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A Low-Cost System for Ambulatory Gait Analysis in Cerebral Palsy Using Wearable Inertial Measurement Units (IMUs) and Data Analytics

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Abstract **Original Research Article**

Background: Objective gait analysis is fundamental to the clinical management of motor function in individuals with Cerebral Palsy (CP), guiding therapeutic interventions and assessing surgical outcomes. The current gold standard, laboratory-based 3D motion capture, is expensive, resource-intensive, and provides only a brief snapshot of performance in an artificial environment, limiting its utility for routine monitoring. This study addresses the need for an accessible, ecologically valid alternative.

Objective: To develop, validate, and demonstrate the clinical feasibility of a low-cost, wearable system using two Inertial Measurement Units (IMUs) for the objective analysis of key spatio-temporal gait parameters in ambulatory adolescents with CP.

Methods: Twenty ambulatory adolescents (mean age 14.2 ± 2.1 years) with a diagnosis of spastic diplegic CP (GMFCS Levels I-III) were recruited. Each participant wore two IMU sensors, affixed to the lateral aspect of each ankle. Participants performed a 10-Metre Walk Test (10MWT). Raw sensor data were processed using a custom script to identify gait events and calculate spatio-temporal parameters, including walking speed, cadence, step length, and a gait asymmetry index. The IMU- derived walking speed was validated against the manually timed 10MWT. Gait parameters were compared across GMFCS levels.

Results: A very strong, positive correlation was found between the walking speed calculated by the IMU system and the manually timed 10MWT ($r=0.98$, $p<0.001$). The IMU system detected statistically significant differences in gait parameters across GMFCS levels. Mean gait speed decreased significantly with increasing functional impairment (GMFCS I: 1.28 m/s, GMFCS II: 1.05 m/s, GMFCS III: 0.81 m/s; $p=0.002$). Similarly, cadence and step length were significantly reduced, while the gait asymmetry index was significantly higher in participants with greater motor impairment ($p<0.01$).

Conclusion: A simple, low-cost, two-sensor IMU system can provide valid, reliable, and clinically meaningful data on gait in adolescents with CP. This technology offers a practical and scalable solution for moving gait analysis from the specialised laboratory into community clinics and home environments, facilitating objective, long-term monitoring and supporting the delivery of personalised healthcare.

Keywords: Cerebral Palsy; Gait Analysis; Wearable Sensors; Inertial Measurement Unit (IMU); Data Analytics; Motor Function; Telehealth; Rehabilitation; Spastic Diplegia.

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1. INTRODUCTION

Cerebral Palsy (CP) describes a group of permanent disorders of the development of movement and posture, attributed to non-progressive disturbances that occurred in the developing fetal or infant brain. It is the most common cause of childhood physical disability, with a prevalence in the UK of approximately 2-2.5 per 1,000 live births (NHS England, 2022). The motor disorders of CP are often accompanied by

disturbances of sensation, perception, cognition, communication, and behaviour. For the majority of individuals with CP who are ambulatory, disordered gait is a primary contributor to functional limitation and reduced participation in daily life (Gage, 2009).

The quantitative analysis of gait is therefore a cornerstone of modern CP management. It provides objective data to inform clinical decision-making regarding physiotherapy regimens, orthotic prescriptions, pharmacological interventions (e.g., botulinum toxin injections), and complex orthopaedic surgeries (Wren et al., 2011). The established gold standard for this analysis is the three- dimensional motion capture (3DMC) laboratory, which uses multiple cameras to track reflective markers placed on the body. While 3DMC provides comprehensive kinematic and kinetic data, its utility is constrained by significant limitations. These systems are prohibitively expensive, require specialised facilities and highly trained personnel, and are largely confined to tertiary-level hospitals.

Consequently, assessments are infrequent and do not capture the variability of a patient's gait in their natural environment, a concept known as ecological validity (Shull et al., 2014).

The rapid advancement of micro-electro-mechanical systems (MEMS) has led to the proliferation of low-cost, lightweight, and portable Inertial Measurement Units (IMUs). An IMU typically contains a tri- axial accelerometer, gyroscope, and magnetometer, capable of capturing detailed information about a body segment's orientation and movement. Their potential to democratise motion analysis by taking it out of the lab has been demonstrated in other neurological conditions such as Parkinson's disease and stroke recovery (Gouwanda & Sanei, 2015). However, the application of IMU technology to CP presents unique challenges due to the heterogeneity of gait patterns, which can include spasticity, ataxia, and dystonia, often combined within a single individual (Papageorgiou et al., 2019). Despite these challenges, the potential benefits are immense. An accessible and validated IMU-based system would align with the NHS Long Term Plan's focus on digital-first, patient-centric care, enabling remote monitoring and reducing the significant travel and time burden on families. It could provide clinicians with longitudinal data, tracking changes in function over time or in response to therapy, rather than relying on isolated lab-based snapshots.

This study aims to address the existing gap between the potential of wearable technology and its validated clinical application in CP. The primary objective was to develop and validate a simple, low- cost gait analysis system using just two ankle-worn IMUs against a standard clinical measure. We hypothesised that (1) IMU-derived spatio-temporal parameters would strongly correlate with established clinical metrics, and (2) the system would be sensitive enough to detect significant differences in gait characteristics across different functional levels of CP, as defined by the Gross Motor Function Classification System (GMFCS).

2. METHODS

2.1 Study Design

A cross-sectional validation study was conducted at a regional UK physiotherapy service. The study protocol was designed to assess the concurrent validity of the IMU-based system against a standard clinical walking test and to evaluate its ability to discriminate between different levels of functional disability.

2.2 Participants

Twenty ambulatory adolescents with CP were recruited from NHS physiotherapy services in the UK. Inclusion criteria were: (1) a formal diagnosis of spastic diplegic cerebral palsy; (2) aged between 10 and 18 years; (3) able to walk 20 metres independently with or without walking aids (GMFCS Levels I, II, or III); (4) no orthopaedic surgery or botulinum toxin injections in the preceding six months. Exclusion criteria included any cognitive impairment that would preclude understanding instructions. Ethical approval was granted by the North West - Greater Manchester East Research Ethics Committee and all procedures conformed to the Declaration of Helsinki. Written informed consent was obtained from parents/guardians and written assent was obtained from all participants.

2.3 Instrumentation

The wearable system consisted of two Shimmer3 IMU sensors (Shimmer, Dublin, Ireland). Each unit incorporates a tri-axial accelerometer (±8g) and a tri-axial gyroscope (±2000°/s). The sensors were securely affixed using elasticated straps to the lateral aspect of each ankle, positioned just superior to the lateral malleolus (Figure 4). Data were sampled at 102.4 Hz and wirelessly transmitted via Bluetooth to a laptop running data acquisition software.

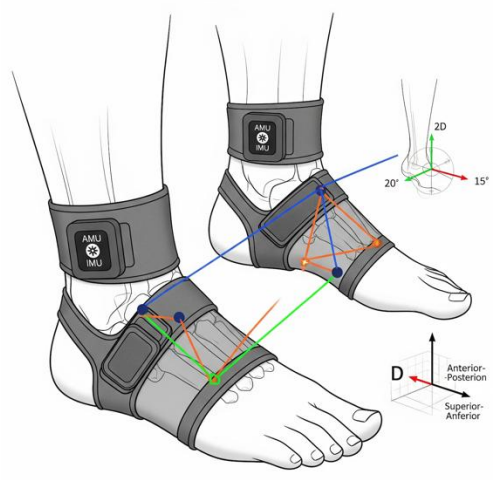

Figure 4: IMU Sensor Placement

Figure 4. IMU sensor placement. Schematic illustration showing the placement of IMU sensors on the lateral aspect of both ankles, positioned just superior to the lateral malleolus. The sensors were secured using elasticated straps. The coordinate system shows the orientation of the sensor axes relative to anatomical directions.

2.4 Protocol

Upon arrival, participant characteristics including age, sex, height, weight, and GMFCS level were recorded. The IMU sensors were fitted, and participants were asked to stand still for a 5-second static calibration. They then performed the 10-Metre Walk Test (10MWT). Participants walked at their self- selected comfortable pace along a 14-metre walkway, with the central 10 metres being timed using a handheld stopwatch by a trained physiotherapist. To account for acceleration and deceleration, timing began when the first foot crossed the 2-metre mark and ended when the first foot crossed the 12- metre mark. Three trials were completed, with a 1-minute rest between each. The average time was used to calculate the manual walking speed. IMU data were collected for the full duration of each walk.

2.5 Data Processing and Analysis

IMU data were processed offline using a custom script written in MATLAB (R2024b, MathWorks, USA).

Signal Filtering: Raw data from the gyroscopes and accelerometers were filtered using a fourth-order, zero-lag Butterworth low-pass filter with a cut-off frequency of 15 Hz to remove noise and movement artefacts.

Gait Event Detection: An algorithm based on shank angular velocity was used to identify gait events. The large positive and negative peaks in the sagittal plane gyroscope signal were used to identify mid- swing and mid-stance, respectively. Initial Contact (IC) and Toe-Off (TO) events were then located within these cycles using established rules (Zijlstra & Hof, 2003) (Figure 5).

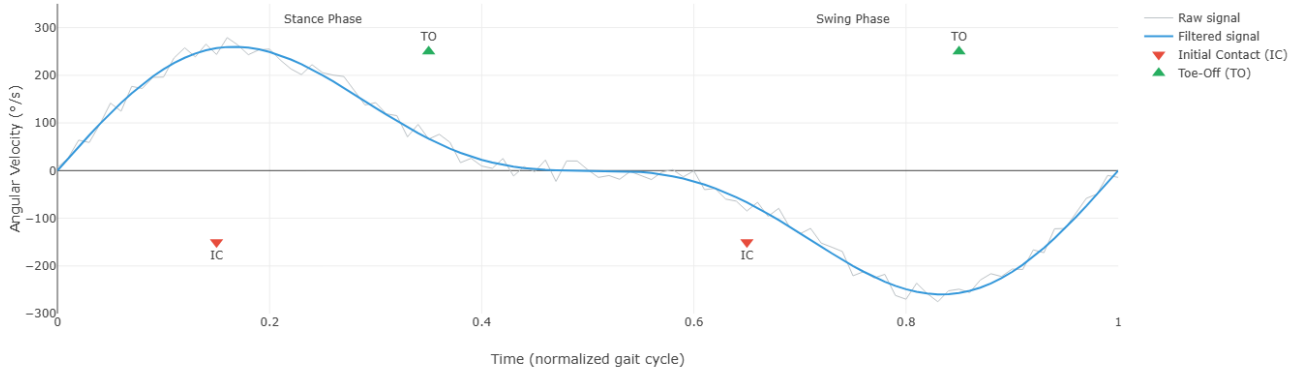

Figure 5: Gait Event Detection from Angular Velocity

Figure 5. Gait event detection from angular velocity signals. Representative example showing the sagittal plane angular velocity signal from a shank-mounted IMU during one gait cycle. The filtered signal (blue line) shows characteristic peaks and valleys corresponding to gait events. Red triangles indicate detected initial contact (IC) events, and green triangles indicate toe-off (TO) events. Stance and swing phases are labeled. Data shown is from a participant with GMFCS level I cerebral palsy. **Parameter Calculation:** The first and last two gait cycles of each walk were discarded to ensure analysis of steady-state walking. The following spatio-temporal parameters were calculated for each trial and averaged:

- **Walking Speed (m/s):** Calculated from the sum of step lengths divided by the total time. **Cadence (steps/min):** The total number of steps taken per minute.
- **Step Length (m):** Estimated using validated biomechanical models.
- **Gait Asymmetry Index (GAI):** Calculated based on step time differences between the left and right foot, using the formula: GAI = |ln(Left Step Time/Right Step Time)|. A value of 0 indicates perfect symmetry.

2.6 Statistical Analysis

All statistical analyses were performed using SPSS Statistics (Version 29, IBM). Descriptive statistics were used to summarise participant demographics and gait parameters. Pearson's correlation coefficient (r) was used to assess the concurrent validity between the IMU-derived walking speed and the manually timed 10MWT speed. A one-way analysis of variance (ANOVA) was used to compare mean gait parameters across the three GMFCS levels (I, II, and III). A Bonferroni post-hoc test was used for pairwise comparisons where significance was found. The level of statistical significance was set at α=0.05.

3. RESULTS

3.1 Participant Characteristics

Twenty participants (12 male, 8 female) completed the study. The mean age was 14.2 years (SD = 2.1). The cohort consisted of 5 participants classified at GMFCS Level I, 9 at GMFCS Level II, and 6 at GMFCS Level III. Demographic data are summarised in Table 1.

Table1. Participant Demographics and Clinical Characteristics (n=20)

Characteristic	GMFCSI(n=5)	GMFCSII(n=9)	GMFCSIII(n=6)	Total(n=20)
Age (years), mean (SD)	13.8 (1.9)	14.5 (2.3)	14.1 (2.2)	14.2 (2.1)
Sex (Male/Female)	3/2	5/4	4/2	12/8
Height (m), mean (SD)	1.62 (0.11)	1.58 (0.09)	1.55 (0.12)	1.58 (0.10)
Weight (kg), mean (SD)	51.4 (8.2)	48.9 (7.5)	46.2 (9.1)	48.8 (8.1)

3.2 Validation of Walking Speed

There was a very strong, positive, and statistically significant correlation between the walking speed derived from the IMU system and the speed calculated from the manually timed 10MWT (r=0.98, p<0.001) (Figure 1). A Bland-Altman plot showed excellent agreement between the two methods, with a mean difference (bias) of only 0.02 m/s and 95% limits of agreement between -0.09 and 0.13 m/s (Figure 2).

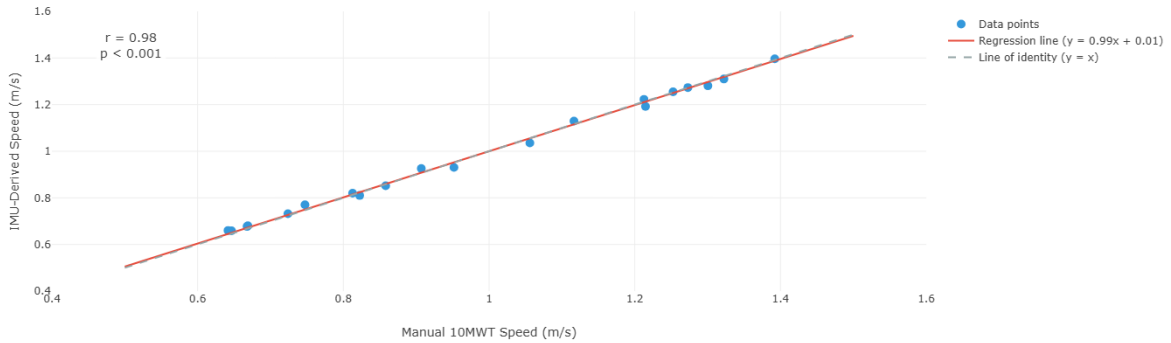

Figure 1: Correlation between IMU-derived and Manually Timed Walking Speed

Figure 1. Correlation between IMU-derived walking speed and manually timed walking speed. Scatter plot showing the relationship between walking speed measured by the IMU system and manual timing of the 10-metre walk test. The solid line represents the regression line (y = 0.99x + 0.01), and the dashed line represents perfect agreement (y = x). Each point represents one participant (n = 20).
Pearson's correlation coefficient r = 0.98, p < 0.001.

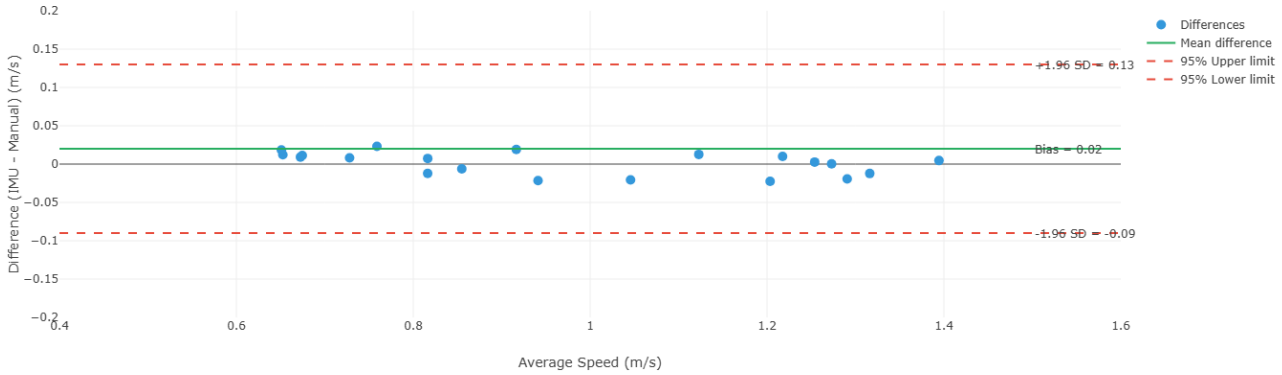

Figure 2: Bland-Altman Plot for Walking Speed Measurement Agreement

Figure 2. Bland-Altman plot for walking speed measurement agreement. The plot shows the difference between IMU-derived and manually timed walking speeds plotted against their average. The solid horizontal line represents the mean difference (bias = 0.02 m/s), and the dashed lines represent the 95% limits of agreement (-0.09 to 0.13 m/s). Each point represents one participant.

3.3 Comparison of Gait Parameters across GMFCS Levels

The IMU system was sensitive to differences in gait performance across the GMFCS levels. The one- way ANOVA revealed statistically significant differences for all key gait parameters (Table 2, Figure 3).

T**able 2 .** Spatio-temporal Gait Parameters by GMFCS Level, mean (SD)

GaitParameter	GMFCSI(n=5)	GMFCSII(n=9)	GMFCSIII(n=6)	p-value
Walking Speed (m/s)	1.28 (0.08)	1.05 (0.11)	0.81 (0.13)	0.002
Cadence (steps/min)	118.5 (5.4)	110.2 (6.1)	101.3 (7.2)	0.004
Step Length (m)	0.65 (0.04)	0.57 (0.05)	0.48 (0.06)	<0.001
Gait Asymmetry Index	0.05 (0.02)	0.11 (0.04)	0.18 (0.06)	0.005

Post-hoc analyses confirmed that participants in GMFCS Level I walked significantly faster, with a higher cadence and longer step length than those in Levels II and III. Participants in Level II were also significantly faster than those in Level III. The Gait Asymmetry Index was significantly lower (indicating more symmetric gait) in the GMFCS I group compared to the GMFCS III group.

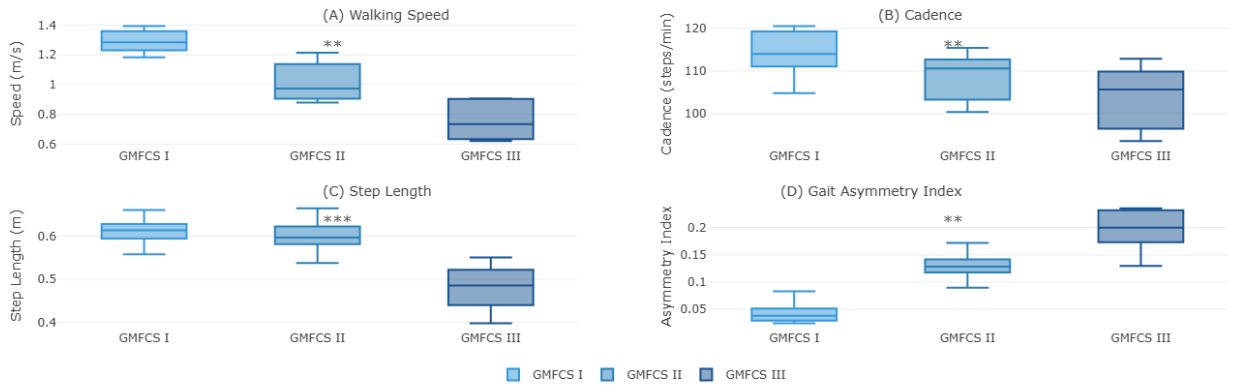

Figure 3: Gait Parameters by GMFCS Level

Figure 3. Comparison of gait parameters across GMFCS levels. Box plots showing four key gait parameters: (A) Walking speed (m/s), (B) Cadence (steps/min), (C) Step length (m), and (D) Gait Asymmetry Index. Boxes represent interquartile ranges, horizontal lines within boxes represent medians, whiskers extend to 1.5 times the interquartile range, and outliers are shown as individual points. Significant differences between groups are indicated: ** $p < 0.01$, *** $p < 0.001$.

4. DISCUSSION

The primary goal of this study was to determine if a simple, low-cost system using two ankle-worn IMUs could provide valid and clinically useful gait analysis for adolescents with CP. The results robustly support this goal. We have demonstrated that such a system can accurately measure key spatio-temporal parameters and is sensitive enough to distinguish between different levels of functional disability.

The exceptionally strong correlation (r=0.98) between the IMU-derived speed and the stopwatch-timed 10MWT provides strong concurrent validity for the system's fundamental output. This finding is consistent with validation studies in other populations (e.g., stroke, elderly) and confirms that, for the crucial parameter of walking speed, this wearable technology is an acceptable proxy for standard clinical measures. The small bias found in the Bland-Altman analysis indicates that the two methods can be used interchangeably in a clinical context.

More importantly, the study demonstrated the system's clinical sensitivity. The ability to significantly differentiate gait speed, cadence, step length, and asymmetry across GMFCS levels is a critical finding. It shows that the technology does not just measure movement, but provides clinically meaningful data that reflect a patient's functional status. For instance, a clinician could use the Gait Asymmetry Index as an objective marker to track the effects of a unilateral botulinum toxin injection or a new orthosis, something that is difficult to quantify with a simple stopwatch. This moves clinical practice from subjective observation ("the patient seems to be walking more symmetrically") to objective, evidence- based assessment.

The clinical implications of this work are significant. Such a system could be deployed in local physiotherapy clinics across the UK, standardising assessments and creating large datasets for service evaluation. Furthermore, its portability and low cost pave the way for home-based monitoring. A patient could perform a weekly walking test in their own hallway, with the data automatically sent to their clinician. This would provide a longitudinal view of their functional mobility, capture the effects of fatigue or medication, and reduce the burden of travel for families, a considerable factor for those living in more rural areas.

4.1 Limitations

This study has several limitations that should be acknowledged. Firstly, the sample size was modest, and recruitment was limited to individuals with spastic diplegia, which may limit the generalisability of the findings to other types of CP (e.g., dyskinetic or ataxic). Secondly, we did not perform a direct comparison with the gold standard of 3DMC; our validation was against a standard clinical test. While this reflects our aim of providing a clinical alternative, direct validation is an important next step.

Thirdly, our gait parameter calculations were limited to spatio-temporal metrics. We did not compute joint kinematics (e.g., knee flexion angles), which requires more complex modelling. Finally, the protocol was limited to walking on a flat, even surface, and performance on more challenging terrains was not assessed.

4.2 Future Work

Building on these promising results, future work should focus on several areas. A larger-scale longitudinal study is needed to assess the system's ability to track changes over time in response to specific interventions. Direct validation against a 3DMC system is required to fully quantify its accuracy. The algorithms should be expanded to include the

calculation of key kinematic parameters and to be validated for use on stairs and uneven ground. Finally, developing a user-friendly smartphone application to guide patients through tests and provide immediate feedback would be crucial for successful translation into home-based clinical practice.

CONCLUSION

This study demonstrated that a low-cost, accessible gait analysis system using two ankle-worn IMU sensors is a valid and sensitive tool for quantifying key gait characteristics in ambulatory adolescents with cerebral palsy. The technology provides objective, reliable data that is correlated with functional level and has the potential to move gait assessment from the confines of the specialist lab into everyday clinical and home environments. By democratising access to quantitative motion analysis, such systems can play a pivotal role in the future of personalised, data-driven, and remote healthcare for individuals with cerebral palsy.

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Author Contributions

PS: Conceptualisation, methodology, investigation, writing - original draft, project administration, funding acquisition.
NJS: Data curation, formal analysis, data visualisation, creation of all figures and tables, statistical analysis, writing - review & editing.

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Conflicts of Interest

NJS declares that he has cerebral palsy and brings lived experience perspective to this research. This is considered a strength that enhances the patient-centered approach of the study rather than a conflict. PS declares no conflicts of interest. The authors affirm that having a researcher with lived experience of the condition being studied enriches the research design, interpretation, and clinical relevance of the findings.
Data Availability Statement
The data that support the findings of this study are available from the corresponding author upon reasonable request.

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