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AI-Enhanced Gait Re-Education: Overcoming Linguistic and Cultural Barriers in Rehabilitation

Marius Dobîndă-Albu
Physical therapist and PhD candidate at the Faculty of Physics, Alexandru Ioan Cuza University of Iași, Romania.
marius.dobinda@student.uaic.ro,
https://orcid.org/0009-0000-4951-8562

Abstract: *The success of motor rehabilitation is closely related to the quality of communication between the therapist and the patient. Cognitive impairment is common among acute stroke survivors and is frequently associated with slowed information processing. Under such conditions, verbal instructions often fail to be conveyed in a form that the patient can effectively translate into action. This paper presents two complementary electronic systems developed to provide language-independent feedback for gait re-education. The first is a low-cost device built on an Arduino MKR1000 platform that combines a triaxial accelerometer and three FSR pressure sensors to provide real-time visual feedback during walking, with no AI on board. The second one uses an STM32 microcontroller with six synchronised accelerometers to record multi-segment gait data for offline processing using GauFlow Analyzer, which provides graphical summaries, descriptive statistics, and an optional AI module that detects deviations from a learned normal gait baseline. Preliminary clinical use with 12 patients over six months suggested that visual cues can prompt movement correction without verbal direction. The STM32 system has additionally been evaluated in a parallel investigation on a cohort of 30 participants (15 neurological participants and 15 healthy controls), thereby providing broader empirical context for the descriptive findings reported here. The two systems are not alternatives. Real-time feedback supports the therapeutic session, whereas offline AI-assisted analysis provides the therapist with an objective assessment of gait asymmetry and its evolution over time. Together, they establish a rehabilitation framework in which therapeutic guidance relies less on verbal communication and more on directly interpretable visual feedback.*

Keywords: *artificial intelligence; gait re-education; biofeedback; wearable sensors; language-independent; feedback; neurorehabilitation; communication barriers.*

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1. Introduction

Gait rehabilitation following a neurological event represents not only a medical challenge but also a significant communication barrier. An effective therapy requires a clear understanding between patients and therapists, a condition that is often difficult to ensure in contemporary European clinical practice.

The European Union encompasses 24 official languages, three alphabets, and 175 nationalities. Immigrant patients experience higher rates of miscommunication in therapy settings (Davies et al., 2016), and the consequences of these misunderstandings can be serious. Beyond language differences, the unfamiliarity with medical terminology among patients from different backgrounds can lead to misinterpretation or ignorance of medical instructions, further complicating communication in clinical settings (Numeroso et al., 2015; Taylan & Weber, 2023). Language barriers, however, represent only one component of the broader communication challenge. Cognitive impairment is common in the acute phase of stroke, with an overall prevalence of 55% among first-stroke patients and up to 74% among patients with cortical involvement. Executive dysfunction is the most frequently reported deficit (Nys et al., 2007). Slowed information processing is among the most consistently observed consequences and contributes independently to long-term functional outcomes (Cumming et al., 2013). A comprehensive neuropsychological assessment of stroke survivors further revealed that slowed information processing affects more than 70% of patients, while at least 40% present with concurrent difficulties in memory, visuospatial tasks, and language—a combination that severely limits the capacity to receive and act upon verbally mediated therapeutic instructions (Hochstenbach et al., 1998). These factors substantially impair the patient's ability to receive, interpret, and respond to verbal instructions, irrespective of linguistic barriers.

Models of differing complexity have been used to describe human communication. Linear models (Aristotle, Lasswell, Shannon-Weaver, and Berlo) describe communication as a one-way process from sender to receiver without feedback or corrective adaptation. Shannon's model (Figure 1) involves an interaction between an information source, a transmitter, a noise source, and a receiver, which transforms it again before sending it to the destination (Shannon, 1948). While useful for communicating basic information flow, such models are not structurally adequate for therapeutic settings, where bidirectionality and correction are crucial.

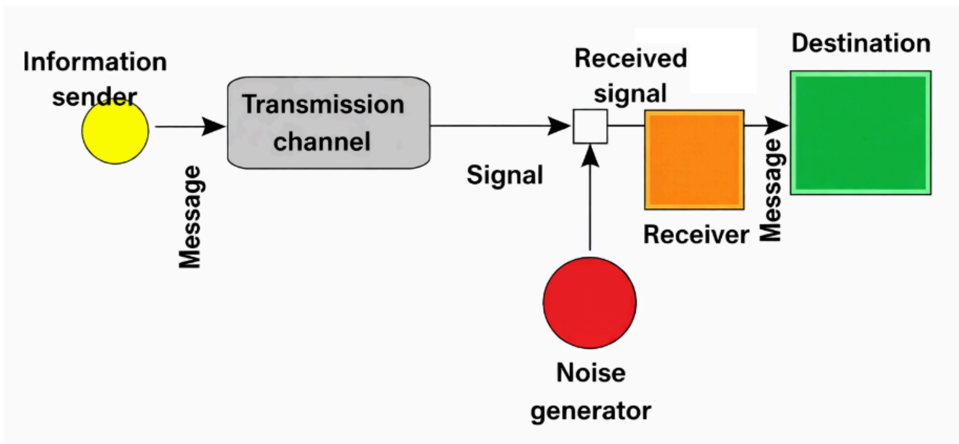

Figure 1. Shannon-Weaver model - unidirectional information transmission (after Shannon, 1948)

This limitation is directly addressed by Schramm's interactive model. It presents feedback and mutual experience between sender and receiver (Steinberg, 1995), showing a communication cycle in which the roles of emitter and receiver are changing all the time (Figure 2). In gait retraining, this feedback does not have to be verbal. It can be through visual or sensor signals that directly inform the patient about loading patterns and segment movement. Thus, biomechanical signals are a form of communication that bypasses language altogether.

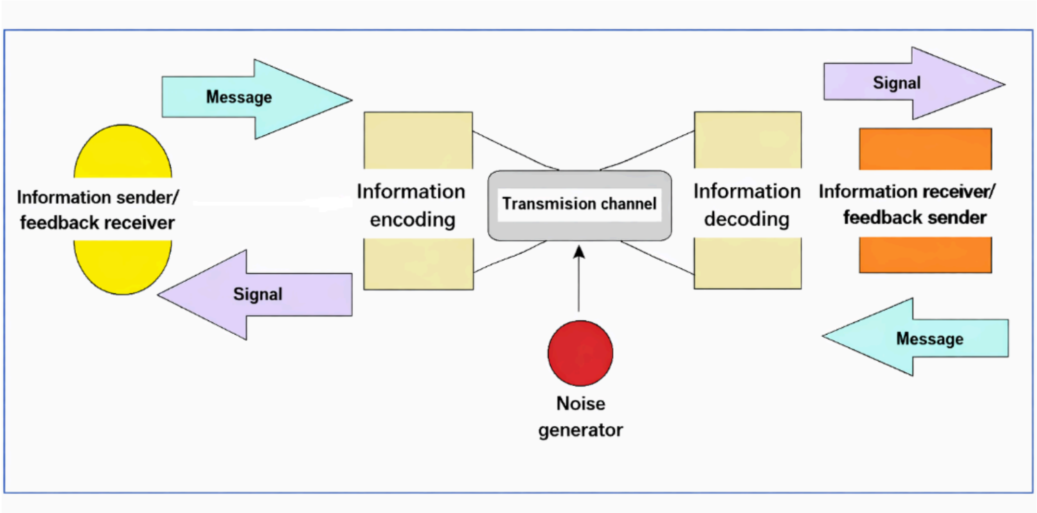

Figure 2. Schramm's model of communication - bidirectional, interactive, adaptive, suitable for rehabilitation work

While sensor-based and AI-assisted tools are increasingly available in rehabilitation, there are few studies on how such systems may reduce the linguistic and cultural barriers limiting patient-therapist communication. Gait assessments powered by technology and AI-driven analysis exhibit significant clinical promise, yet implementation remains restricted. Affordable, effective, and clinically flexible solutions are still needed (Mohan et al., 2021). In this context, cognitive elements are especially important, particularly attentional capacity. Post-stroke attention deficits have been associated with increased disability and poorer functional recovery and may therefore constrain the efficacy of verbal instructions independent of language barriers. These results support the use of simple visual feedback strategies (Belda-Lois et al., 2011).

The present work addresses this gap. We present two complementary electronic systems for language-independent feedback in gait re-education and AI-assisted offline analysis. The question is whether the combination of real-time visual biofeedback with an AI-assisted offline gait analysis platform can support re-education in patients with linguistic, cultural, or attentional barriers during rehabilitation.

The hypothesis underlying this study is that language-independent visual cues delivered through a rule-based real-time device, combined with AI-assisted multi-sensor gait analysis performed offline, may improve the interpretability of therapeutic guidance and provide a more objective characterisation of gait asymmetry while remaining feasible for clinical implementation across diverse patient populations.

2. Literature Review and Human-Computer Interaction in Rehabilitation

Rehabilitation is becoming increasingly reliant on electronic devices and computer-based systems, which changes the way patients are involved in their own recovery. The multimodal feedback technologies (visual, auditory, and haptic) allow the patient to receive information on the quality of movement without verbal explanation. This represents a significant advantage in contexts where communication is constrained by linguistic, cultural, or cognitive factors.

Sensor-based rehabilitation platforms that also provide visual and interactive feedback have proven effective in facilitating active patient participation and reducing reliance on verbal instructions, particularly in the context of neurorehabilitation (Vanoglio et al., 2024). A clear example of this is the Gloreha Aria (currently BTL R-Lead) (Gloreha, 2023), which uses infrared motion tracking with a Leap Motion controller to offer neurocognitive training for the upper limbs via interesting game-based activities (Figure 3) (Vanoglio et al., 2024).

The patient responds directly to visual stimuli without requiring continuous verbal guidance.

Figure 3. Exercises based on human–computer interaction, using interactive games to stimulate movement and coordination. Source: author's archive

Similar principles underlie the Balance Tutor system (Figure 4), which combines force and motion sensors with a 4D treadmill to generate multidirectional perturbations and train both reactive and proactive postural control responses within a safe environment supported by a protective harness throughout the intervention (MediTouch USA, n.d.; Hu et al., 2023).

Figure 4. Adult patient on BalanceTutor treadmill. Computer-assisted training with visual and postural feedback Source: author's archive.

AI applications in rehabilitation extend beyond automation. Rather than using one-size-fits-all treatment structures, AI-backed systems allow therapists to leverage the data from motion sensors to gain a better understanding of how each patient performs. The interpretation of these data, supported by AI-assisted analytical tools, allows the observation of recovery trends and the adjustment of interventions as the patient progresses — a function fulfilled in the present framework exclusively through offline post-session analysis. This is especially important when verbal reporting of progress is not reliable due to communication barriers (Mohan et al., 2021).

Cognitive factors become of central importance in this context. Reduced attentional resources in post-stroke patients have been linked with increased disability and poorer functional outcomes. Such limitations could decrease the effectiveness of verbal instruction, regardless of linguistic barriers (Belda-Lois et al., 2011). These findings support feedback systems that transmit information via direct sensory pathways, rather than language.

Portable gait analysis systems utilising inertial sensors have been demonstrated to reliably capture segmental gait dynamics and to discriminate between physiological and pathological walking patterns, thus supporting their use as practical substitutes for laboratory-based motion capture (Park et al., 2016). In particular, trunk accelerometry offers sensitive markers of posture and gait control, being able to detect differences between physiological and pathological walking patterns that traditional spatiotemporal metrics could not reveal (Sejdić et al., 2014).

Robotic exoskeletons used in gait rehabilitation include tethered systems, such as the Walkbot (P&S Mechanics), and overground wearable systems, such as the ReWalk (Lifeward Ltd.). The Walkbot uses a rigid articulated frame combined with body-weight support to guide lower-limb movement. The ReWalk relies on articulated joints and an onboard control system to enable a more natural overground walking experience. These systems have received considerable attention in gait rehabilitation, particularly in stroke populations. Among chronic stroke patients, wearable robot-assisted training has been associated with improvements in walking speed, balance, and endurance (Cha et al., 2025). However, the evidence appears less consistent when robotic training is introduced earlier after stroke (Cha et al., 2025). Similar systems have also been explored in spinal cord injury, cerebral palsy, and Parkinson's disease, although the level of evidence varies across conditions and further disease-specific clinical studies are still needed (Cha et al., 2025).

Despite their clinical potential, wider adoption of these technologies in everyday rehabilitation practice continues to be limited by factors such as device weight, high cost, and reduced adaptability to real-world conditions. Another limitation, which is important for the present study, is that these systems do not directly solve the communication problem between therapist and patient. A patient with reduced attention, limited language skills, or impaired comprehension may have difficulty understanding therapeutic instructions or the technical feedback displayed by the device. In many cases, these interfaces are designed mainly for clinicians and not for the patient's direct understanding.

The present study follows a different direction. It does not aim to replace therapist-guided rehabilitation with robotic assistance but to use sensor-based visual biofeedback to help the patient directly understand movement-related information without relying on verbal explanations. The offline AI-assisted analytical component is intended for the therapist, with the aim of supporting gait assessment, including asymmetries and deficits, and understanding the changes that occur during rehabilitation sessions. Although the number of available technologies is increasing, few studies have specifically investigated how sensor-based and AI-assisted systems can reduce the linguistic or cultural barriers that limit communication between patients and therapists. Technology-based gait assessment and AI-based analysis offer considerable potential, but their use in routine rehabilitation practice remains limited. For this reason, rehabilitation requires tools that are affordable, easy to use, and adaptable to ordinary clinical scenarios (Mohan et al., 2021).

3. Materials and Methods

Building on the concepts reviewed above, this section presents the practical implementation of two electronic systems designed for gait re-education and the offline analytical software that processes their output.

Methodological overview. Two complementary systems were designed to support gait re-education based on principles of human–computer interaction. The first is a low-cost portable device that provides real-time, rule-based visual feedback to assist motor learning during therapy sessions. The second is a high-fidelity wearable platform with multiple synchronised accelerometers used to collect detailed motion data for offline AI-assisted analysis through the GaitFlowAnalyzer software. Both systems were iteratively tested during rehabilitation sessions to assess usability and the practical responsiveness of the feedback provided.

3.1. Real-Time Biofeedback Device for Gait Re-Education (Arduino-Based; No AI On-Board)

A portable device was assembled on the open-source Arduino MKR1000 platform, integrating an ADXL345 triaxial accelerometer and three FSR pressure sensors embedded in an insole (Figure 5). FSR sensors were used to detect relative plantar loading patterns rather than absolute ground reaction forces — a distinction relevant to the interpretive scope of the data.

Figure 5. Real-time biofeedback device (Arduino MKR1000 + ADXL345 + three FSRs). Function: immediate, rule-based visual feedback for gait re-education (no AI).

Data are transmitted wirelessly and visualised in real time, allowing patients to receive immediate and intuitive feedback on heel, midfoot, and forefoot loading, as well as on segmental acceleration. This design supports motor learning and self-correction without relying on verbal instruction. The recognition of discrepancies between intended and actual movement outcomes is a key condition for error-driven learning — a process that can be effectively facilitated through visual feedback (Belda-Lois et al., 2011). The module operates with rule-based thresholds and visual cues only. No AI inference is performed on the device.

During a preliminary six-month observational period, the device was used with 12 patients with hemiparesis or hemiplegia and was observed to support step-pattern correction and load redistribution on the affected limb. The prototype offers practical advantages in clinical use: low cost, compact dimensions, light weight, and battery autonomy sufficient for standard therapy sessions. Precision is currently limited by the characteristics of FSR sensors and the absence of gyroscopes or high-resolution force sensors — limitations that will be addressed in further development. This device provides rule-based visual cues only and does not perform artificial intelligence processing or adaptive inference.

A real-time graphical representation of gait is displayed on screen, enabling the patient to monitor movement and modify motor actions to approximate a physiological gait pattern. The pressure sensors located at the heel, midfoot, and metatarsophalangeal region, together with the accelerometer, provide the corresponding signal curves.The light green curve corresponds to loading in the forefoot/metatarsophalangeal and midfoot regions, according to the sensor configuration used. The magenta curve reflects Y-axis acceleration of the affected lower limb; its elevated amplitude may indicate reduced forward propulsive capacity, with compensatory acceleration changes occurring to maintain body velocity (Figure 6).

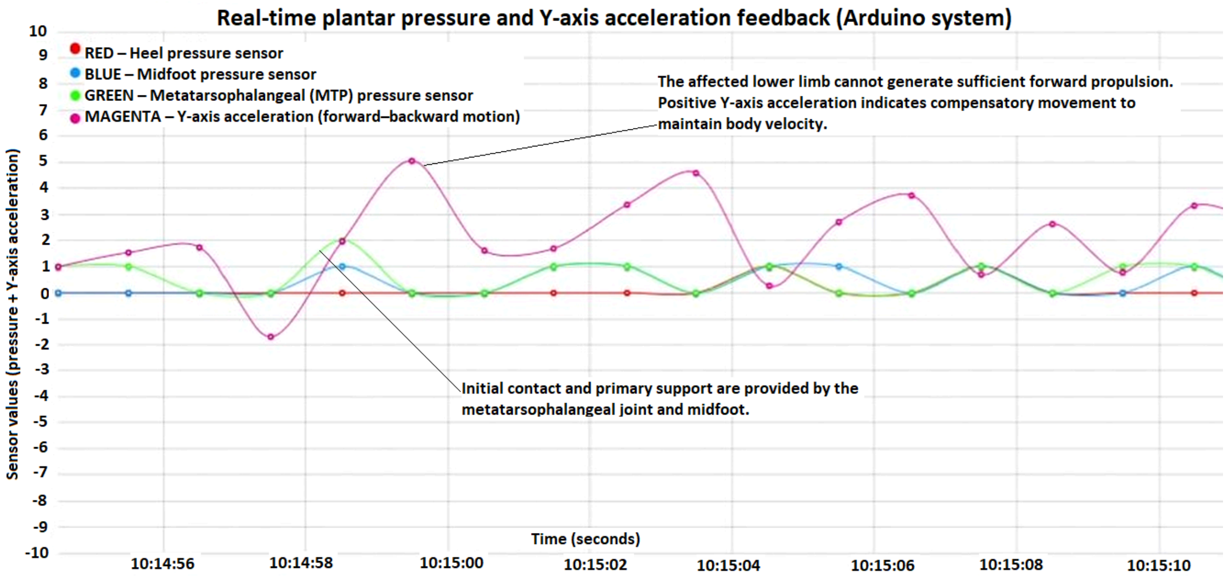

Figure 6. Example of real-time traces (FSR heel/midfoot/metatarsophalangeal + accelerometer). The green curve reflects forefoot/midfoot support at initial contact; the magenta acceleration peak indicates insufficient forward support of the affected limb (biofeedback only; no AI).

3.2. High-Fidelity Data-logger for Advanced Analysis (STM32-Based; Offline Processing)

A second custom-built wearable system based on the STM32 microcontroller, equipped with six synchronised accelerometers, was developed to record multi-segment gait dynamics at higher fidelity (Figure 7).

Figure 7. The STM32 wearable system with six synchronised accelerometers during tests

[1] This platform was designed exclusively for data collection and provides no real-time feedback to the patient during acquisition. Compared to the Arduino prototype, it provides higher

sampling rates, synchronised acquisition from six accelerometers, and improved signal stability. These advantages enable reconstruction of multi-joint acceleration patterns with greater precision, thereby forming the basis for subsequent AI-assisted analysis.

Portable gait analysis systems based on inertial sensors have demonstrated the capacity to reliably characterise segmental gait dynamics and distinguish pathological from physiological walking patterns, thereby supporting their use as practical alternatives to laboratory-based motion analysis systems (Park et al., 2016). The STM32 platform records 18 synchronised acceleration channels — one triaxial sensor for each of six monitored segments: hip, knee, and ankle on both sides. Each accelerometer records acceleration along three anatomical axes: X (medio-lateral), Y (antero-posterior), and Z (vertical). These definitions ensure consistent interpretation across all sensor locations and allow direct comparison between patient and control datasets.

Measures derived from trunk and segmental acceleration along these anatomical directions have been shown to provide sensitive indicators of gait control and to capture differences between physiological and pathological walking patterns beyond traditional spatiotemporal metrics (Sejdić et al., 2014). The STM32 device performs no real-time interpretation or feedback. All processing is performed offline. The GaitFlow Scanner prototype has been registered with the State Office for Inventions and Trademarks (OSIM), Romania, as an individual research initiative.

3.3. AI-Enhanced PC Software (Offline): GaitFlowAnalyzer

The AI-assisted analytical component resides within the PC application GaitFlowAnalyzer (v.1.2.1), which processes files recorded using the STM32 system together with patient demographic data (Figure 8).

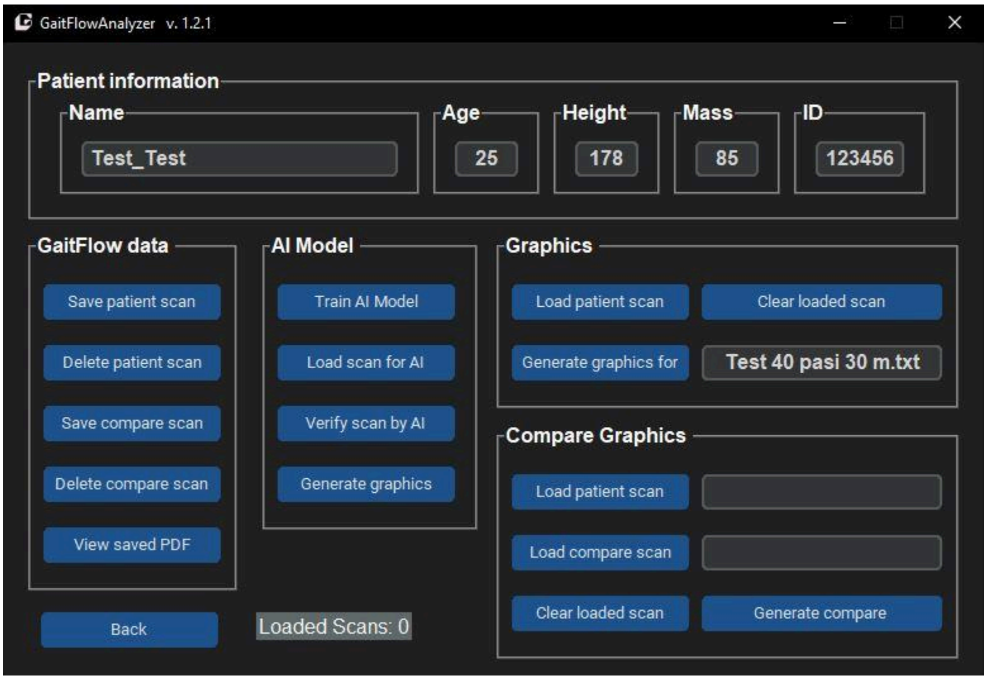

Figure 8. GaitFlowAnalyzer v.1.2.1

The software performs three sequential operations: automated preprocessing (artefact detection and basic descriptive statistics), feature extraction (cycle-level descriptors and temporal or spatial surrogates derived from acceleration signals), and AI-assisted interpretation (adaptive thresholds, asymmetry-related pattern recognition, trend analysis, and predictive flags for progression monitoring).

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The output includes per-axis acceleration plots, descriptive statistics, and flagged signal segments summarised in automatically generated reports for therapist review (Figure 9).

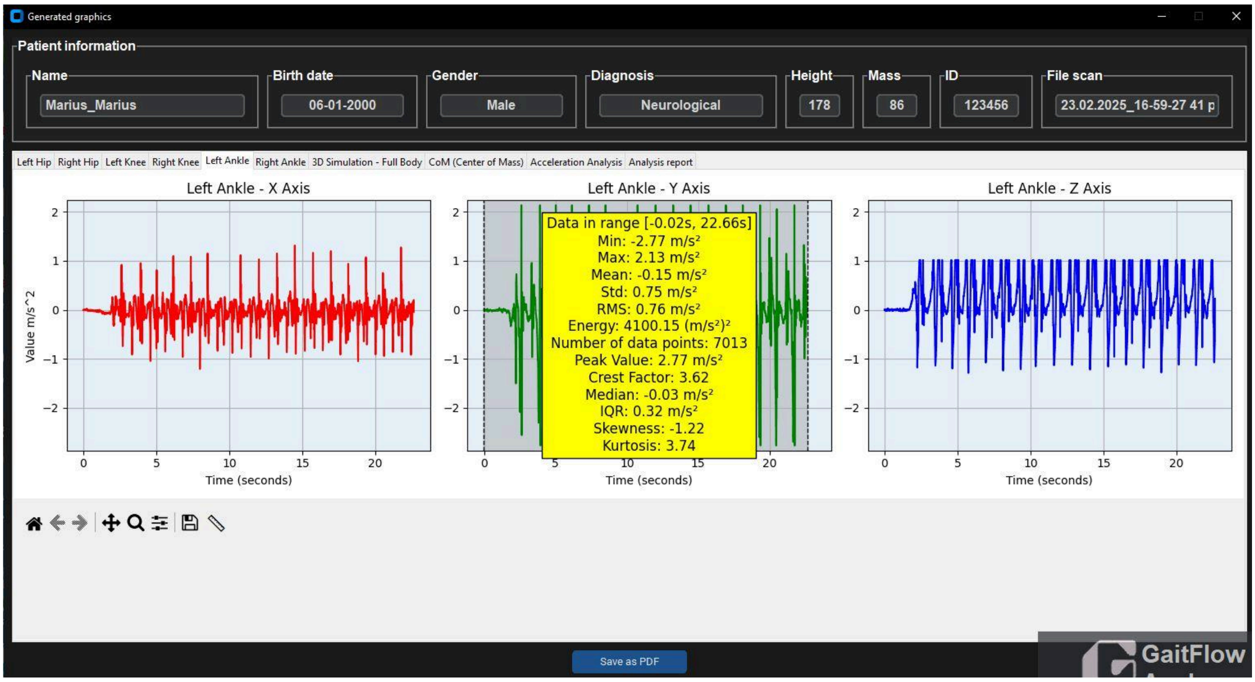

Figure 9. Automatically generated analysis report illustrating acceleration variation for the patient's left ankle along the X (medio-lateral), Y (antero-posterior), and Z (vertical) axes over approximately 25 seconds, including descriptive statistics and flagged data segments for therapist review (AI-assisted offline analysis).

No clinical decision is automated. The AI module functions as an assistive analytical layer intended to support, rather than replace, therapist interpretation.

To clarify the distinct roles of the three components within the proposed framework, Table 1 summarises their functions and level of AI integration.

Table 1. Summary of devices and their AI integration

Device/System	Function in Study	AI Integration
Arduino MKR1000-based device	Real-time biofeedback for gait re-education (visual, rule-based)	No AI (rule-based only)
STM32 multi-sensor wearable	Data collection — 6 accelerometers — for post-hoc analysis	No AI (data acquisition only)
GaitFlowAnalyzer software	Offline analysis and visualisation on PC	Yes (AI-assisted interpretation, adaptive thresholds, predictive trends)

The GaitFlowAnalyzer software (v.1.2.1) was independently developed and registered with the Romanian Office for Copyright (ORDA), certifying the originality of the analytical algorithms used for gait interpretation.

AI Training Module. GaitFlowAnalyzer includes an optional AI training function implemented as an autoencoder neural network, which learns a reference gait baseline from recordings collected from 40 healthy subjects (male and female, aged 15–65 years). Once this reference pattern is established, the programme compares any new gait file against the learned baseline and highlights points that fall outside the expected range of variation. The algorithm evaluates 18-dimensional acceleration patterns against the previously learned distribution. Any deviation from the normal manifold is flagged as a potential anomaly (Figure 10). The graphical representation illustrates a simplified projection of the multichannel anomaly detection process. This is not a per-axis analysis; rather, it evaluates the global multichannel structure of the gait cycle.

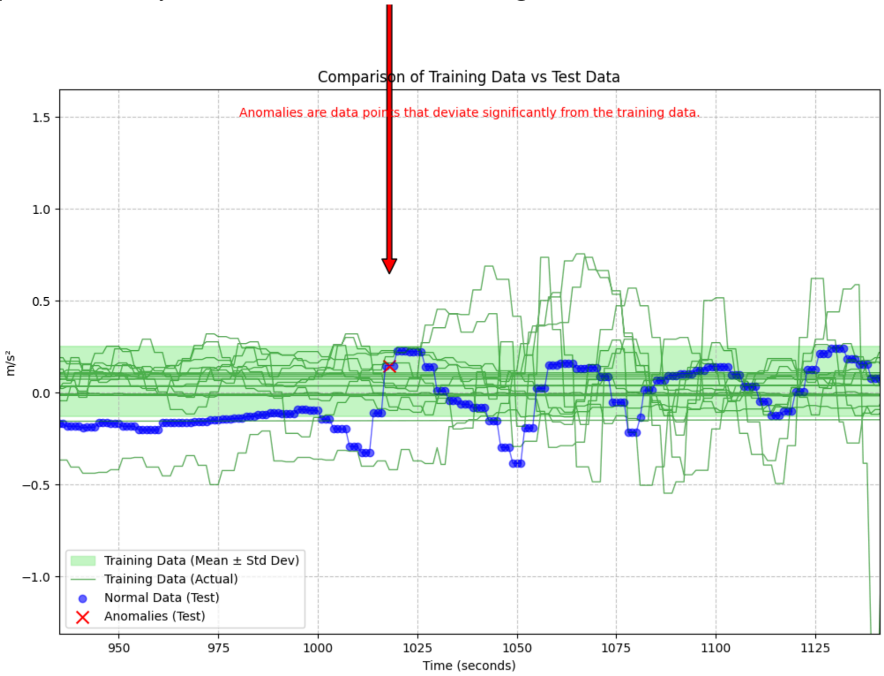

Figure 10. AI-based anomaly detection using the Train AI module after model training. The green band represents the normal reconstruction range learned by an autoencoder model trained on recordings from 40 healthy subjects; red markers indicate signals exceeding the expected reconstruction boundaries, flagged as potential anomalies.

4. Results

4.1. Qualitative Observations from Processed STM32 Multi-Sensor Data

The plots generated by GaitFlowAnalyzer, using data recorded with the STM32 multi-sensor system, offer both a visual and a statistical overview of how ankle accelerations evolve across multiple gait cycles. Figures 11 and 12 show the acceleration signals recorded at the left ankle along the three anatomical axes — X (medio-lateral), Y (antero-posterior), and Z (vertical) — for a representative hemiparetic participant (PT_007) and a matched healthy control (CF_007), selected from their respective groups on the basis of comparable anthropometric characteristics. Both participants were male and aged 43 years, with a height of 178 cm and body weights of 83 kg (PT_007) and 80 kg (CF_007), respectively. For each axis, the software displays the raw time-series together with a set of descriptive indicators: minimum and maximum values, mean, standard deviation, RMS, energy, skewness, and kurtosis.

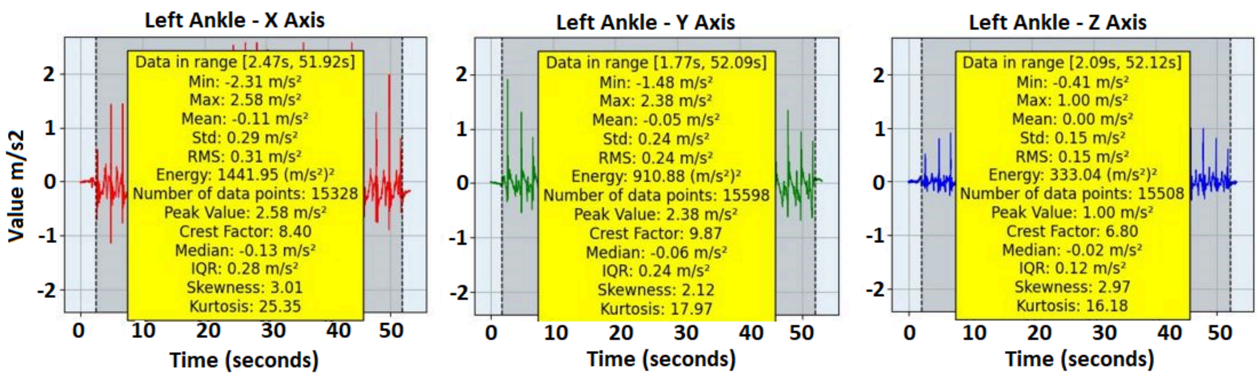

Figure 11. Left ankle acceleration signals (X, Y, Z axes) in a hemiparetic patient (PT_007)

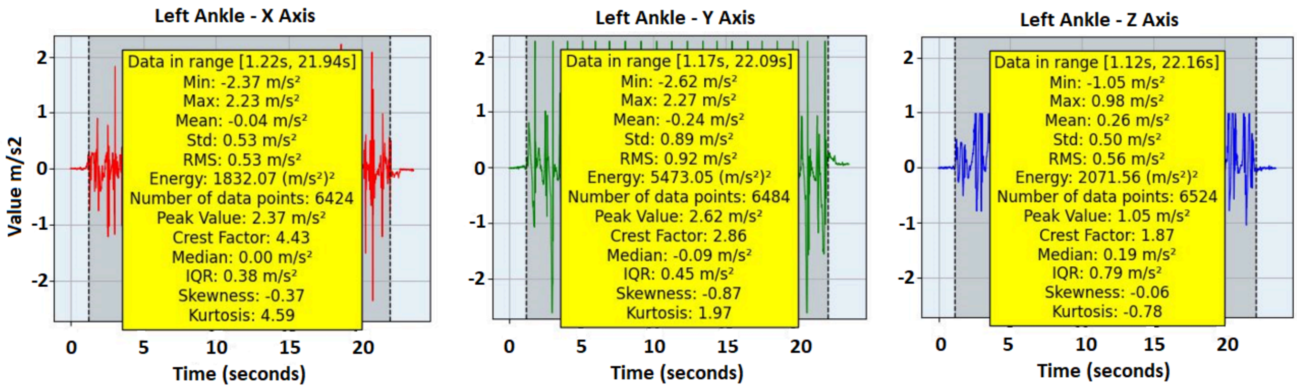

Figure 12. Left ankle acceleration signals (X, Y, Z axes) in a healthy control (CF_007)

RMS values differed across axes between participants, with the hemiparetic participant exhibiting particularly elevated RMS values along the medio-lateral (X) axis, consistent with increased lateral instability and compensatory balance adjustments during gait.

Differences between mean and peak acceleration values reflect isolated high-amplitude events, while distribution-based descriptors such as skewness and kurtosis characterise the overall regularity and symmetry of segmental motion.

In the hemiparetic participant (PT_007), the processed signals exhibit irregular oscillatory patterns and axis-specific variations in amplitude and dispersion. These features indicate reduced stability during the stance phase and less coordinated motion during swing on the affected limb. The X-axis signal in particular shows elevated skewness (3.01) and kurtosis (25.35) relative to the healthy control — isolated high-amplitude events superimposed on an otherwise low-amplitude baseline. This pattern is consistent with compensatory lateral weight shifts during single-limb support.

The healthy control signal (CF_007) demonstrates a markedly different pattern. The signal exhibits more regular oscillatory bursts concentrated within the active walking phase, together with a more balanced distribution of descriptive statistics across all three axes. Skewness and kurtosis values remain closer to zero, reflecting a more symmetric, Gaussian-like distribution of acceleration characteristic of regular and well-coordinated gait cycles. Compared to the healthy control, the hemiparetic participant exhibited disproportionately elevated RMS values along the medio-lateral axis, consistent with increased lateral instability and compensatory gait adjustments. The difference in recording duration — approximately 50 seconds for PT_007 versus 22 seconds for CF_007 — reflects the reduced gait velocity of the hemiparetic participant rather than a methodological inconsistency, as both recordings were collected over the same 30-metre indoor walking path under identical conditions.

Compared to the healthy control, the hemiparetic patient exhibits increased dispersion and irregularity across all three axes, indicating higher gait variability and reduced segmental stability — findings consistent with the presence of compensatory balance strategies during pathological gait (Sekine et al., 2013).

4.2. Quantitative Segmental Acceleration Results

Objective maximum and minimum acceleration values were extracted along the medio-lateral (X), antero-posterior (Y), and vertical (Z) axes, bilaterally, at the knees and ankles, using the complete recording file for each participant. These unfiltered peak values are presented in Table 2 as descriptive indicators of the magnitude of segmental acceleration for the two participants. The signal plots in Figures 11–12 were generated using the interval inspection ("Ruler") function of GaitFlowAnalyzer.

This function allows the selection and analysis of a specific portion of the recorded signal. Accordingly, the descriptive statistics shown in the figures reflect only the selected time window and do not numerically correspond to the overall peak values reported in Table 2. No inferential interpretation is intended.

Table 2. Maximum and minimum segmental accelerations (m/s²) recorded at knee and ankle level in a hemiparetic patient (PT_007) and a healthy control (CF_007). X = medio-lateral, Y = antero-posterior, Z = vertical. Values represent unfiltered peak accelerations; presented as descriptive indicators, not inferential statistics.

Segment	**Axis**	**Max (patient)**	**Min (patient)**	**Max (control)**	**Min (control)**
Left knee	X	1.14	−1.58	0.91	−1.11
Left knee	Y	1.06	−1.37	2.48	−2.30
Left knee	Z	1.36	−1.15	1.28	−0.87
Right knee	X	1.77	−1.32	0.89	−1.29
Right knee	Y	1.77	−1.10	2.38	−2.49
Right knee	Z	1.15	−1.06	1.12	−1.04
Left ankle	X	2.30	−2.59	1.16	−1.71
Left ankle	Y	2.36	−1.51	2.08	−2.81
Left ankle	Z	0.99	−0.41	1.02	−1.44
Right ankle	X	0.85	−1.75	1.69	−1.52
Right ankle	Y	2.38	−2.51	2.22	−2.68
Right ankle	Z	1.24	−1.20	1.26	−1.50

4.3. Summary and Interpretation of Quantitative Findings

The quantitative data presented in Table 2 demonstrate consistent segmental differences between the hemiparetic participant and the healthy control. At the knee, the hemiparetic patient presents antero-posterior acceleration at the left affected knee below half the control value on the Y axis — 1.06 versus 2.48 m/s².

This finding is consistent with reduced propulsive force generation during terminal stance. At the ankle, the affected limb shows elevated medio-lateral acceleration: 2.30 m/s² maximum on the X axis versus 1.16 m/s² for the control. This pattern is consistent with compensatory lateral weight-transfer strategies adopted to maintain dynamic stability in the presence of impaired muscular control.

Trunk accelerometry studies have reported that medio-lateral components are particularly sensitive to balance control impairment, while antero-posterior and vertical components are more closely related to forward progression and energy exchange during walking (Sekine et al., 2013). This distinction is directly reflected in the pattern of differences observed in Table 2.

The healthy control exhibited regular and nearly symmetric maximum acceleration values across all segments and axes, reflecting the coordinated structure of physiological gait cycles.

These quantitative descriptors constitute a preliminary objective confirmation of gait asymmetry in the hemiparetic participant and provide an interpretable basis for guiding rehabilitation sessions. These findings should not be interpreted as inferential results generalisable beyond the individual case presented.

4.4. Group-level Context: Multiscale Gait Dynamics in a Neurological Cohort

The single-case comparison in Sections 4.1–4.3 provides a detailed descriptive picture of segmental acceleration asymmetry in one hemiparetic participant. To place these findings within a broader empirical context, reference is made here to a parallel investigation conducted with the same STM32 wearable system on a larger cohort: 15 neurological participants presenting gait disorders — including post-stroke hemiparesis, Parkinson's disease, and other central nervous system conditions — and 15 healthy controls, evaluated under identical testing conditions on a 30-metre indoor walking path (Ethics Committee approval No. 1/14.02.2025, "Sf. Gheorghe" Rehabilitation Hospital, Botoșani, Romania).

In that study, fractal and multifractal analysis of anteroposterior acceleration signals — using Detrended Fluctuation Analysis (DFA), Multifractal DFA (MFDFA), and Multifractal Detrended Cross-Correlation Analysis (MFDCCA) — revealed systematic differences in signal organisation between groups that were not fully captured by classical linear descriptors. The neurological group exhibited a proximal-to-distal gradient of gait control deficit. Scaling exponents overlapped substantially at the hip level, showed moderate group separation at the knee, and became most clearly differentiated at the ankle — the same segment highlighted in the present case comparison. Effect size analysis confirmed negligible differences at the hip (Cliff's $\Delta = -0.08$), moderate differences at the knee ($\Delta = -0.34$), and large differences at the ankle ($\Delta = -0.50$).

At the level of concrete statistical outcomes, ankle-level differences were significant: the Hurst exponent was markedly lower in the neurological group relative to controls (median 1.06 vs. 1.16, $p = 0.009$, Cliff's $\Delta = -0.56$), and local DFA variability (σH) was substantially elevated (median 0.05 vs. 0.02, $p = 0.003$, Cliff's $\Delta = 0.65$), indicating greater instability of temporal gait organisation at the distal segment. At the knee, inter-limb cross-correlation (ρ_DCCA) was considerably reduced in the neurological group (median 0.10 vs. 0.26, $p = 0.008$, Cliff's $\Delta = -0.57$), reflecting impaired bilateral coordination during the propulsive phase of gait. Multifractal spectrum width ($\Delta\alpha$) at the ankle was markedly higher in the neurological group (median 0.49 vs. 0.11, $p = 0.038$, Cliff's $\Delta = 0.45$), consistent with increased heterogeneity of local scaling behaviour rather than a uniform reduction in movement amplitude (Dobinda-Albu, 2025).

These cohort-level findings are consistent with the individual differences described in Sections 4.1–4.3. They support the interpretation that the acceleration asymmetries identified through GaitFlowAnalyzer reflect genuine structural characteristics of pathological gait rather than isolated measurement artefacts. Taken together, they strengthen the clinical rationale for the dual-system framework presented in this work: real-time visual biofeedback addresses the immediate guidance need during sessions, while offline multi-sensor analysis — whether through descriptive acceleration statistics or through advanced multiscale methods — provides the therapist with an increasingly detailed picture of gait organisation and its departure from physiological patterns.

4.5. Real-time Biofeedback: Observational Findings

During the six-month observational period, the Arduino-based device was used with 12 patients with hemiparesis or hemiplegia. Informal therapist observations indicated that patients responded to visual cues more consistently than to verbal instructions alone — particularly in cases where attention or language barriers complicated comprehension. Patients generally oriented their gaze towards the real-time display without requiring repeated prompting. Therapists reported that the visual representation of plantar loading simplified the correction of asymmetric weight transfer during stance.

These observations are reported as qualitative clinical impressions. They do not constitute validated efficacy data. They are consistent, however, with motor learning frameworks that identify immediate sensory feedback as a facilitator of error-driven correction (Belda-Lois et al., 2011), and with feasibility findings reported in balance training studies involving patients with cognitive or communicative limitations (Trampisch et al., 2023). A structured usability evaluation from the perspectives of both patients and therapists remains a priority for future work.

5. Discussion

5.1. Architectural Separation Between Real-Time Feedback and Offline AI Analysis

A central design decision in the proposed framework is the explicit separation between the real-time guidance layer and the AI-based analytical layer. The Arduino-based device delivers immediate language-independent visual cues during therapy sessions and performs no onboard AI inference. The STM32 wearable system collects high-fidelity multi-segment gait data without providing real-time feedback. After the session, GaitFlowAnalyzer performs AI-assisted interpretation offline. This separation is not a technical limitation, but a conscious clinical design decision.

Separating real-time visual biofeedback from subsequent AI-assisted analysis makes therapy sessions safer and easier to adjust. The patient can respond to simple visual signals during movement, without the need for language-mediated explanation. This is consistent with the principles of error-driven motor learning (Belda-Lois et al., 2011). The therapist then reviews the recorded data and obtains an objective representation of movement changes across rehabilitation sessions. Thus, one layer is active during the rehabilitation session, while the second layer supports longitudinal interpretation of accumulated gait data over time.

This two-layered approach is in line with evidence suggesting that combining complementary strategies may be more effective than relying on a single modality alone (Belda-Lois et al., 2011). It is also consistent with recent reviews highlighting the potential of wearable sensors and offline AI-assisted analysis as tools for bridging research and clinical practice in post-stroke gait rehabilitation (Mohan et al., 2021). Perturbation-based treadmill training has also been shown to be feasible in groups with limited communicative capacity (Trampisch et al., 2023). Therefore, the present approach can be placed within a broader body of evidence supporting simplified, non-verbal feedback in motor rehabilitation.

5.2. Interpretation of Quantitative Findings in the Neurophysiological Context

The data presented in Table 2 provide descriptive evidence, at the level of a single case, of the gait asymmetry characteristic of hemiparetic walking. Reduced antero-posterior acceleration was observed at the affected left knee, with Y-axis values measuring less than half the corresponding control value. Elevated medio-lateral acceleration was also identified at the left ankle. These quantitative findings are consistent with compensatory motor strategies adopted to maintain gait stability. Such compensatory mechanisms likely contribute to maintenance of dynamic stability despite impaired muscular control on the affected side.

From a neurophysiological perspective, these patterns reflect the partial disruption of the corticospinal tract and its consequences for motor unit recruitment, proprioceptive feedback loops, and the coordination of peripheral motor nerves — femoral, peroneal, tibial — that govern lower limb dynamics during gait (Belda-Lois et al., 2011). Medio-lateral components are particularly sensitive to balance control impairment. Antero-posterior and vertical components are more closely related to forward progression and energy exchange (Sekine et al., 2013). This distinction is directly reflected in Table 2**.** Motor performance and proprioceptive accuracy are also sensitive to movement direction and testing conditions, which underscores the importance of well-defined acquisition contexts when interpreting sensor-derived gait measures. This sensitivity extends to the joint level: body orientation and direction of movement have been shown to significantly influence proprioceptive performance even in healthy subjects, thereby highlighting the broader importance of standardised testing conditions in movement assessment (Wieber et al., 2023).

The individual pattern observed here is consistent with cohort-level evidence from a parallel investigation using the same STM32 system (Dobinda-Albu, 2025). In that study, the neurological group exhibited a proximal-to-distal gradient of gait control deficit, with the largest group separation occurring at the ankle along the anteroposterior axis — precisely the segment and direction most clearly affected in the present case. Reduced long-range temporal persistence (lower

Hurst exponent: median 1.06 vs. 1.16, $p = 0.009$, Cliff's $\Delta = -0.56$) and markedly elevated local scaling variability (σH: median 0.05 vs. 0.02, $p = 0.003$, Cliff's $\Delta = 0.65$) at the ankle indicate that the asymmetry observed through peak acceleration values reflects a deeper reorganisation of gait dynamics — not an isolated deviation of a single parameter. Impaired inter-limb coordination at the knee (ρ_DCCA: median 0.10 vs. 0.26, $p = 0.008$, Cliff's $\Delta = -0.57$) further corroborates the bilateral control deficit suggested by the asymmetric acceleration profiles in Table 2. Taken together, the single-case descriptive findings and the cohort-level multiscale results point to the same underlying mechanism: a loss of coordinated, temporally organised motor output on the affected side, expressed both in the amplitude and in the structural organisation of segmental acceleration signals.

Biofeedback-assisted correction may support functional compensation within these pathways by providing immediate sensory input capable of reinforcing impaired cortical control mechanisms (Belda-Lois et al., 2011). This is operationally consistent with the Schramm model of bidirectional, adaptive communication discussed in the Introduction. The patient receives sensory feedback, responds through movement adaptation, and is subsequently monitored by the therapist, thereby maintaining a continuous therapeutic interaction that operates independently of verbal language.

5.3. Positioning Relative to Existing Systems

Systems such as the Walkbot and the ReWalk have demonstrated clinical value in improving walking speed, balance, and endurance, particularly in chronic stroke populations, but their adoption remains limited by device weight, cost, and poor adaptability to real environments (Cha et al., 2025). More relevant to the present discussion, none of these systems were specifically designed to address the communicative dimension of therapy, namely, how patients with limited language proficiency or reduced attentional capacity interpret device-mediated feedback or therapeutic expectations.

Other technology-mediated rehabilitation approaches — the Meditouch Balance Tutor, R-Gait, and Gloreha — employ visual, auditory, and haptic feedback to support patient engagement and reduce dependence on verbal instruction. The present framework shares this orientation. What it adds is an AI-assisted offline analysis layer directly coupled to the real-time feedback device — immediate guidance and longitudinal monitoring within a single clinical workflow. AI functions here not only as a technical component but as a support tool for communication between patients and therapists (Vanoglio et al., 2024).

The cultural and linguistic dimension of the framework was not empirically measured in the current study. The design principle of language-independent visual cues reduces reliance on linguistic decoding. Whether this translates into measurable clinical benefit for patients with diverse linguistic or cultural backgrounds remains an open question — and a primary direction for future investigation.

5.4. Ethical Considerations Regarding AI in Rehabilitation

The AI module of GaitFlowAnalyzer operates exclusively as a decision-support tool. It flags deviations from a learned normal gait baseline. These deviations are presented to the therapist in graphical and statistical form. The system does not autonomously generate therapeutic recommendations. No autonomous intervention is performed in real time. All clinical decisions remain with the therapist.

This is consistent with the current consensus in medical AI ethics: human oversight, transparency of algorithmic outputs, and no automation of decisions that carry clinical responsibility (Topol, 2019). The anomaly detection module is trained on recordings from approximately 40 healthy subjects. This dataset is sufficient for preliminary pattern-learning purposes. However, it is not sufficient for a validated clinical classification. Accordingly, the generated outputs should be interpreted as indicative rather than diagnostic.

Patient data are processed offline and not transmitted to external servers, which limits privacy exposure relative to cloud-based systems. Informed consent was obtained from all participants in accordance with the ethical standards of the Alexandru Ioan Cuza University of Iași and with the 1964 Helsinki Declaration and its later amendments. As AI becomes more deeply integrated into rehabilitation workflows, structured ethical evaluation frameworks — transparency, accountability, data governance, and patient autonomy — will be increasingly necessary (Topol, 2019).

5.5. Limitations

The real-time device relies on FSR sensors without gyroscopes or high-resolution force sensors. Consequently, measurement precision remains limited. Accordingly, the biomechanical scope of the captured data remains limited. The AI analyses performed by GaitFlowAnalyzer have not been validated in a prospective clinical trial. The normal gait baseline was learned from approximately 40 healthy subjects — a sample that does not represent the full diversity of age, body morphology, and walking conditions encountered in clinical practice.

The patient sample used during the observational period was small — n = 12 — and was not designed for hypothesis testing. No control group was included. No validated gait outcome measures were collected alongside the sensor recordings. The qualitative observations regarding patient response to visual cues reflect informal therapist impressions. They should not be interpreted as evidence of efficacy.

The cultural and linguistic dimension of the framework — central to its design rationale — was not empirically measured in the current study. Future work will include structured clinical validation on larger and more diverse populations. The question of whether language-independent feedback measurably reduces communication-related barriers in rehabilitation remains open. Indeed, this represents one of the central research questions generated by the present framework.

6. Conclusions

This study presented the development and preliminary evaluation of two complementary wearable systems for gait re-education, tested in real rehabilitation settings, together with the offline AI-assisted analytical software that processes their output.

The results obtained from the STM32 multi-sensor wearable and GaitFlowAnalyzer provide objective descriptive evidence of gait asymmetry at the ankle and knee level in a hemiparetic participant compared with a healthy control, as demonstrated through the representative signal plots and quantitative descriptors presented in Figures 11–12 and Table 2. The findings included irregular oscillatory patterns, increased signal variability on the affected side, reduced antero-posterior acceleration components at the affected knee — measuring less than half the corresponding control value along the Y axis — and elevated medio-lateral components at the affected ankle. These findings are consistent with compensatory balance strategies observed during pathological gait. Collectively, these quantitative findings reflect adaptive motor compensation associated with impaired central motor control.

The Arduino-based device was used exclusively for real-time visual feedback during training sessions, allowing patients to adjust limb loading and movement execution without relying on verbal explanation. The separation between real-time guidance — rule-based, language-independent — and offline quantitative assessment enabled both intuitive patient feedback during sessions and objective post-session evaluation by the therapist. This architectural separation is the primary practical contribution of the present framework. It maintains clinical transparency, avoids overstating the role of AI, and preserves the therapist's decision-making authority throughout the rehabilitation process.

The findings reported in the present study are descriptive in nature. The study sample remains limited. What they demonstrate is feasibility — that combining rule-based visual biofeedback with offline AI-assisted analysis can characterise gait deviations in neurological rehabilitation and support therapists in identifying asymmetries and monitoring changes over time. This may be particularly relevant in patients presenting linguistic, attentional, or cultural limitations that reduce the effectiveness of verbal instruction.

Future work will focus on three directions. These include extending quantitative validation to larger and more diverse cohorts. Further objectives include refinement of sensor accuracy through integration of gyroscopes and higher-resolution force sensors. And developing a structured evaluation of the relationship between feedback modality and communication barrier type — including a usability study from the perspectives of both patients and therapists — to provide empirical grounding for the language-independent design rationale that motivates the present framework.

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All procedures performed in this study were conducted in accordance with the ethical standards of the Alexandru Ioan Cuza University of Iași and with the 1964 Helsinki Declaration and its later amendments. Formal ethics committee approval was not considered necessary for the present exploratory, non-interventional study in accordance with institutional requirements.

The parallel cohort investigation referenced in Section 4.4 was conducted under separate ethics committee approval (No. 1/14.02.2025, "Sf. Gheorghe" Rehabilitation Hospital, Botoșani, Romania).

AI use statement: Artificial intelligence tools were used to assist in the editing and linguistic revision of this manuscript. The analytical software GaitFlowAnalyzer, described in Section 3.3, was independently developed by the author. Its core processing architecture is based on descriptive signal analysis and rule-based processing; the optional anomaly-detection module incorporates an autoencoder-based pattern recognition model trained on accelerometric data collected from healthy subjects by the author.

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