

TEACHING BIOMECHANICAL FEATURES OF HEMIPLEGIC GAIT USING OpenCap.ai: A VALIDATION STUDY FOR CASE-BASED LEARNING

Kuvijitsuwan P^{1*}, Thawinchai N² and Klaphajone J¹

¹*Department of Rehabilitation Medicine, Faculty of Medicine, Chiang Mai University, Thailand*

²*Department of Physical Therapy, Faculty of Associated Medical Sciences, Chiang Mai University, Thailand*

Abstract: Developing competency in gait analysis is essential for healthcare students involved in stroke rehabilitation, particularly for identifying biomechanical deviations associated with hemiplegic gait. Although three-dimensional motion capture (3DMoCap) is considered the reference standard for gait analysis, its high cost, technical complexity, and limited availability restrict its integration into routine educational activities. This case study evaluated the validity of OpenCap.ai, a smartphone-based markerless motion capture system, as an instructional tool for case-based learning in hemiplegic gait assessment. Lower-limb kinematic data were obtained during walking from a hemiplegic patient, focusing on sagittal-plane joint motion at the hip, knee, and ankle. Joint kinematic waveforms derived from OpenCap.ai were compared with those from a laboratory-based BTS 3DMoCap system using Lin's concordance correlation coefficients (CCC). On the affected limb, OpenCap.ai demonstrated excellent concordance with 3DMoCap for hip (CCC = 0.977) and knee (CCC = 0.982) kinematics, effectively capturing reduced flexion patterns. Agreement at the affected ankle was poor (CCC = 0.420), and sound limb concordance ranged from moderate to poor. These results suggest that while OpenCap.ai does not fully replicate laboratory-grade precision for distal joints, it provides sufficiently accurate representations of proximal gait abnormalities, offering a low-cost platform to support case-based teaching.

Keywords: *biomechanics, education, ai platform, health care students*

Introduction

Teaching human movement and biomechanics is a critical component of educating medical and occupational therapy students, preparing them to assess physical functions and develop clinical reasoning skills in rehabilitation practice. Developing competency in clinical gait analysis is particularly essential for identifying the classic biomechanical deviations associated with post-stroke hemiplegic gait. Stroke survivors typically exhibit severe spatial-temporal asymmetries, including prolonged swing duration on the paretic side, shortened stance phases on the affected limb, reduced walking velocity, and noticeable step and stride length asymmetry (Kim et al., 2016; Wang et al., 2020). Furthermore, a common gait deviation in this population is "stiff-knee gait," characterized by diminished and delayed knee flexion during the

*Corresponding Author's Email: pornsuree.k@cmu.ac.th

swing phase, which often stems from underlying physiological impairments. Traditionally, rehabilitation educators have faced significant challenges in teaching these complex biomechanical concepts due to limited access to advanced gait analysis tools. Current teaching methods often rely heavily on subjective visual observation or basic 2D video applications that provide disjointed visual shots rather than continuous, quantifiable movement patterns.

While marker-based three-dimensional motion capture (3DMoCap) remains the gold standard for clinical movement evaluation (Baker, 2006), its integration into routine educational activities or services which the graduates can get access in the future, is severely restricted by massive financial barriers as well as prolonged data collection and analysis. To address the need for innovative and accessible teaching methods, AI-driven markerless motion capture systems like OpenCap.ai have emerged as a promising solution (Uhlrich et al., 2023). By utilizing scalable cloud computing, deep learning, and musculoskeletal simulation, OpenCap.ai quantifies human movement dynamics using only simultaneous video capture from IOS smartphones, fitting within a fraction of the budget of traditional labs.

This technology has been of great interest in many clinical applications and sports (Horsak et al., 2025; Min et al., 2024; Turner et al., 2024; Yeom et al., 2026). Initial validation study suggests that it can provide kinematic measurements with acceptable agreement compared to criterion-standard motion capture systems (Uhlrich et al., 2023). However, its performance remains dependent on task complexity and joint-specific demands, and its application in routine clinical practice is still evolving. Consequently, further validation across diverse patient populations, functional tasks, and standardized protocols is required to establish its role in clinical decision-making (Çabuk et al., 2026). The objective of this study is to validate OpenCap.ai as an instructional tool for case-based learning in hemiplegic gait assessment. By transitioning from subjective observation to continuous, data-driven analysis, students can objectively practice mapping visual biomechanical deviations to their specific physiological root causes using standardized frameworks. Ultimately, evaluating the validity of this low-cost, accessible platform leads to drive medical learning reform, empowering students to better understand, diagnose, and treat gait issues in a personalized educational environment.

Materials and Methods

The protocol was approved by Research Ethic Committee, Faculty of Medicine, Chiang Mai University (approval number REH-2567-0737). The informed consent was obtained prior to the data collection.

Participant

A single case of a male patient with chronic left hemiplegia secondary to hemorrhagic stroke (3 years post-onset; age 40 years; height 1.75 m; weight 87 kg) was included. The participant presented with no joint contractures but demonstrated limited active ankle dorsiflexion with the knee extended, muscle strength graded as follows (affected/unaffected side muscle strength using Muscle manual testing ;0-5): plantarflexors (5/5), dorsiflexors (3/5), knee extensors (5/5), knee flexors (4/5), hip extensors (5/5), hip flexors (5/5), and hip abductors/adductors (4/5). Clonus was observed during passive dorsiflexion of the affected side)

Equipment

Reference standard (3DMoCap)

A BTS Bioengineering ((BTS Bioengineering, Milan, Italy) optical motion capture system consisting of twelve high-resolution infrared cameras at a sampling frequency of 100 Hz and 3 force plates and two video cameras, was used to track movement of 22 reflective markers placed according to the Helen Hayes lower-limb model. Marker trajectories were used to compute joint kinematics.

Investigational system (OpenCap.ai)

OpenCap.ai (Stanford, USA), an open-source markerless motion capture platform, utilized two synchronized iOS devices mounted on tripods to record video (Uhlrich et al., 2023). Data were processed through a cloud-based pipeline incorporating pose estimation algorithms, long short-term memory (LSTM) models, and OpenSim musculoskeletal modelling to generate three-dimensional joint kinematics.

The assessment focused heavily on sagittal-plane joint motion, specifically targeting the flexion and extension patterns of the hip, knee, and ankle. The walking cycles were captured using two systems: 3D motion capture and OpenCap.ai simultaneously.

Data Collection Protocol

The participant wore tight-fitting clothing to minimize motion artifacts. Anthropometric data, including height, weight, leg length, anterior superior iliac spine (ASIS) distance, and joint widths, were recorded.

For the 3DMoCap system, reflective markers were attached to anatomical landmarks including the sacrum, Anterior superior iliac spines, thighs, knees, shanks, ankles, heels, and toes. Following static calibration, the participant walked barefoot along a walkway at a self-selected speed.

Both systems recorded simultaneously. Multiple walking trials were performed until six complete gait cycles with clean data were obtained. The total data collection session lasted approximately two hours.

Processing and Statistical Analysis

Sagittal-plane joint kinematics (hip, knee, and ankle flexion–extension) were extracted from both systems for analysis. Spatial–temporal parameters were also computed.

Agreement between OpenCap.ai and 3DMoCap kinematic waveforms was quantified using Lin's concordance correlation coefficient (CCC). CCC values were interpreted according to McBride (2005): <0.90 (poor), $0.90\text{--}0.95$ (moderate), $0.95\text{--}0.99$ (substantial), and >0.99 (almost perfect agreement) (McBride, 2005).

Analyses were performed separately for the affected and unaffected limbs to assess system performance in capturing clinically relevant asymmetries.

Results and Discussion

The comparative analysis revealed that the markerless AI system's accuracy varied significantly depending on the joint and the limb evaluated: Spatial and temporal parameters were extracted from six complete gait cycles, highlighting clear asymmetrical differences between the patient's affected and unaffected limbs. The data recorded by both the 3DMoCap system and OpenCap.ai is summarized in Table 1 below.

Spatial temporal parameters

Spatial–temporal parameters derived from six gait cycles showed that OpenCap.ai produced values broadly comparable to 3DMoCap. On the affected limb, stride length, step length), and stance were similar between systems, although swing phase was slightly overestimated. On the unaffected limb, OpenCap.ai slightly underestimated stride length and overestimated stance phase. Despite these differences, both systems consistently captured the asymmetrical gait pattern.

Table 1. Spatial temporal parameters from six gait cycles

Parameters	3DMoCap system		OPenCap.ai	
	Affected limb	Unaffected limb	Affected limb	Unaffected limb
Stride length (m)	0.94±0.11	1.16±0.10	0.95±0.35	0.87±0.26
Step length (m)	0.42±0.03	0.52±0.01	0.40±0.03	0.49±0.03
Stance phase (%)	52±2.0	66±2.0	53±2.2	71±1.9
Swing phase (%)	43.±2.0	34±2.0	47±1.7	29±1.9
Speed(m/s)	0.70±0.4		0.64±0.5	
Cadence (steps/minutes)	82.2±1.0		82.2±1.0	
Step width (m)	0.13±0.05		0.14±0.04	

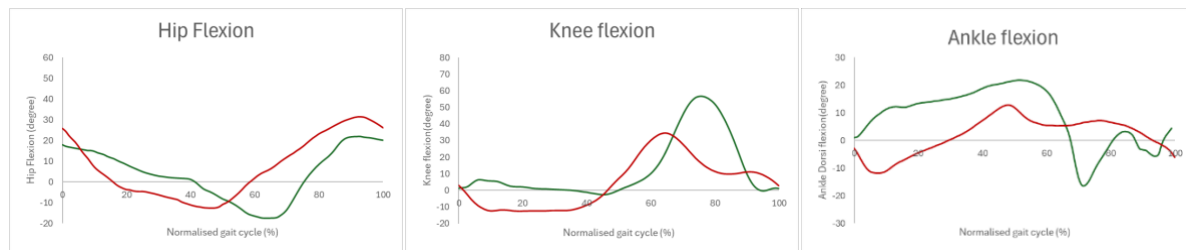
Angular data

According to Table 2 and Figure 1, OpenCap.ai demonstrated substantial agreement with 3DMoCap for proximal joints on the affected limb (hip CCC = 0.977; knee CCC = 0.982), accurately reflecting reduced flexion patterns compared with the unaffected side. The knee extension beyond neutral appeared to be limited on both sides when using OpenCap.ai. In contrast, ankle agreement was poor (CCC = 0.420). On the unaffected limb, agreement was also poor (hip CCC = 0.833; knee CCC = 0.628; ankle CCC = 0.361).

Table 2: Lin 's concordance coefficient between two systems at lower limb joints

Joint		Lin's concordance coefficient	95%CI
Hip	Affected	0.977	0.970-0.982
	Unaffected	0.833	0.764-0.883
Knee	Affected	0.982	0.976-0.986
	Unaffected	0.628	0.547-0.697
Ankle	Affected	0.420	0.397-0.538
	Unaffected	0.361	0.335-0.501

3D motion capture



OpanCap.ai

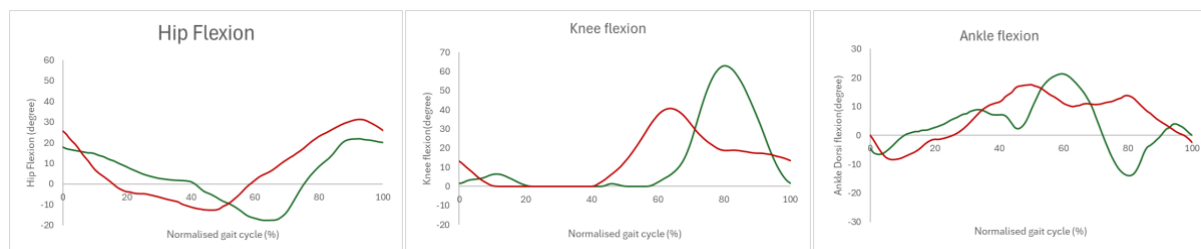


Figure 1 Example of kinematic report of a gait cycle

The results of this study suggest that OpenCap.ai does not fully replicate laboratory-grade motion capture for distal joint mechanics (the ankle) or bilateral precision on the unaffected limb. However, the substantial

agreement for the affected hip and knee confirms that OpenCap.ai provides sufficiently accurate representations of key proximal gait abnormalities for educational purposes.

Based on the literature detailing common gait deviations in stroke survivors, the 40-year-old left hemiplegic patient featured in the manuscript exhibits several classic biomechanical abnormalities (Chen et al., 2005; Patterson et al., 2010; Roth et al., 1997; Wang et al., 2020). By cross-referencing the patient's data with the stroke literature provided, the following specific gait deviations can be identified:

1. Prolonged swing duration on the paretic (affected) side and prolonged stance duration on the nonparetic (unaffected) side as hallmark features of hemiparetic gait indicates impair function as supporting limb (Brandstater et al., 1983). The patient's data clearly reflects this asymmetry. The swing phase on the affected limb is prolonged at 43% of the gait cycle, compared to only 34% on the unaffected limb. Conversely, the stance phase on the affected side is shortened to 52%, while the unaffected side exhibits a prolonged stance phase of 66%. This is likely due to the stability of the supporting limb.
2. Step and stride length asymmetry stroke survivors typically experience significantly reduced step and stride lengths, as well as pronounced spatial asymmetry between their affected and sound limbs (Gatti et al., 2012; Kim et al., 2016). The patient demonstrates reduced spatial parameters overall, with noticeable asymmetry. The affected limb shows a shortened stride length of 0.94 m (compared to 1.16 m on the unaffected limb) and a shortened step length of 0.42 m (compared to 0.52 m on the unaffected limb). This may be a result of limited range of movement due to muscle imbalance. This asymmetry also leads to decrease in walking speed.
3. Reduced gait velocity, decreased cadence and significantly reduced gait velocity are common functional limitations in post-stroke locomotion (Kim et al., 2016; Wang et al., 2020). The patient walked at a reduced speed of 0.70 m/s with a cadence of 82 steps per minute, which falls below the normal expected values for healthy individuals (often exceeding 100 steps/min and >1.0 m/s depending on age and height) (Wang et al., 2020).
4. Stiff-knee gait and reduced primary joint flexion, stroke survivors frequently suffer from reduced range of motion in primary joints (hip, knee, and ankle) (Kim et al., 2016). A highly common angular deviation is "stiff-knee gait," which is characterized by diminished and delayed knee flexion during the swing phase, often due to rectus femoris spasticity, weak hip flexors, or weak ankle plantar flexors (Campanini et al., 2013; Gatti et al., 2012; Lewek et al., 2007). The continuous flexion -extension curves derived during the

walking trials successfully captured these exact reduced flexion patterns in the patient's proximal joints. Specifically, the presence of delayed or decreased knee flexion during the early swing phase.

These angular deviations correlate directly with the patient's specific physical impairments including limited active dorsiflexion, moderate weakness in the ankle dorsiflexors (Grade 3/5), mild weakness in the knee flexors (Grade 4/5), and the presence of clonus.

For case-based learning, this continuous, data-driven analysis is transformative. By providing opportunity for students to collect and analysis data using ai platform, with interactive graphical illustrations with accurate flexion and extension graphs for the hip and knee, students can practice mapping observed biomechanical deviations to specific physiological impairments using standardized frameworks. For example, when the delayed or decreased knee flexion during the swing phase appeared, students can learn to correlate this deviation to an underlying issue such as rectus femoris spasticity or decreased push-off.

By successfully integrating AI technologies into the curriculum, students in rehabilitation departments can overcome the limitations of subjective observational teaching. Utilizing a mobile-based setup drastically reduces the financial barrier, fitting within total typical project budgets for two mobile phones while delivering comprehensive, cost-effective educational solutions.

While the integration of AI-based markerless motion capture presents a significant advancement for rehabilitation education, several limitations must be acknowledged. System accuracy at distal joints: the primary limitation of the OpenCap.ai system is limitation of distal joint measurements of the hemiplegic patient as seen in the concordance coefficient at the affected ankle ($CCC = 0.420$). Secondly, methodological constraints: to minimize data artifact errors from computer vision pose detectors, participants are strictly required to wear tight, form-fitting clothing during data collection. However, compared with the 3Dmotion capture, the process is more friendly to the patients as it is quicker and less skin exposure. The quick process is beneficial as patients attending the rehabilitation are likely to have limited strength.

Despite the limitations regarding distal and unaffected limb measurements, the use of OpenCap.ai as an educational tool is highly justified for several key reasons because it can provides sufficiently accurate representations of reduced knee and hip flexion, spatial-temporal parameters of hemiplegic gait. These are key proximal gait abnormalities for educational purposes, despite cautions will be given for more distal joints with flexible/structural deformities. Current teaching methods heavily rely on subjective visual observation or basic 2D video that present disjointed visual shots. OpenCap.ai utilizes scalable cloud computing, open-source pose detectors, and musculoskeletal simulation to provide a continuous,

quantifiable pattern of movement. This allows students to objectively practice mapping observed biomechanical deviations to specific physiological impairments. The system is cost-effective and accessible as the utilization of marker-based 3D motion capture is restricted by high costs alongside with relatively long-time data collection and analysis. Moreover, by delivering comprehensive, cost-effective educational solutions, this AI-driven approach successfully drives medical learning reform. It overcomes the limitations of subjective observational teaching, empowering rehabilitation students to better understand, diagnose, and treat gait issues in a personalized, case-based learning environment. Finally, future studies should directly measure the educational impact of these technologies on students. Research should evaluate whether utilizing these continuous, data-driven visualizations in case-based learning significantly improves students' clinical reasoning, diagnostic accuracy, and ability to design effective rehabilitation interventions compared to traditional observational methods.

Conclusion

OpenCap.ai offers a low-cost, accessible platform to support case-based teaching and learning of hemiplegic gait biomechanics in health professions education. While it cannot replace the diagnostic precision of marker-based labs for distal extremities, its exceptional accuracy in capturing proximal deviations empowers students to better understand, diagnose, and treat gait issues, advancing comprehensive healthcare training.

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Declaration of Interest Statement

The authors declare that they have no conflict of interests.

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