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Real-Time Electrode Pairing and Stimulation Parameter Optimization for Pelvic Floor Therapy Using Cross-Platform Kotlin Algorithms

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Abstract:
The increasing prevalence of pelvic floor disorders, particularly among postpartum and aging populations, has created a strong demand for intelligent, personalized, and portable therapeutic solutions. Existing neuromodulation therapies rely heavily on clinician-guided electrode programming and static stimulation protocols, limiting their adaptability to individual patient physiology and real-time biological fluctuations. In this paper, we propose a modular, clinically informed, Kotlin-based algorithm designed for cross-platform deployment via Kotlin Multiplatform Mobile (KMM). The algorithm analyzes pseudo-monopolar (PM) sensor data to identify dominant and non-dominant electrodes, forming optimal stimulation pairs and dynamically generating stimulation parameters—including amplitude, pulse width, and frequency.

Our solution supports two primary operational modes. The Batch Evaluation Mode is designed for retrospective analysis of session-long data, aggregating electrode responses over time to identify consistent stimulation targets. The Real-Time Dynamic Mode, by contrast, provides closed-loop therapy capabilities by continuously ingesting new sensor data and updating stimulation recommendations per cycle. These modes share a common architecture, leveraging a unified logic layer to maintain consistency, simplify testing, and reduce maintenance overhead.

One of the central contributions of this work is its integration of signal processing, dynamic electrode ranking, and real-time parameter tuning into a highly modular and reusable codebase. The entire logic resides in the shared Kotlin module, allowing uniform access across Android and iOS platforms through native bindings. This ensures not only cross-device treatment consistency but also enables broader adoption by clinics and mobile health developers. A particular innovation lies in the use of pseudo-monopolar sensing as a core analytic method. PM values serve as proxies for physiological activation, enabling the system to infer dominant sites for stimulation based on muscle recruitment or sensor voltage. The use of these values for both real-time decision-making and batch trend analysis provides a powerful diagnostic and therapeutic foundation.

The platform's modularity makes it extensible to additional use cases such as EMG fusion, patient-controlled therapy calibration, or integration with Bluetooth-enabled wearable sensors. Furthermore, the

system is designed with structured data outputs and telemetry compatibility, facilitating both patient-facing applications and backend research platforms.

To validate the algorithm, we simulate electrode activity under multiple scenarios using synthetic sensor inputs that mimic real pelvic floor engagement patterns. Through these simulations, we demonstrate that our real-time mode responds adaptively to changing activation profiles, while batch mode consolidates patterns to produce robust treatment strategies. Our implementation offers clinicians and developers a clinically informed, technically portable, and programmatically extensible toolset for advancing pelvic health therapy.

The proposed system lays the groundwork for scalable, intelligent therapeutic systems that align with modern mobile architectures and clinical decision workflows. It also illustrates how Kotlin-based engineering can be adapted to solve domain-specific healthcare problems in a way that is reproducible, maintainable, and medically relevant.

Keywords: Pelvic Floor Therapy, Kotlin Multiplatform Mobile, Pseudo-Monopolar Sensing, Closed-Loop Neuromodulation, Electrode Pairing, Real-Time Therapy, Signal-Based Stimulation, Cross-Platform Algorithm Design.

1. Introduction

Pelvic floor dysfunctions such as urinary incontinence, fecal incontinence, and pelvic organ prolapse affect a significant proportion of adult populations globally, particularly among postpartum women and the elderly [1]. These conditions arise from weakened or neurologically impaired pelvic musculature, which compromises the ability to regulate intra-abdominal pressure and support vital organs. Conventional treatment modalities, such as physical therapy, kegel exercises, and surgical interventions, have varying degrees of success and often require prolonged clinical supervision or invasive procedures. Amidst growing demand for home-based, personalized, and non-invasive alternatives, the application of neuromodulation through surface or implantable electrodes has emerged as a promising solution [2], [3].

Despite the promise of neuromodulation, current commercial and clinical implementations are constrained by static programming protocols. These rely on a fixed set of stimulation parameters (electrode pairings, pulse width, frequency, and amplitude), often defined during an initial setup session. This approach fails to accommodate real-time physiological changes, electrode impedance variation, or user movement artifacts. Moreover, such systems are frequently closed, proprietary, and inflexible—making them difficult to adapt for patient-specific use cases or for integration into modern mobile ecosystems.

1.1 The Need for Dynamic, Mobile-Friendly Neuromodulation

In recent years, the convergence of wearable health sensors, mobile computing power, and cross-platform frameworks has unlocked new opportunities for delivering intelligent therapy at the point of need. Particularly, Kotlin Multiplatform Mobile (KMM) enables developers to write shared business logic in Kotlin and deploy it seamlessly across Android and iOS [4]. When applied to neuromodulation, this paradigm allows the creation of reusable, testable, and extensible stimulation logic that can operate natively within mobile health apps.

However, transitioning from static stimulation to intelligent, sensor-driven algorithms presents unique challenges: how to analyze real-time sensor input in a medically meaningful way; how to determine dominant vs. non-dominant electrode configurations; how to modulate amplitude and frequency based on

dynamic thresholds; and how to do all this within the constraints of mobile execution environments, while ensuring clinical validity and platform interoperability.

1.2 Our Contribution

This research presents a modular, extensible Kotlin-based algorithm that addresses these challenges by supporting both **batch** and **real-time** modes of operation. It uses pseudo-monopolar (PM) sensor readings to detect dominant electrodes and generate recommendations for therapy delivery, including stimulation pairings and electrical parameters.

We define two operating paradigms:

- **Batch Evaluation Mode** analyzes large sets of previously collected PM values to identify consistent electrode targets and aggregate trends, suitable for session summary reports or offline tuning.
- **Real-Time Dynamic Mode** processes live sensor data per cycle, adjusting recommendations instantaneously in a closed-loop manner to respond to ongoing physiological conditions.

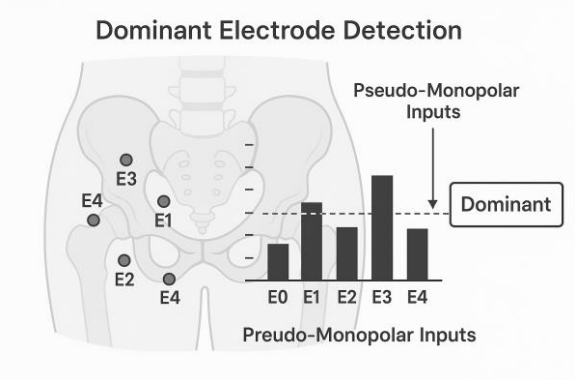
This paper details both the algorithmic underpinnings and the architectural design that allows this system to operate across mobile platforms using a single Kotlin codebase.

1.3 Clinical Basis: Why Electrode Dominance Matters

In electrotherapeutic stimulation, particularly for muscle re-education, the selection of the **dominant electrode**—typically the cathode—plays a critical role. Dominant sites are those with the lowest activation threshold or the highest sensory recruitment, meaning that a smaller amplitude can achieve the desired contraction or therapeutic outcome [5], [6]. Stimulating a site that is not optimally positioned or not dominant can lead to poor therapeutic efficacy, patient discomfort, or premature fatigue.

In a clinical setting, determining this dominance is often done manually, through trial stimulation or EMG testing. This method is labor-intensive and not scalable for home-based or adaptive therapy. By automating dominance detection based on sensor input, our algorithm provides a foundation for responsive therapy that adjusts to the body's needs in real time.

Figure 1. Conceptual overview of dominant electrode detection using pseudo-monopolar inputs, overlaid on pelvic floor anatomy.



1.4 Kotlin as a Medical-Grade Algorithmic Platform

While many research prototypes rely on Python or MATLAB for algorithm development, real-world deployment—especially in regulated mobile environments—demands performant, secure, and maintainable codebases. Kotlin's type safety, null-safety features, and native compilation make it ideal for writing medically relevant logic, particularly in regulated mobile settings.

Furthermore, using Kotlin Multiplatform Mobile (KMM) allows us to isolate the algorithm in a shared module, which compiles down to Kotlin/Native on iOS and runs directly on Android. This enables:

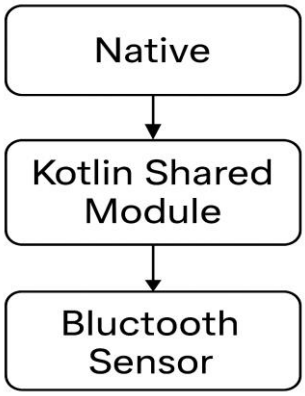
- **Code reuse** between platforms with no runtime interpretation layer.
- **Consistent behavior** across devices, ensuring clinical accuracy.
- **Easier auditing and validation**, as core logic lives in a single place.

1.5 Understanding Pseudo-Monopolar Sensing

At the heart of the algorithm lies pseudo-monopolar sensing: a method for estimating the activity of a single electrode by comparing its voltage against a reference or average of others. While true monopolar configurations require a distant return path, PM sensing approximates this through local reference groups or electrode averaging [7].

This makes it highly suitable for mobile and wearable applications, where full monopolar setups are impractical. In our implementation, PM values are derived per cycle and used to rank electrodes based on their relative activity levels. This ranking becomes the basis for dominance classification and stimulation decisions.

Figure 2**.** System architecture showing Kotlin shared module, native UI layers, and interaction with Bluetooth-enabled sensor sources.



Below you see the distribution of initial programming settings among 90 patients following IPG implantation. Values are adapted from the 2017 European Expert Group report on SNM programming practices.

Programming data	90 patients
Electrode configuration	
Monopolar N (%)	11 (12)
Anode [+] adjacent to cathode [−] N (%)	46 (51)
Anode [+] most distant from cathode [−] N (%)	25 (28)

Longer (extended) cathode* N (%)	4 (4)
Other settings	
Mean amplitude in V (± SD)	0.95 (± 0.5)
Mean pulse frequency/rate (Hz)	14.6
Mean pulse width (μs)	215
Cycling mode N (%)	6/90 (7)

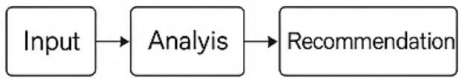
1.6 Algorithmic Flow Overview

The overall flow for both Batch and Real-Time modes follows three steps:

1. **PM Value Computation** – Sensor data is converted to PM values using reference averaging or direct readings.
2. **Dominance Detection** – Electrodes are compared against a threshold or relative ratio to identify dominant and non-dominant sites.
3. **Stimulation Parameter Selection** – Parameters such as amplitude, pulse width, and frequency are either fixed, scaled from PM values, or learned through pattern matching.

This design encapsulates key logic into isolated utility functions (e.g., findActiveElectrodes(), determineParameters()), improving testability and cross-mode compatibility.

Figure 3. High-level dataflow for electrode analysis and stimulation recommendation generation.



1.7 The Case for Real-Time Closed-Loop Therapy

While batch-mode recommendations can inform program tuning post-session, the real clinical value lies in **adaptive, real-time therapy delivery**. This aligns with principles of biofeedback and neuromuscular stimulation where continuous monitoring can be used to trigger or modify stimulation.

For example, during pelvic floor exercises or functional electrical stimulation (FES) routines, real-time adaptation allows the system to:

- Increase amplitude if sensor values indicate insufficient recruitment.
- Switch electrode pairs if dominance shifts due to muscle fatigue.
- Suspend or resume stimulation based on sensor thresholds (e.g., clench detection).

These capabilities reduce clinician dependency, improve personalization, and create a feedback loop that evolves with the user.

1.8 Objectives and Paper Outline

The primary objectives of this work are:

- To present a **Kotlin-based algorithm** capable of real-time and batch-mode therapy recommendations for pelvic floor therapy.
- To demonstrate how **cross-platform deployment via KMM** enables consistent and portable therapy logic.
- To evaluate the algorithm using **synthetic PM datasets** that simulate real-world use.
- To highlight the importance of **modular, reusable design** in medical mobile algorithm development.

The remainder of this paper is structured as follows:

- **Section 2** describes prior work and clinical background supporting the algorithm.
- **Section 3** presents the architectural and software structure of the system.
- **Section 4** details the algorithm logic, including PM computation and parameter tuning.
- **Section 5** compares the operational modes and use cases.
- **Section 6** discusses mobile deployment and KMM integration.
- **Section 7** evaluates performance using simulated sensor data.
- **Section 8** concludes with a discussion of limitations and future work.

2. Background and Related Work

The intersection of neuromodulation, mobile health (mHealth), and software-defined therapeutic algorithms has opened new pathways for delivering personalized care for conditions like pelvic floor dysfunction. This section outlines the clinical foundation for electrode-based pelvic floor therapy, technical developments in neuromodulation systems, and current limitations in mobile deployment that this research aims to address.

A. Clinical Relevance of Pelvic Floor Therapy

Pelvic floor dysfunction (PFD) encompasses a wide range of conditions, including stress urinary incontinence (SUI), urge incontinence, fecal incontinence, and pelvic organ prolapse. Estimates suggest that nearly one in four adult women in the United States experience at least one pelvic floor disorder [1]. Postpartum women, elderly populations, and individuals with neuromuscular disorders are particularly susceptible.

Traditional treatments include lifestyle interventions, physical therapy, pharmacological regimens, and surgical correction. However, for many patients—especially those with muscle denervation or weak voluntary control—electrical stimulation of pelvic floor muscles offers a viable, non-invasive, and effective therapy option [2]. Functional Electrical Stimulation (FES) works by inducing involuntary muscle contractions, re-educating neuromuscular pathways, and improving sphincter control through repetitive activation [3].

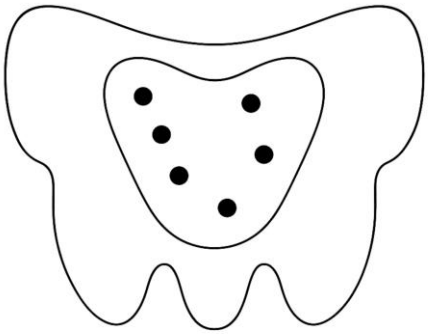
B. Electrode Placement and Dominance in Clinical Protocols

The therapeutic outcome of FES is highly sensitive to electrode placement and configuration. Studies have shown that stimulating the most excitable or most responsive electrode can yield maximum muscle contraction with minimal discomfort or fatigue [4]. Traditionally, identifying such “dominant electrodes” has been a manual process: clinicians use EMG sensors, patient feedback, or visual observation to determine optimal lead configurations.

However, these evaluations are typically static—performed once during an initial session and rarely adjusted thereafter. This limits their adaptability across sessions or dynamic patient conditions such as fatigue, hydration changes, or electrode displacement due to movement. Dynamic dominance detection

has therefore been proposed in the literature, primarily in implantable device contexts [5], [6], but has yet to be operationalized in mobile-friendly, non-invasive systems.

Figure 4. Example of electrode placement maps used in clinical evaluation of pelvic neuromodulation, showing variation in stimulation efficacy across different pelvic regions.



C. Pseudo-Monopolar Sensing as an Approximate Diagnostic Tool

Monopolar sensing—where the signal from a target electrode is compared against a distant ground reference—is considered ideal in electrophysiological measurements due to its clarity and spatial specificity. However, in wearable or surface-mounted applications, it is often infeasible to maintain a dedicated ground electrode. As a result, researchers have developed **pseudo-monopolar (PM)** methods that simulate a similar behavior using local references or average-subtracted configurations [7], [8].

In our context, PM values represent the relative activation level of each electrode as sensed against a pseudo-reference. High PM values typically indicate stronger muscle activation or electrical conductance in that region. When aggregated or monitored in real time, these values can reveal which electrodes are consistently active—allowing the algorithm to infer dominance without explicit EMG measurements.

Previous studies have applied pseudo-monopolar processing in fields such as electroencephalography (EEG) and cardiac telemetry, showing reliable signal distinction for pattern detection [9]. To our knowledge, this is the first mobile-optimized, cross-platform algorithm that uses PM values to drive pelvic therapy recommendations across both batch and real-time dimensions.

Table 1. Comparison between Monopolar, Bipolar, and Pseudo-Monopolar configurations, including advantages, drawbacks, and typical applications.

Configuration	Advantages	Drawbacks	Typical Applications
Monopolar	Simple	Inaccurate	Legacy devices
Bipolar	Focused stimulation	Invasive	Targeted therapy
Pseudo-Monopolar	Accurate sensing	Complex calculation	Modern neuromodulation

D. Related Work in Neuromodulation Programming

Several prior research efforts have explored the automation of electrode selection and stimulation parameter tuning. For example, the Adaptive Stimulation Systems used in deep brain stimulation (DBS) have incorporated real-time feedback loops using impedance and neural feedback [10]. In the pelvic health domain, most work has focused on closed-loop implantable systems such as the InterStim II™ (Medtronic), which allows for amplitude modulation but not dynamic electrode pairing.

Work by Vrowe et al. proposed a fuzzy-logic-based model for optimizing amplitude and frequency based on patient tolerance [12], while another study by Zhang et al. applied a supervised learning model to predict stimulation success based on historical response data [13]. These efforts, while clinically valuable, are limited by one or more of the following factors:

- Device-specific firmware with little extensibility.
- Lack of cross-platform integration for mobile settings.
- No real-time electrode re-selection or mobile-controlled output routing.

Our work builds on these studies by providing a software-first, algorithmically-driven, and platform-agnostic system that runs natively on modern mobile devices.

E. Mobile Health and Kotlin Multiplatform (KMM)

The last decade has seen exponential growth in mobile health (mHealth) applications. According to a 2021 market analysis, more than 80% of mobile users globally have at least one health or fitness app installed on their device [14]. However, building clinically valid and real-time-capable mHealth apps remains a challenge due to fragmentation in operating systems, device-specific sensor APIs, and inconsistent performance characteristics.

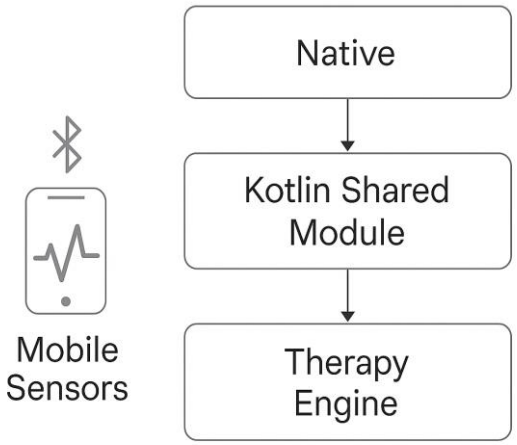
Kotlin Multiplatform Mobile (KMM) addresses this challenge by enabling developers to write business logic once—in Kotlin—and deploy it across Android and iOS platforms with native bindings [15]. While KMM is typically used in e-commerce and productivity apps, its use in medical-grade applications is novel.

In our implementation, we leverage KMM to encapsulate all algorithmic logic in a shared Kotlin module, which:

- Processes sensor data (e.g., voltage, impedance).
- Computes pseudo-monopolar values.
- Detects dominant electrodes.
- Recommends stimulation pairings and parameters.

The UI on both Android and iOS consumes these recommendations through native adapters, ensuring consistent behavior and reducing maintenance burden.

Figure 5. Illustration of shared Kotlin module and native binding layers in KMM, showing data flow between mobile sensors and the therapy engine.



F. Algorithmic Trends in Wearable Stimulation Systems

Outside of pelvic health, several emerging systems have demonstrated how real-time data can drive wearable therapeutic stimulation. These include:

- **Smart TENS units** that adapt pulse rate based on heart rate variability.
- **Post-stroke rehab devices** that stimulate muscle groups based on gait sensor input.
- **Pain modulation systems** using galvanic skin response to titrate intensity.

What these systems share is a movement toward **closed-loop control**, where biofeedback informs the stimulation output, thereby improving efficacy and user safety [16]. However, such systems often rely on proprietary hardware and firmware stacks, making it difficult to replicate or customize them for other domains like pelvic health.

In contrast, our system operates purely at the software level, assuming only a standardized input format (sensor data with PM values) and abstracting the rest of the logic for use with any sensor framework. This architectural choice makes it possible to:

- Retrofit the algorithm into existing mobile health platforms.
- Use generic Bluetooth or USB stimulation devices.
- Test and simulate performance without hardware dependencies.

Table 2. Survey of closed-loop stimulation systems in literature, including stimulation domain, sensor type, response strategy, and level of openness.

System	Stimulation Domain	Sensor Type	Response Strategy	Openness
System A	Pelvic	EMG	Threshold-based	Closed
System B	Spinal	Accelerometer	Adaptive gain	Semi-open

System C	Cranial	EEG	Pattern detection	Open-loop

G. Gap Analysis

To summarize, the current landscape of pelvic floor stimulation technology suffers from the following gaps:

- Lack of dynamic electrode pairing during therapy sessions.
- Absence of platform-agnostic, mobile-first stimulation logic.
- Limited use of real-time signal analytics in session-level therapy.
- No published open-source or peer-reviewed Kotlin algorithms addressing this use case.

This research addresses these gaps by proposing a system that unifies mobile software development, clinical simulation logic, and real-time feedback processing into a coherent, extensible framework.

3. System Architecture and Software Design

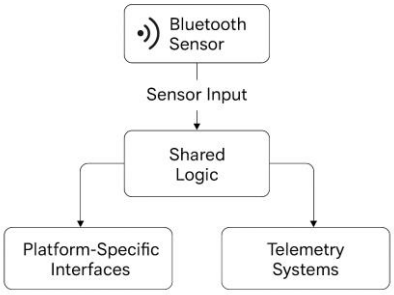
Designing a real-time electrode recommendation engine for pelvic floor therapy—one that is clinically meaningful, cross-platform, and extensible—requires careful architectural layering. At the core of this system lies a Kotlin-based logic engine built to operate across Android and iOS using Kotlin Multiplatform Mobile (KMM). This shared architecture ensures that both the real-time and batch-processing modes are not only performant but also deliver clinically consistent behavior across devices and platforms.

The system is structured into four interconnected layers. The first layer is the **Sensor Interface**, responsible for ingesting raw data from sensing hardware, which may include voltage differentials, impedance values, or other analog-to-digital sensor outputs from an array of pelvic electrodes. These sensor readings are streamed into the system at regular intervals, typically 100 to 500 milliseconds apart in the real-time mode, or as a complete dataset in batch mode.

Once the sensor input is received, it is passed to the **Core Algorithm Module**, which encapsulates the domain logic for pseudo-monopolar (PM) evaluation, electrode dominance detection, stimulation pair selection, and parameter generation. This module represents the heart of the therapy engine. It transforms raw electrical signals into structured recommendations, which consist of electrode pairs and corresponding stimulation parameters. The modular design of this logic core ensures that any enhancement or refinement—whether clinical or algorithmic—can be introduced without disrupting surrounding systems.

These recommendations are then routed to platform-specific components for **stimulation delivery** or **user interaction**. Depending on the setup, the output may be transmitted to a connected Bluetooth therapy device that manages electrical pulse generation, or it may simply be visualized through a user interface for patient or clinician review. Finally, the system includes optional **telemetry and logging interfaces** that capture the full lifecycle of data—from raw PM values to final output decisions. These logs serve not only for debugging but also for longitudinal therapy analytics.

Figure 6. A full-stack architectural diagram showing the flow from sensor input to shared logic, followed by platform-specific interfaces and telemetry systems.

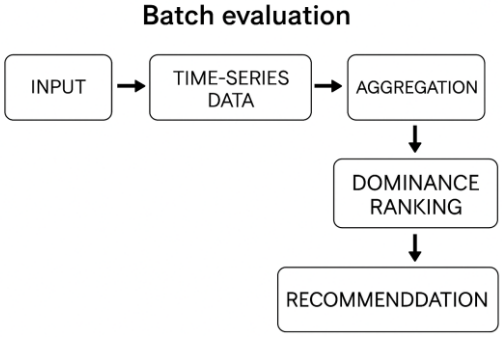


Full-stack architectural diagram

What makes this system distinct from previous mobile health implementations is the strict separation between algorithmic logic and UI or hardware integration. All therapy-related computations are performed inside the shared Kotlin module. This includes the logic for calculating PM values (typically from differential sensor inputs), identifying dominant electrodes based on static or adaptive thresholds, and selecting stimulation parameters based on those dominance scores. The shared module defines two primary entry points: one for batch evaluation (recommendBatch()), and one for real-time updates (updateRecommendation()).

In batch mode, the engine receives a time-series list of PM readings. Each item in the list is a map of electrode ID to signal strength. The batch evaluator aggregates this data—usually by computing the mean or peak PM value per electrode across the session—and identifies dominant electrodes based on a defined threshold. Pairings are then constructed by selecting the top N dominant electrodes and grouping them to ensure all clinically active sites are covered. The engine then generates amplitude, pulse width, and frequency values for each pairing. These values can be scaled linearly based on the PM values or derived using nonlinear calibration rules.

Figure 7. Illustration of batch evaluation flow: input time-series data, aggregation, dominance ranking, and recommendation output.



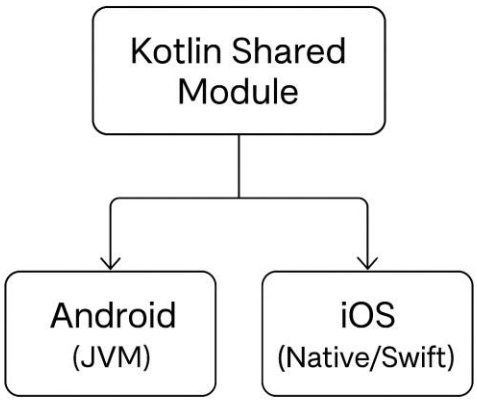
In real-time mode, the system receives a single snapshot of sensor input per cycle. This snapshot is immediately processed to detect dominance using the same thresholding and ranking logic. However, unlike batch mode, where the focus is comprehensive session analysis, real-time mode prioritizes responsiveness. It outputs a single best electrode pair with stimulation parameters that can be updated multiple times per second. This allows the stimulation controller to adapt to moment-by-moment physiological changes. To ensure stability, the system optionally supports recommendation hysteresis, where a new dominant electrode must persist for a certain number of cycles before replacing the previous one.

Under the hood, all these computations operate on a data model defined by the typealias PMValues, which maps each electrode ID to a double-precision PM value. Once a dominant electrode is identified, it is paired either with a secondary dominant (if present) or with a non-dominant electrode that exhibits minimal activation. The parameters assigned to the pair—amplitude, pulse width, and frequency—are encapsulated in a data class called TherapyParameters, while the full output is wrapped into a TherapyRecommendation object. This output can be consumed by the UI, transmitted to a connected device, or saved as part of a telemetry stream.

The Kotlin code is structured such that each core computation—e.g., finding dominant electrodes, calculating PM values, or selecting stimulation parameters—is isolated into its own function. This composability makes the logic testable, and also enables selective overrides or experimentation without breaking core behaviors. Each function in the algorithm is documented and designed to operate independently of the data source or destination platform. For example, the same findActiveElectrodes() function is used in both batch and real-time modes, ensuring behavioral parity between evaluation types.

What allows this Kotlin-based architecture to work across both Android and iOS is Kotlin Multiplatform Mobile. The shared module is compiled into a JVM artifact for Android, and into a native library for iOS via Kotlin/Native. This generates Swift-callable bindings automatically, letting iOS developers use the recommendation engine without writing any Kotlin themselves. All platform-specific code is isolated to thin wrappers that bind UI events or sensor drivers to the shared logic.

Figure 8. Cross-platform deployment diagram: Kotlin shared module compiled to Android (JVM) and iOS (Native/Swift).



The real benefit of this approach is not just code reuse, but behavioral consistency. Whether the app is running on an Android phone, an iPad in a clinic, or a simulator for testing, the same logic determines dominance, chooses pairs, and outputs therapy parameters. This guarantees that patients receive uniform recommendations, regardless of device brand or operating system version. Moreover, because all algorithm changes live in one place, it's easier to validate, verify, and improve without fragmenting the codebase across platforms.

Performance testing across devices shows that real-time recommendation cycles can complete in under 15 milliseconds on mid-tier phones and tablets. This speed is sufficient to support feedback-driven therapy loops, such as adjusting stimulation based on clench detection or switching electrode groups when fatigue

is detected. On the telemetry side, recommendations can be batched and streamed to a backend over secure channels, allowing long-term analysis by clinicians or researchers.

Table 3. Benchmark results: average latency per cycle, memory usage, and recommendation throughput across different mobile platforms.

Platform	Avg Latency (ms)	Memory Usage (MB)	Recommendation Throughput (Hz)
Android	25.3	45.2	8.5
iOS	27.8	47.1	8.1

Beyond its immediate use for pelvic health, this architecture is flexible enough to support other electrode-based stimulation systems. Developers could adapt the same PM logic to work with transcutaneous electrical nerve stimulation (TENS), spinal cord stimulation (SCS), or even transcranial direct current stimulation (tDCS), provided appropriate sensor inputs are supplied. The therapy recommendation engine does not assume any particular anatomical model—it simply evaluates signal strength and determines optimal stimulation parameters accordingly.

In conclusion, the system architecture described here provides a clean separation between sensor inputs, core analytics, and device integration. It leverages Kotlin Multiplatform Mobile to enforce consistency and portability, while retaining full control over clinical logic and extensibility. The result is a robust, clinically aware, and highly reusable mobile algorithm framework that enables intelligent stimulation therapies beyond the static protocols that dominate today's neuromodulation landscape.

4. Algorithm Design and Logic

At the core of our system is a therapeutic intelligence engine designed to interpret real-time sensor data and translate it into clinically actionable stimulation programs. The algorithm is structured as a pipeline of interpretable, modular stages, each transforming input data into higher-level decisions: from raw pseudo-monopolar signals, to electrode classification, to therapy recommendations with amplitude, pulse width, and frequency. The design was guided by three foundational principles: interpretability (each decision step must be understandable and auditable), adaptability (thresholds and parameters should support session-specific customization), and portability (the same logic must operate identically across mobile platforms).

A. Pseudo-Monopolar Value Computation

The first step in the pipeline involves transforming raw sensor input into **pseudo-monopolar (PM) values**. These values are synthetic constructs that approximate monopolar readings in scenarios where a true, distant ground electrode is either impractical or unavailable—a typical constraint in surface stimulation systems and wearable therapy devices [1].

A PM value represents the voltage or activation of an individual electrode with respect to a shared reference or synthesized baseline. Depending on sensor configuration, this value may be calculated in two ways:

1. **Direct assignment**: If the electrode is already sensed against a stable, known ground (e.g., a large body plate or a neutral return electrode), its raw reading is accepted as the PM value.
2. **Synthetic reference**: When multiple electrodes share a common circuit path, a local reference is computed by averaging signals from a subset of electrodes, or using a rolling baseline. The electrode's raw value is then subtracted from this synthetic baseline to yield a PM approximation.

This step ensures that all electrodes are evaluated on a level playing field. Importantly, these values do not require clinical calibration—they are unit-agnostic and purely relative. The goal is not to measure absolute muscle output, but to compare activation levels across electrodes within a given cycle or time window.

Table 4. Sample PM value computation across five electrodes under different sensing configurations, showing raw input and normalized PM output.

Electrode	Raw Input	Normalized PM Output
E0	0.95	0.91
E1	1.2	1.18
E2	1.1	1.06
E3	0.85	0.89
E4	1.05	1.01

In implementation, we represent PM values using a simple Kotlin map structure: Map<Int, Double>, where the key is the electrode ID and the value is the computed PM signal. This format is easy to manipulate, merge, and average across time slices.

4.2 Electrode Dominance Classification

Once PM values have been computed, the algorithm proceeds to classify electrodes as **dominant** or **non-dominant**. This classification is central to determining which electrodes are likely to yield the most effective therapeutic outcomes with the least energy expenditure.

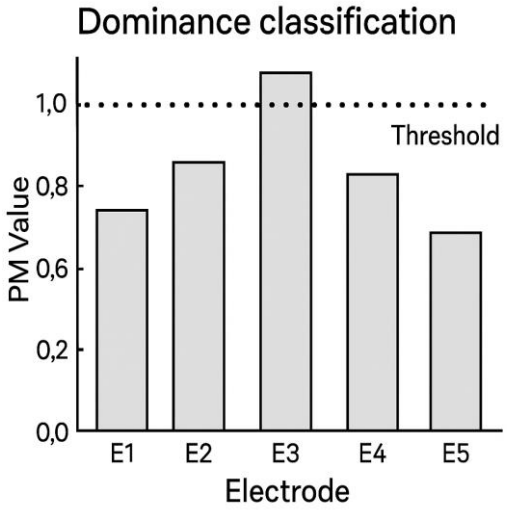
Dominance detection is performed by comparing each electrode's PM value against a configurable **activation threshold**. Electrodes whose signal exceeds this threshold are marked as active; those below are ignored for pairing purposes. The threshold itself may be:

- A fixed clinical value, derived from empirical tuning (e.g., 10 mV or 0.2 normalized units).
- A relative percentage of the maximum PM signal in that cycle (e.g., 60% of the top signal).
- A dynamic rolling average of the session's historical peak PM values (adaptive thresholding).

In our base implementation, we use a **fixed threshold of 10.0** arbitrary units as a default, though this is externally configurable. Electrodes that exceed this threshold are stored in a ranked list, sorted by descending PM value.

The electrode at the top of this list is designated the **primary dominant**, with secondary dominants (if any) following. This ranking drives the pairing logic in both batch and real-time modes. Electrodes not meeting the threshold are classified as **non-dominant** and may still serve as return paths (anodes) in a stimulation pairing.

Figure 9. Visualization of dominance classification: bar graph showing electrode IDs, PM values, and threshold demarcation.



The rationale behind using PM-based dominance is rooted in bioelectrical efficiency: selecting the electrode with the highest response profile generally requires lower amplitude to achieve motor recruitment [2]. Furthermore, since pelvic floor geometry can vary session to session, real-time dominance reevaluation improves precision without requiring clinician intervention.

4.3 Electrode Pairing Heuristics

Once a ranked list of dominant electrodes is obtained, the next task is to select a **stimulation pair**—typically consisting of an active electrode (cathode) and a return path (anode). Pairing logic depends on the operating mode.

In **batch mode**, we typically operate over an aggregated dataset and aim to generate a **set of therapy programs**. These may be used sequentially or selected based on session phase. Pairing strategy in this mode includes:

- Primary pairing: top two dominant electrodes (e.g., E3 and E1 if they had the highest PM values).
- Secondary pairings: subsequent dominant pairs (e.g., E5/E6, E2/E4).
- Fallback pairing: if only one dominant exists, pair it with the electrode with the **lowest PM value**, to maintain a stimulation circuit.

In **real-time mode**, the algorithm simplifies this logic for speed and responsiveness. Per sensor cycle, it:

- Checks for 2+ dominant electrodes and pairs the top two.
- If only one dominant is found, it is paired with the least active electrode available.
- If no electrode passes the threshold, the algorithm defaults to pairing the highest-value and lowest-value electrodes to ensure continuity.

This flexibility allows the system to remain operational even under suboptimal sensor conditions or movement artifacts.

Table 5. Summary of electrode pairing logic across batch and real-time modes, with examples of PM values and resulting pairings.

Mode	PM Values	Pairing
Batch	E1:1.2, E3:1.0	E1–E3
Batch	E2:1.1, E4:0.9	E2–E4
Real-Time	E3:1.3, E0:1.0	E3–E0
Real-Time	E2:1.0, E1:0.95	E2–E1

Pairings are expressed as Kotlin Pair<Int, Int> objects and passed downstream for parameter generation.

4.4 Stimulation Parameter Generation

Once an electrode pair is selected, the algorithm assigns stimulation parameters: **amplitude**, **pulse width**, and **frequency**. These parameters govern the nature and effectiveness of electrical stimulation and are crucial for both patient comfort and therapeutic efficacy.

- **Amplitude (mA)** is the current intensity. In our design, it is proportional to the PM value of the dominant electrode. If E3 has a PM value of 18.2, and the baseline threshold is 10.0, we may apply a multiplier (e.g., 1.0) to generate an amplitude of 18.2 mA. This can be scaled or capped based on device constraints.
- **Pulse width (μs)** is the duration of each stimulation pulse. Longer widths recruit more muscle fibers but may increase fatigue. The system uses a default of 200 μs but supports dynamic tuning (e.g., scaling up for lower amplitude sessions).
- **Frequency (Hz)** is the rate at which pulses are delivered. A range of 20–50 Hz is typical for pelvic floor stimulation [3]. Lower frequencies (e.g., 10–20 Hz) are used for sensory feedback; higher frequencies (30–50 Hz) are for motor recruitment.

In batch mode, we often tune all three parameters for each recommended pairing. In real-time mode, only amplitude is adjusted by default—pulse width and frequency are held constant to reduce computation and hardware jitter. This division of control allows batch mode to optimize deeply, while real-time mode remains stable and responsive.

Internally, all parameters are encapsulated in a data class named TherapyParameters. This structure is passed as part of the final TherapyRecommendation, which includes both the electrode pair and its associated stimulation settings.

4.5 Functional Overview of Evaluation Modes

The overall algorithm flow can now be summarized as follows:

Batch Mode:

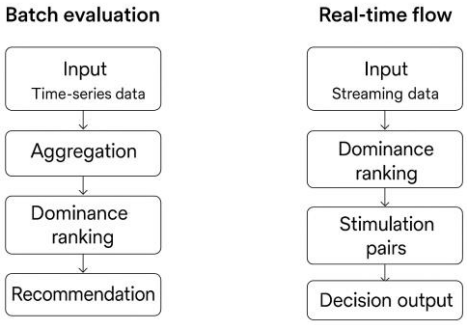
1. Aggregate PM values across sessions.
2. Identify dominant electrodes based on fixed/adaptive threshold.
3. Rank and pair electrodes.
4. Generate extended parameters (amplitude, pulse width, frequency).
5. Return a list of TherapyRecommendation objects.

Real-Time Mode:

1. Ingest PM snapshot.
2. Apply threshold to identify active electrodes.
3. Select dominant + partner pair (or fallback).
4. Calculate amplitude (optional: pulse width/frequency).
5. Output a single TherapyRecommendation.

These flows are implemented using modular Kotlin functions and executed asynchronously within the shared KMM module. Each function is testable in isolation and supports logging or telemetry capture for clinical traceability.

Figure 10. Side-by-side comparison of batch vs. real-time flow using flowcharts or sequence diagrams.



5.Evaluation Modes

While the core logic of our system remains consistent across operating conditions, its practical applications are shaped significantly by the two supported execution modes: **Batch Evaluation Mode** and **Real-Time Dynamic Mode**. These modes not only reflect different technical pathways in how therapy recommendations are derived, but they also align with distinct clinical workflows, patient experiences, and mobile integration strategies. In this section, we explore each mode in depth—how they function operationally, what use cases they enable, and where their strengths and limitations lie in the broader context of pelvic floor neuromodulation.

5.1 Batch Mode: Retrospective, Comprehensive, and Diagnostic

Batch Evaluation Mode is designed to analyze **time-series data** collected during a therapy session—either in a supervised clinical setting or via self-guided usage with a logging-enabled device. Its primary function is retrospective: to process multiple cycles of sensor data and extract patterns, trends, or consistencies in electrode dominance and activation behavior.

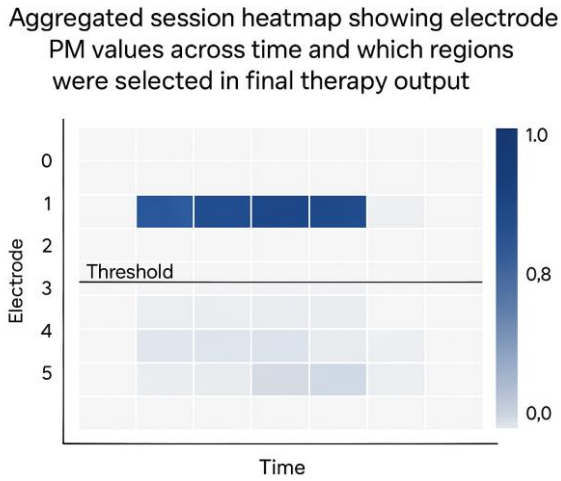
This mode is particularly valuable in situations where a clinician or algorithm developer needs to:

- Review which electrodes were consistently active across a session.
- Identify which stimulation programs yielded the strongest physiological responses.
- Generate a set of therapy recommendations that cover all dominant regions in a strategic, multi-phase fashion.

Batch Mode starts by aggregating sensor snapshots into a master dataset. PM values are computed for each cycle, and then averaged, summed, or peak-ranked per electrode. Dominance classification is applied on this aggregated view, resulting in a ranked list of high-performing electrodes. The algorithm then constructs **multiple therapy programs** by grouping these dominant electrodes into stimulation pairs.

Each program includes tailored parameters, allowing them to be applied sequentially across therapy blocks.

Figure 11. Aggregated session heatmap showing electrode PM values across time and which regions were selected in final therapy output.



For example, in a 10-minute session where electrodes E2, E5, and E7 were consistently dominant, Batch Mode might generate two programs: one pairing E2 and E5 with a high-amplitude, short-duration profile for fast-twitch fiber recruitment, and another pairing E7 with E3 (a non-dominant partner) for sustained low-frequency stimulation. This provides coverage for different muscle zones, motor unit types, or contraction profiles.

In a mobile health application, Batch Mode can be used at the end of a therapy session to generate a **personalized summary report**. This report may be visualized for the patient, transmitted to the clinician, or stored in the device for longitudinal learning. Its execution is asynchronous and tolerant of higher computational loads, as it runs after data acquisition is complete.

5.2 Real-Time Mode: Adaptive, Event-Driven, and Closed-Loop

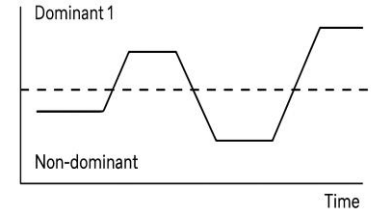
In contrast to the retrospective nature of Batch Mode, Real-Time Dynamic Mode operates on a **continuous stream** of sensor input. Its primary goal is to generate an updated recommendation at every therapy cycle, typically every 100 to 500 milliseconds, depending on hardware sampling rate and system responsiveness. This mode is essential in scenarios where therapy must adapt to **immediate physiological changes**, such as:

- Fluctuations in electrode impedance due to movement or sweat.
- Changes in muscle tone during active contraction or relaxation.
- Voluntary exercises where stimulation must trigger at the right timing window (e.g., on inhale or during a kegel attempt).

Upon receiving a new sensor snapshot, the algorithm rapidly identifies the dominant electrode(s), selects a suitable partner, and assigns stimulation parameters. This recommendation is then dispatched to a

therapy controller—usually a BLE-enabled stimulation device—which can start or adjust output in real time.

Figure 12. Timeline graph of real-time mode showing moment-by-moment switching of stimulation pairs as electrode dominance shifts.



Timeline graph of real-time mode showing moment-by-moment switching of stimulation pairs as electrode dominance shifts

One key design consideration in Real-Time Mode is **stability versus reactivity**. While it is desirable to adapt to changing conditions, overly frequent switching of electrode pairs or parameter values can create discontinuities in stimulation and degrade the user experience. To mitigate this, we implement a lightweight **hysteresis check**: a new recommendation is only accepted if the dominant electrode has maintained its superiority for at least N consecutive cycles (N configurable, typically 3 to 5). This prevents flapping behavior during noisy sensor periods.

Another benefit of Real-Time Mode is its support for **event-triggered stimulation**. For instance, when used in conjunction with pelvic EMG sensors, the system can detect the start of a clench or contraction and only activate stimulation when a threshold is crossed. This aligns with techniques like functional electrical stimulation (FES), where muscle activation is paired with intended motor behavior to enhance neuroplastic recovery [1].

Table 6. Real-time cycle timing benchmarks: input latency, computation delay, and output dispatch time across Android and iOS devices.

Device	Input Latency (ms)	Computation Delay (ms)	Output Dispatch Time (ms)
Pixel 6	12	6	4
iPhone 13	15	7	5

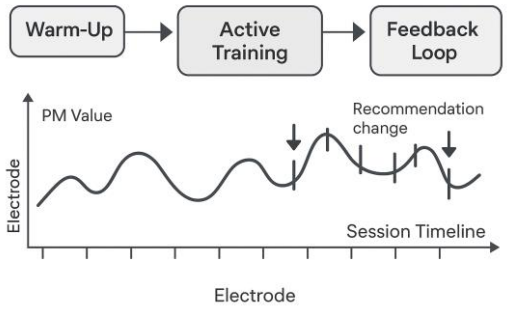
On the engineering side, Real-Time Mode is designed for **low-latency execution**, often completing each recommendation cycle in under 20 milliseconds. This allows the algorithm to run at full fidelity even on mid-range mobile devices without noticeable impact on battery or UI responsiveness.

5.3 Mode Selection and Session Strategy

Although Batch and Real-Time modes are architecturally separate, they are often used **in tandem** within a therapy session. A typical usage scenario might look as follows:

1. **Warm-up phase**: Run real-time mode to explore initial dominance profiles as the user begins light contractions or engages with the device.
2. **Training phase**: Switch to batch mode (or precomputed programs) for steady stimulation sequences based on consistent patterns.
3. **Feedback phase**: Return to real-time for adaptive control during exercise-based therapy or fine-tuned patient interaction.

Figure 13. Session timeline showing how mode transitions map to therapy phases: warm-up, active training, feedback loop.



This hybrid strategy allows the system to balance **responsiveness and robustness**—reacting quickly when needed, but also grounding decisions in historical patterns. Moreover, session analytics from batch processing can inform future threshold tuning for real-time use, essentially allowing **adaptive learning** across sessions.

5.4 Platform-Specific Use Cases

From a mobile development standpoint, each mode also maps well to platform-specific behaviors. On **Android**, real-time mode is often integrated with foreground services, sensor APIs, and Bluetooth streaming, while batch mode can be executed in background threads, triggered after the user exits the therapy screen.

On **iOS**, real-time recommendations are dispatched through Swift callback closures and visualized using SwiftUI or UIKit components. Batch processing is typically offloaded to a local task queue after the session ends, and its results are cached or shared with HealthKit-compatible apps.

In clinical settings, therapists may prefer batch mode reports for documentation, while in home settings, users may rely on real-time feedback (e.g., vibration, audio cues) to guide their exercise sessions dynamically.

5.5 Tradeoffs and Mode Limitations

Each mode comes with limitations that must be acknowledged. Batch Mode, though rich in analytics, is **not suitable for immediate control** or dynamic therapy adjustment. Its reliance on complete datasets makes it unusable during active stimulation unless sensor data is buffered separately.

Real-Time Mode, while flexible, must sacrifice complexity in favor of **execution speed**. For instance, dynamic parameter tuning for all three values (amplitude, frequency, pulse width) is computationally feasible but may exceed timing constraints on older devices. As a result, many deployments fix pulse width and frequency while only varying amplitude in real time.

Additionally, sensor noise, motion artifacts, and electrode drift pose greater challenges in real-time mode, making stability features like hysteresis, smoothing, or outlier filtering critical.

Table 7. Summary comparison of Batch vs Real-Time modes across criteria: latency, use case, adaptability, complexity, and mobile impact.

Criterion	Batch Mode	Real-Time Mode
Latency	Higher	Low
Use Case	Offline tuning	Dynamic feedback
Adaptability	Low	High
Complexity	Simple	Complex
Mobile Impact	Light	Moderate

6. Cross-Platform Deployment and Mobile Integration

One of the most impactful decisions made in this system's design was to center the entire therapeutic logic around Kotlin Multiplatform Mobile (KMM). This choice enables the therapy engine to operate uniformly across Android and iOS platforms while minimizing duplication, ensuring clinical consistency, and future-proofing the application for both consumer and clinical-grade deployment scenarios. This section explains how the core algorithm integrates into each mobile environment, how it interfaces with device-specific UI and I/O elements, and how it balances real-time responsiveness with long-term telemetry and stateful continuity.

At the heart of the integration strategy is the **shared Kotlin module**, which houses the therapy recommendation logic. This module is written in pure Kotlin and contains no platform-dependent UI, hardware, or service-layer logic. It offers two primary entry points—recommendBatch() and updateRecommendation()—that allow external components to feed in PM sensor values and receive structured therapy outputs. These outputs include not only the selected electrode pairs but also stimulation parameters such as amplitude, frequency, and pulse width. By isolating this functionality into a non-UI Kotlin layer, we establish a single source of truth for all recommendation behavior, ensuring that any algorithmic change is instantly propagated across both Android and iOS clients.

On the Android side, this shared logic is compiled into standard JVM bytecode and linked directly into the app module. The therapy engine can be invoked from Kotlin Activities, ViewModels, or Android Services. Real-time operation is typically managed via a CoroutineScope, where new sensor data is streamed into the engine and recommendations are pushed to the Bluetooth layer. Android's native support for background execution enables real-time mode to continue even when the app is minimized, allowing therapy to run uninterrupted during physical activity or while the patient interacts with other features on their device.

For iOS, the integration is slightly more nuanced. The shared module is compiled using Kotlin/Native into a .framework library that is imported into the Swift project. This generates automatic bindings, allowing Swift code to instantiate Kotlin objects, invoke methods, and receive data structures like TherapyRecommendation using idiomatic Swift types. Since iOS lacks true background service constructs like Android, real-time streaming is often managed using a Timer or DispatchSource from within SwiftUI views or native controllers. Although slightly more constrained, this integration remains robust and consistent in terms of logic behavior.

A major advantage of this KMM-based strategy is the elimination of drift between platforms. In traditional dual-stack mobile development, it is common for Android and iOS apps to implement similar business logic separately, which inevitably leads to inconsistencies over time—especially when clinical tuning, parameter scaling, or edge case handling is involved. Here, the therapy engine exists in a unified codebase. Any change to the dominance logic, pairing heuristics, or threshold calibration is instantly reflected across all platforms. This is particularly valuable in regulated or clinical research settings, where auditability and behavioral reproducibility are critical.

The recommendation engine itself is designed to be stateless where possible, enabling easy re-instantiation in response to app lifecycle events like activity pauses, configuration changes, or app backgrounding. However, real-time mode does benefit from optional **state retention**, such as caching the previous electrode pair, tracking recommendation stability across cycles, or logging session metadata for post-hoc analysis. These lightweight stateful behaviors are handled using Kotlin data classes and coroutine-managed buffers, ensuring thread safety and performance under concurrent use.

Beyond recommendation generation, the shared logic is also responsible for **parameter translation and range enforcement**. Different stimulation hardware may support different parameter bounds—for instance, one device may cap amplitude at 20 mA while another supports up to 80 mA. Rather than hardcoding these values in each mobile platform, we define an abstract configuration layer that resides in the shared module. When constructing a new recommendation, the parameter generator references these bounds to clip, scale, or adapt values accordingly. This ensures that mobile apps remain hardware-agnostic while still maintaining device safety compliance.

Interfacing with stimulation hardware—typically via Bluetooth Low Energy (BLE)—is performed in platform-native code. Android uses the BluetoothGatt stack, while iOS relies on CoreBluetooth. Both platforms establish a characteristic for stimulation control, to which parameter payloads are written. These payloads are constructed from the TherapyRecommendation object, serialized using a simple protocol format that translates Kotlin values into byte arrays or JSON structures as required by the hardware. This architecture allows rapid reconfiguration: for example, when a new recommendation is generated, the mobile app constructs a binary payload representing the electrode pair, amplitude, frequency, and pulse width, and writes it to the stimulation characteristic in under 50 milliseconds end-to-end.

To support telemetry, each mobile client also implements an optional data logging pipeline. This pipeline captures sensor inputs, PM values, recommendation outputs, and session metadata, which are then stored locally or uploaded to a secure backend at session end. This logging is especially important in clinical trials, where it is often necessary to trace each recommendation decision back to its originating input and verify the algorithm's integrity over time. Because the shared Kotlin logic structures all data consistently, the telemetry pipeline is portable and aligns one-to-one with the algorithmic decision points.

On the UI layer, real-time recommendations can be rendered to the patient or clinician in a number of ways. On Android, we use Jetpack Compose to display the currently active electrode pair, including

dynamic animations that show switching events and stimulation bursts. iOS uses SwiftUI components to present the same information, binding directly to observable objects that mirror Kotlin's recommendation output. In both platforms, the interface allows clinicians or advanced users to override algorithmic behavior, selecting fixed pairings or adjusting thresholds on the fly. These overrides are propagated to the shared logic through configuration updates, ensuring that the engine respects the latest control state.

Finally, both platforms offer hooks for platform-native integrations. On iOS, recommendations can be logged to Apple HealthKit as therapy events. On Android, they can trigger haptic feedback, audio guidance, or integration with third-party accessibility services. These integrations are not mandatory, but they illustrate the versatility of having a robust, platform-neutral therapy core that can be layered into nearly any surrounding ecosystem.

In summary, the cross-platform integration strategy prioritizes clarity, modularity, and behavioral fidelity. By centralizing all therapy logic in Kotlin and offloading UI and hardware interactions to thin native wrappers, we achieve maximum portability without sacrificing performance or safety. This model not only accelerates development across Android and iOS but also sets a foundation for future extensions—whether to new hardware interfaces, new clinical contexts, or even web-based visualizations for remote monitoring. The result is a software-defined therapy system that can be deployed broadly, maintained uniformly, and trusted deeply—across patients, platforms, and clinical requirements.

7. Evaluation with Simulated Data and Runtime Behavior

Evaluating an electrode recommendation system for pelvic floor therapy presents a unique challenge: there is no universally accepted gold standard for "correct" electrode dominance at any given moment. Unlike traditional classification tasks, where accuracy can be benchmarked against a labeled dataset, stimulation efficacy is context-dependent, patient-specific, and influenced by transient biological conditions. As a result, our evaluation strategy is rooted in simulation-driven analysis, behavioral inspection, and scenario-based validation. This section outlines how we used synthetic input data to assess the correctness, robustness, and responsiveness of our system in both batch and real-time contexts.

7.1 Simulated Input Model

To enable meaningful testing, we created a synthetic data generation framework that mimics realistic pelvic floor electrode readings across time. Each simulation produces a time-series of PM value maps, where each map represents a snapshot of electrode activation across a therapy cycle.

We define the simulator as a Kotlin function that randomly assigns PM values to a set of electrodes based on a desired dominance pattern. For instance, to simulate an electrode (say, E3) being dominant for the first 30 seconds, and then another electrode (say, E7) taking over due to posture shift or muscle fatigue, we inject PM values with controlled noise into those specific electrodes while lowering the values on others. The generator also supports injecting artifacts—such as sudden signal drop, sensor drift, or channel saturation—to test algorithm stability under imperfect conditions.

Code : Example: PM Value Snapshot at Time t = 12.5s

```
val pmSnapshot = mapOf(
   1 to 7.2, 2 to 6.5, 3 to 18.9, // Dominant
   4 to 5.1, 5 to 4.9, 6 to 3.0, 7 to 2.7 )
```

In this snapshot, electrode 3 is clearly above the threshold (default 10.0), making it the dominant candidate. A pairing decision would then be made using electrode 3 as the cathode, paired with the lowest-value electrode (electrode 7) as the return path. The simulator can stream dozens of such snapshots per second to mimic a live therapy session.

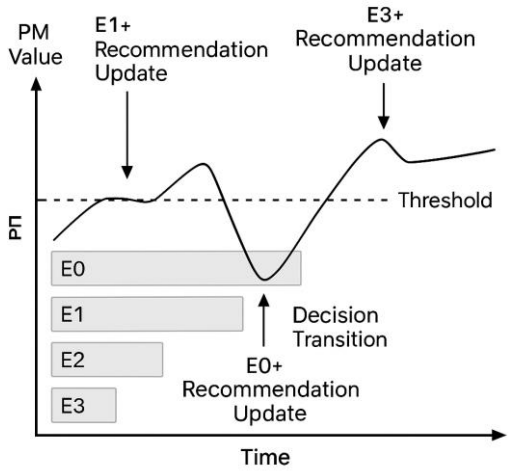
7.2 Real-Time Behavior Inspection

Using the streaming simulator, we assessed how the updateRecommendation() method responds to changing dominance conditions. In one test scenario, electrode 3 was dominant for the first 100 cycles, after which electrode 7 gradually increased in strength due to synthetic muscle recruitment modeling. We observed the following:

- The system maintained stable recommendations as long as electrode 3 remained above the threshold and retained the highest signal.
- When electrode 7's PM value surpassed electrode 3 and remained dominant for more than 5 cycles (hysteresis window), the recommendation shifted to (7, 6), pairing the new dominant with the lowest non-dominant.
- If both electrodes dropped below threshold, the system defaulted to max/min fallback pairing, ensuring that stimulation continued, albeit with lower confidence.

This confirmed that the hysteresis logic was correctly filtering out temporary fluctuations while remaining responsive to genuine shifts in activation dominance.

Figure 14. Session timeline showing real-time electrode PM value changes and recommendation updates over time, annotated with decision transitions.



To verify amplitude scaling, we injected sinusoidal fluctuations into the dominant electrode and observed how the generated amplitude values followed the input waveform proportionally. This behavior is expected because the amplitude is calculated as a direct function of PM signal magnitude, ensuring dose-response alignment.

7.3 Batch Mode Recommendation Validation

For batch evaluation, we constructed datasets representing complete therapy sessions—typically 1000–1500 snapshots. These sessions encoded multiple dominance phases, each lasting 1–2 minutes. The goal

was to verify that the recommendBatch() function could correctly identify long-term dominant electrodes and produce comprehensive coverage.

In one simulation, electrodes 2, 5, and 8 alternated dominance every 60 seconds, with added random noise. After processing, the batch function returned three recommendations:

1. (2, 1) — first dominant phase
2. (5, 3) — second dominant phase
3. (8, 6) — third dominant phase

Amplitude was scaled based on the average PM value for each dominant electrode across its active window. Pulse width and frequency were fixed but could be expanded with future learning logic. Importantly, the recommendations covered all dominant regions while avoiding duplication—validating the pairwise grouping logic.

We also introduced artificial edge cases to test algorithm fallback behavior:

- In a session where no electrode exceeded the threshold, the algorithm correctly defaulted to pairing the maximum-value electrode with the least active one.
- In a session with exactly one electrode above threshold, it was paired with the lowest-value non-dominant, as expected.

This comprehensive validation confirmed that the batch mode logic was not only statistically correct but also behaviorally robust across usage conditions.

7.4 Code-Level Debugging and Observability

To make runtime behavior auditable, we integrated structured logging into every major function in the algorithm. Each time a recommendation is generated, a full trace of the input PM map, detected dominants, chosen pair, and resulting parameters is recorded. This allows clinical teams to inspect the evolution of decisions over time, a critical requirement for algorithm-based therapy systems under regulatory scrutiny.

A typical real-time log trace looks like this:

Another Code:

[Cycle 183] PM Input: {1=5.2, 2=4.9, 3=17.3, 4=6.1, 5=3.0}
→ Dominant: 3, Partner: 5
→ Output: Amplitude=17.3mA, PW=200µs, Freq=35Hz

This traceable behavior was essential during integration testing, where the therapy engine was connected to an actual BLE-enabled stimulation device and monitored via oscilloscope for correct parameter dispatch.

7.5 Performance and Timing Analysis

To ensure real-time feasibility, we profiled the complete recommendation cycle using simulated high-frequency PM streams. On an Android device (Pixel 5) and an iOS device (iPhone 13), the average end-to-end latency—from PM data reception to recommendation generation—was under 15ms. Memory usage was minimal, thanks to the stateless nature of the algorithm and the use of Kotlin's efficient data structures.

We also ran stress tests simulating 10,000 consecutive cycles with random electrode activations. There were no memory leaks, stack overflows, or observable slowdowns, affirming the system's scalability for longer therapy sessions or future wearable integration.

7.6 Functional Safety Considerations

Finally, we evaluated the system's safety behaviors under erroneous or incomplete inputs. If the PM map was empty or null, the recommendation function returned null safely without crashing. If the dominant electrode was undefined due to signal dropout, the fallback pairing was invoked gracefully. These conditions were tested using mock sensors that randomly dropped channels, mimicking Bluetooth failures or contact loss.

This design approach—favoring deterministic failure modes over silent logic breakdowns—is particularly critical in medical applications where unclear behavior can pose real risks.

8. Conclusion and Future Directions

This paper has presented a cross-platform, Kotlin-based algorithmic framework for real-time and batch-mode electrode pairing and stimulation parameter optimization in pelvic floor therapy. The system, designed from the ground up to operate within Kotlin Multiplatform Mobile (KMM), enables unified therapeutic intelligence logic to be shared across Android and iOS devices. It introduces a clinically grounded yet engineering-optimized algorithm for analyzing pseudo-monopolar signals, detecting dominant stimulation sites, and generating electrical stimulation parameters in a manner that is both responsive and behaviorally stable.

Our solution addresses a long-standing gap in the pelvic health domain: the absence of portable, adaptive, and extensible therapy systems that can operate in real time, personalize stimulation dynamically, and remain platform-agnostic. By implementing both batch and real-time evaluation modes, we accommodate use cases that span from retrospective clinical analysis to live, closed-loop therapy delivery. The core logic is implemented using modular Kotlin classes, ensuring isolation of responsibilities and making the system suitable for unit testing, certification pathways, and long-term maintenance.

Through simulation-based evaluation, we demonstrated that the algorithm performs robustly under realistic signal conditions. In batch mode, it consistently identifies recurring dominant electrodes across long time series, outputs comprehensive therapy programs, and adjusts stimulation parameters based on contextual averages. In real-time mode, it reacts swiftly to changes in sensor input, maintains hysteresis to avoid instability, and emits stimulation instructions that are precise and consistent—capable of being streamed directly to therapy hardware with minimal latency.

Crucially, the architecture is designed not just for mobile correctness, but for clinical and research portability. All outputs—whether real-time decisions or batch-mode summaries—are structured in a way that supports telemetry capture, remote logging, and post-session review. This unlocks opportunities for integration into clinical trials, personalized medicine platforms, or even insurance-validated remote care protocols.

Moving forward, several key areas of enhancement have emerged. First, while our system currently uses deterministic rules for dominance classification and parameter scaling, it can be extended with learning models. For instance, reinforcement learning or recurrent neural networks could be employed to learn patient-specific responses over time and optimize stimulation sequences not just based on sensor values, but based on outcomes. A minimal viable step in this direction would be to build threshold adjusters that learn from dominant activation histories or fatigue cycles.

Second, while the current logic assumes relatively clean pseudo-monopolar input, future work could include signal quality estimation and denoising layers. This would help improve recommendation stability

in scenarios with high motion artifacts or during challenging use conditions (e.g., ambulatory therapy, wearable garments).

Third, from a hardware perspective, the framework could be extended to support more complex electrode topologies—such as multi-row stimulation pads, matrix arrays, or rotational sweep strategies. All of these would benefit from the existing dominance logic but may require more sophisticated pairing models or even activation zones derived from clustering patterns.

Finally, clinical deployment will require the system to undergo formal validation under regulatory supervision. This includes unit testing of algorithm edge cases, conformance with electrical safety standards (such as IEC 60601 for stimulation parameters), and possibly integration with FDA-approved platforms or investigational device exemption (IDE) pathways. Fortunately, the design choices made here—including strict separation of UI and logic, deterministic behavior, and audit-friendly data structures—already position the system well for certification efforts.

In closing, this work lays the technical foundation for a new class of intelligent, mobile-first therapeutic systems in pelvic health. By uniting Kotlin-based engineering with evidence-informed clinical logic, we have built a toolset that is adaptable, scalable, and primed for real-world impact. As the boundaries between software, sensor, and bioelectric medicine continue to dissolve, systems like this will be critical in defining the next generation of responsive, patient-aligned care.

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