XDF)**. XDF is the native format for the Lab Streaming Layer (LSL). It supports multi-modal data containers, allowing the EEG samples and the discrete event markers to be stored in parallel streams with unified timestamps, ready for post-processing in Python (MNE).

5 Validation and Results

6 Conclusion and Future Work

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