Development of an Artificial Intelligence System for Real-Time Analysis and Feedback in Silk Reeling Training of Chen-Style Taijiquan

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***Abstract*— This paper introduces TaijiFlow AI, a web-based prototype serving as the core analytical module within the broader TaijiFlow Learning Ecosystem. Utilizing Artificial Intelligence and Computer Vision for real-time qualitative movement analysis, the system is designed to support independent practitioners of Chen-style Taijiquan by addressing the lack of expert feedback for foundational techniques such as Silk Reeling. By integrating Google MediaPipe Pose with an explainable, rule-based Heuristics Engine, TaijiFlow AI translates traditional Taiji principles into quantifiable kinematics. The system was developed under the ISO/IEC 29110 software engineering standard and ensures strict data privacy through 100% client-side processing on standard consumer hardware. Evaluation results show a 100% pass rate across all functional tests and high overall user satisfaction.**

I. Introduction

In the digital era, self-study of physical wellness practices has grown exponentially. Taijiquan, a traditional internal martial art characterized by fluid, continuous movement and mind–body harmony, remains highly popular [1]-[3]. In Chen-style Taijiquan, the core practice is **"Silk Reeling"** (Chán Sī Jìn) [4]—a spiral kinetic chain that originates from the waist and propagates through the limbs. Modern practitioners, however, face significant constraints in time and location: restrictive professional schedules, distance from traditional schools, and limited access to expert masters [5]. While online tutorials improve accessibility, solo practitioners still lack real-time qualitative feedback, increasing the risk of developing improper habits or musculoskeletal injuries.

Artificial Intelligence (AI) and Computer Vision (CV) have transformed sports analytics [6], but their application to Taijiquan remains challenging. Most existing systems excel at high-velocity actions or static pose-matching, yet struggle to evaluate the slow, continuous, and internally driven movement quality characteristic of internal martial arts.

Existing solutions often rely on prohibitive hardware or opaque black-box models lacking pedagogical explainability. To bridge this gap, we present **TaijiFlow AI**, a web-based prototype that translates Chen-style Silk Reeling principles into quantifiable metrics by integrating MediaPipe Pose [7] with a deterministic heuristics engine. Built on a client-side architecture adhering to the ISO/IEC 29110 standard [8], the system ensures privacy, maintainability, and hardware-agnostic accessibility.

II. Related Works

A. Concepts and Theories

1) Theoretical Framework: Taijiquan Silk Reeling

Chen-style Taijiquan is fundamentally centered on "Silk Reeling" (Chán Sī Jìn)—a core spiral kinetic chain that originates from the waist and propagates through the limbs in a continuous, helical path [1], [2]. Unlike linear sports movements, Silk Reeling emphasizes an "internal connection" where the practitioner's intention (Yi) leads the movement through a sequence of complex joint rotations [3], [5]. This qualitative complexity presents a significant challenge for digital assessment, as it requires evaluating the process of movement and the internal coordination of the kinetic chain rather than just static postural similarity or surface-level geometry.

Fig. 1. Chen-style Taijiquan Silk Reeling Practice

2) Advancements in Human Pose Estimation

Human Pose Estimation (HPE) has evolved significantly from reliance on specialized sensors (e.g., IMUs or depth cameras) to lightweight, vision-based models that extract skeletal landmarks using deep learning [9]. Modern frameworks like Google MediaPipe Pose offer a top-down landmark detection approach that identifies 33 3D keypoints in real-time [7]. By leveraging WebAssembly (WASM) and WebGL for hardware acceleration, these models enable high-fidelity kinetic analysis directly in the browser environment, providing a privacy-preserving and hardware-agnostic foundation for movement assessment systems [10], [11].

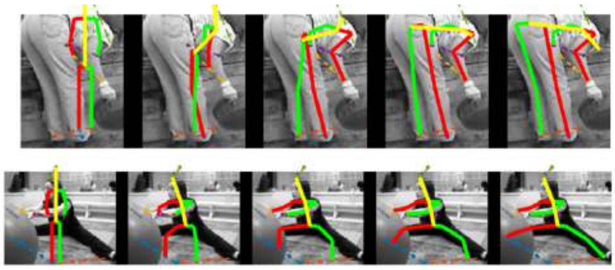

Fig. 2. Keypoint Extraction Using Pose Estimation

B. Relevant Studies

1) Existing Movement Assessment Systems

The intersection of artificial intelligence and physical movement assessment has historically transitioned from hardware-dependent solutions to accessible computer vision approaches. Early systems relied heavily on external sensors; Ho et al. [12] used the Microsoft Kinect to quantify kinematic differences between masters and novices, while Li et al. [13] employed wearable IMUs for postural balance assessment. However, these solutions face usability barriers in general wellness training due to hardware costs or physical sensor attachment.

More recent algorithmic standards, such as Dynamic Time Warping (DTW) and Deep Learning models (e.g., OpenPose [14]), focus primarily on geometric similarity. Feng et al. [15] utilized DTW to calculate similarity scores against master templates, yet this approach often fails to capture the underlying Taiji principles, such as whether movement initiates from the waist. Recent work has demonstrated the feasibility of rule-based digital heuristics; Das [16] applied real-time pose estimation for Yoga posture correction, and Pataranutaporn et al. [17] modeled complex heuristics for traditional Thai dance. Further integration of AI in martial arts training has been observed in specialized Taekwondo scoring systems [18] and broad survey analyses of internal arts automation [19].

2) Innovation Gap and Comparison

Table 1 summarizes the innovation gap addressed by TaijiFlow AI. Unlike prior hardware-dependent or opaque scoring systems, TaijiFlow AI provides a hardware-agnostic, browser-based solution using deterministic heuristics to deliver explainable feedback grounded in **Traditional Taiji Principles**.

TABLE I. COMPARISON OF RELATED ASSESSMENT SYSTEMS

Literature / Project	Platform	Assessment Method	Domain	Ext. Hardware	Real-time Feedback	Qualitative Evaluation
Ho et al. [12]	Desktop	Kinect Sensor	Taijiquan	Kinect	No	Kinematic Position
Li et al. [13]	Wearable	IMU Sensors	Taijiquan	IMUs	Partial	Movement Recognition
Feng et al. [15]	Desktop	DTW Algorithm	Taijiquan	None	Partial	Geometric Similarity
Das [16]	Mobile / Web	Pose Estimation	Yoga	None	Yes	Joint Angels Only
Pataranuta-porn et al. [17]	Digital	CV / AI	Thai Dance	None	Yes	Co-creation Focus
Sin et al. [18]	Native	Multi-modal AI	Taekwondo	None	Yes	Technical Performance
Taiji Flow AI	**Browser**	**Heuristics**	**Taijiquan (Chen)**	**None**	**Yes**	**Taiji Principles**

III. SYSTEM DESIGN AND ARCHITECTURE

A. Development Process Framework

To ensure reliability and traceability, the development lifecycle adhered to the ISO/IEC 29110 Basic Profile for Very Small Entities (VSEs), producing formal Project Management (PM) and Software Implementation (SI) artifacts like the SRS and SDD. Quality was assured using a Traceability Matrix that mapped each requirement to an architectural component, validated via automated Unit and Integration test scripts to minimize architectural debt and scope creep.

B. System Requirements Analysis

TaijiFlow AI provides real-time qualitative feedback for solo practitioners of Chen-style Taijiquan. The system focuses on Silk Reeling techniques, covering four single-hand patterns across three difficulty levels (seated, standing, and crouching).

Requirements analysis identified twelve use cases (UC-01 to UC-12) that support trainees and administrators/experts. Key features include real-time training with multimodal feedback, body calibration, movement replay, gesture control, and a "Flow State" mode for continuous practice.

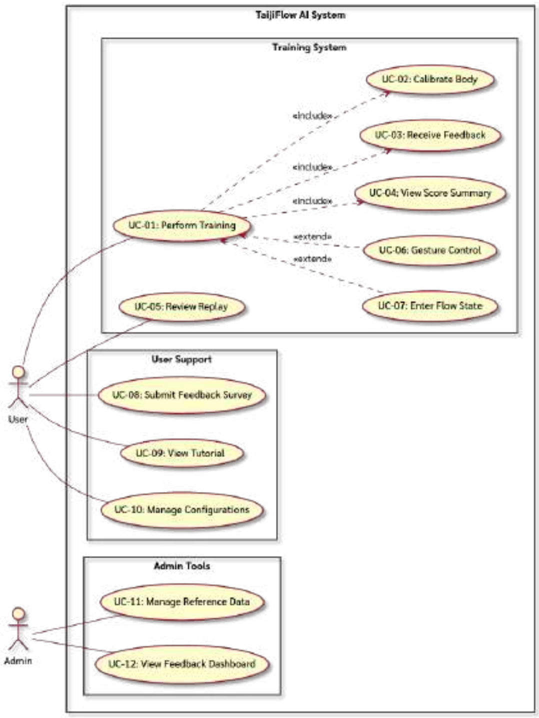

Fig. 3. Use Case Diagram for TaijiFlow AI System

System design is guided by three Non-Functional Requirements (NFRs):

1) Privacy: 100% client-side AI processing; no video data is transmitted to external servers.

2) Performance: Real-time optimization ensures processing at a minimum of 25 frames per second (FPS) on consumer-grade hardware.

3) Maintainability: A modular design allows for the independent addition or modification of heuristic rules.

To ensure verification completeness, all functional use cases and non-functional requirements are mapped via the Traceability Matrix to specific verification test cases detailed in Section V.

C. System Architecture

For high accessibility and data privacy, the system utilizes a browser-native, client-side technology stack. It processes video streams from a standard RGB webcam locally, leveraging WebAssembly (WASM) for low-latency MediaPipe Pose inference and WebGL for GPU-accelerated skeletal rendering. Under this runtime framework, the software is developed in compliance with the ISO/IEC 29110 standard and specifically adopts the Layered Architectural Pattern to enforce separation of concerns. As illustrated in Figure 4, this logical architecture is structured into five functional tiers:

1) Presentation Layer: Manages the user interface and specialized rendering. It decouples UI components (Feedback Manager, UIManager) from the DrawingManager, which handles high-frequency WebGL skeleton overlays and flow-state visualizations.

2) Controllers Layer: Functions as system orchestrator. The TrainingFlowController manages the state transition for the progressive learning system, while the PoseProcessor serves as midware to normalize raw landmarks before they move to the analytical engine.

3) Business Logic Layer: The core analytical tier, featuring a modular Heuristics Engine and a discrete Rules Library. By isolating the nine heuristics rules into independent modules through the Strategy Design Pattern, the architecture facilitates rule-specific calibration and logic updates without affecting the core engine.

4) Data Layer: Handles localized persistence (Scoring Manager) and session states (SessionManager) using browser-native storage (LocalStorage), maintaining 100% data residency on the user's device.

5) External Services Layer: Interfaces with specialized libraries and APIs, including Google MediaPipe for local inference and auxiliary services such as the Web Speech API for auditory coaching.

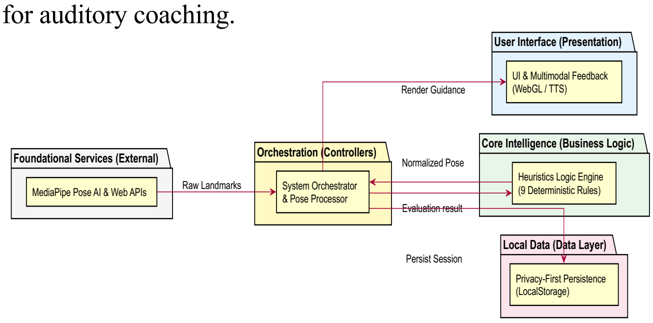

Fig. 4. Simplified System Architecture and Component Data Flow

IV. System Implementation

A. Implementation Overview

TaijiFlow AI is realized as a modular web application through a modern, 4-layer JavaScript technology stack. While the logical architecture defines five conceptual tiers of responsibility, the concrete implementation is optimized into a high-performance 4-layer stack to maximize browser-native performance and maintain internal decoupling:

- *Layer 1 (Presentation & Interaction):* Built with WebGL and HTML5/CSS3 for high-performance skeletal rendering and custom UI components.
- *Layer 2 (AI Inference):* Leverages MediaPipe Pose and WebAssembly (WASM) for real-time skeletal landmark extraction directly in the browser.
- *Layer 3 (Pedagogy & Logic):* Consolidates the Heuristics Engine and the Web Speech API for intelligent posture analysis and auditory coaching.
- *Layer 4 (Data Persistence):* Employs browser-native Local Storage for session management and anonymous performance tracking.

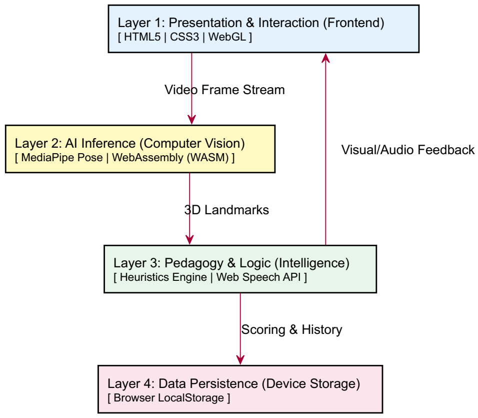

Fig. 5. Implementation Tech-Stack Layers

B. Real-time AI Analysis Flow

The system processes motion data through a conceptual pipeline that transforms raw video frames into qualitative pedagogical feedback. This flow serves as a data acquisition and analysis foundation, allowing the architecture to function as an organic collector of expert-validated motion data for future training phases.

The analysis flow follows a five-stage sequence, as illustrated in the conceptual pipeline in Figure 6:

1) Acquisition: Capturing the raw video stream directly within the browser environment.

2) Estimation: Extraction of 33 3D skeletal landmarks in real-time using the MediaPipe Pose model.

3) Normalization: A "T-pose" calibration calculates a personalized body-scale factor, ensuring spatial heuristic accuracy regardless of user height or camera distance.

4) Orchestration (Priority Logic): In instances where multiple principles are violated, the system employs a Conflict Resolution Policy to select the most fundamental technical error for display, preventing user information overload.

5) Multimodal Output: Real-time rendering of color-coded skeletal overlays and TTS auditory coaching.

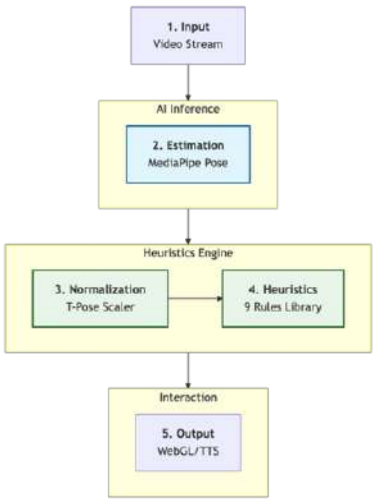

Fig. 6. Five-stage conceptual flow of the real-time AI analysis pipeline

C. Heuristics Engine Core

A primary contribution of this research is the translation of traditional Taijiquan principles into computational logic. The rule-based heuristics engine provides Explainable AI (XAI) [20], enabling the system to pinpoint specific technical deviations from Taiji principles.

1) Traditional Principles Translation

The engine operationalizes nine distinct principles drawn from classical Chen-style treatises, transforming abstract concepts into deterministic rules:

- *Path Shape (圆转如意 - Yuan Zhuan Ru Yi) [1]:* Evaluates the circular symmetry and spatial roundness of movement trajectories.
- *Elbow Sinking (沉肩坠肘 - Chen Jian Zhui Zhou) [3]:* Monitors the alignment of elbows relative to shoulders and wrists.
- *Continuity (绵绵不断 - Mian Mian Bu Duan) [3]:* Detects unintended pauses to ensure unbroken energy flow.
- *Arm Rotation (旋腕转臂 - Xuan Wan Zhuan Bi) [4]:* Tracks the characteristic spiral Silk Reeling rotation of the limbs.
- *Waist Initiation (腰為主宰 - Yao Wei Zhu Zai) [1]:* Analyzes whether movement is driven by core rotation rather than isolated limb movement.
- *Vertical Stability (虚领顶劲 - Xu Ling Ding Jin) [3]:* Measures head and spine alignment for a stable, upright posture.
- *Smoothness (如抽丝 - Ru Chou Si) [4]:* Assesses the uniformity of velocity, analogous to drawing silk from a cocoon.
- *Weight Shift (分虚实 - Fen Xu Shi) [4]:* Evaluates displacement to ensure clear separation of empty and full stances.
- *Coordination (上下相随 - Shang Xia Xiang Sui) [3]:* Analyzes the harmony between the upper and lower body.

2) Adaptive Rule Architecture

The Heuristics Engine manages user cognitive load by staggering the nine rules across three adaptive training levels:

- *Level 1 (Beginner):* Designed for practitioners with limited mobility, this level enforces three fundamental rules that focus on the upper body and basic rhythm, helping to avoid cognitive overload.
- *Level 2 (Intermediate):* Builds upon the beginner level by introducing three intermediate rules that focus on maintaining proper posture and initiating movement from the core.
- *Level 3 (Advanced):* This level activates all nine rules simultaneously, incorporating lower-body weight shifts and whole-body synchronicity.

TABLE II. PRINCIPLES TO COMPUTATIONAL METRICS AND LEVELS

Level	Taiji Principle	Core Evaluation	Operational Metric / Logic
L1	Path Shape	Circular symmetry	Directional Cross-Product Consistency
	Elbow Sinking	Joint alignment	Vertical Coordinate Constraint
	Continuity	Motion flow	Pause Detection (Velocity Floor)
L2	Arm Rotation	Spiral dynamics	Spatial Finger Displacement (Thumb vs Pinky)
	Waist Initiation	Rotation timing	Angular Velocity Ratio (Shoulder vs Hip)
	Vertical Stability	Upright posture	Windowed Head Displacement (Min-Max Y)
L3	Smoothness	Consistent speed	Differential Acceleration (Jerk)
	Weight Shift	Lower-body balance	Support Base Centering (Hip vs Ankles)
	Coordination	Whole-body harmony	Directional Velocity Correlation

D. User Interface

1) Individual Body Calibration Interface

Prior to active training, practitioners interact with a mandatory calibration interface. Because anatomical proportions and camera setups vary significantly between users, this interface requires the practitioner to hold a standard "T-pose" for a brief duration. The system calculates a personalized Body Scale Factor to normalize the incoming 3D landmark coordinates. This crucial step ensures that spatial heuristic rules evaluate movement accurately and fairly, regardless of the user's height or their distance from the camera (Figure 7).

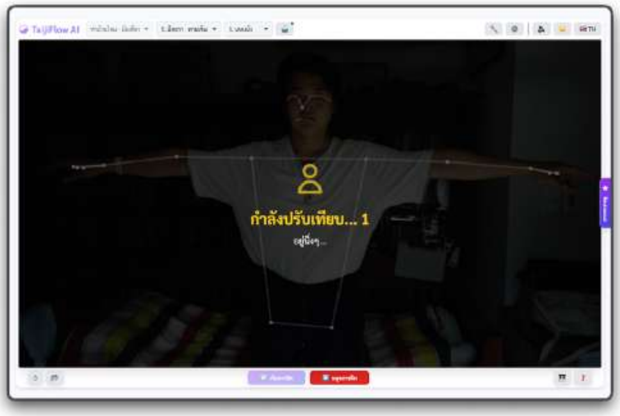

Fig. 7. Immersive Flow Mode designed for moving meditation

2) Heuristic-Driven Evaluation Interface

This primary interface is designed for the Cognitive and Associative stages of learning. It provides a skeletal overlay and real-time heuristics feedback to guide practitioners through technical corrections (Figure 8).

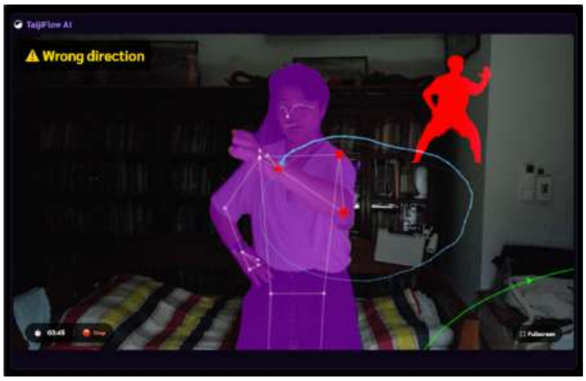

Fig. 8. Guided Training View with Feedback and Visual Corrections

3) *Post-session Analytical Dashboard*

After each session, the system provides a comprehensive quantitative summary of performance via an interactive dashboard (Figure 9). Beyond static scoring, the dashboard serves as an active learning portal with three primary functions: (1) Practice Again via seamless restart skipping re-calibration, (2) Reflective Replay using a skeleton buffer and (3) Strategic Data Storage for exporting anonymous JSON landmark coordinates for future research.

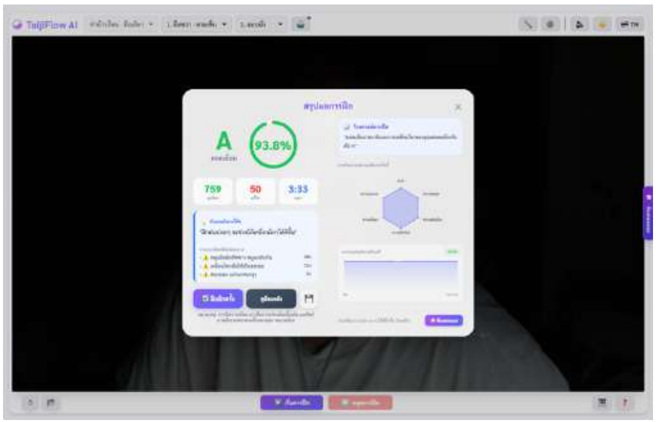

Fig. 9. Analytical Dashboard showing score summary

4) *Expert Reference Data Acquisition Interface*

To establish the ground truth baseline for the AI heuristics, a specialized interface (data_collector.html) was developed for instructors. This tool allows for the capture and export of expert landmark trajectories, ensuring that the system is calibrated against high-fidelity technical templates.

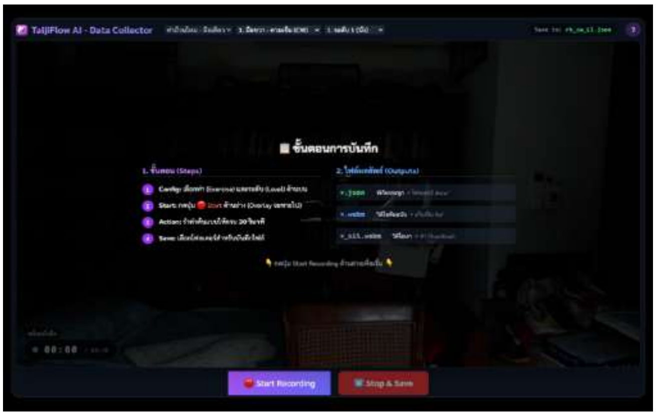

Fig. 10. Expert Reference Data Collector Tool

V. EVALUATION AND RESULTS

A. *Evaluation Setup and Testing Protocol*

The experimental environment simulated real-world conditions for independent practitioners across macOS and Windows using standard Chrome and Edge browsers. Hardware profiles ranged from high-end Apple Silicon (M1/M2) to legacy Intel i5 processors, utilizing standard 720p/1080p webcams without external acceleration.

The testing protocol comprised three stages:

1) Functional Verification (UTC, ITC, STC):

a) Unit Testing (UTC): 72 cases covering core math, calibration, and all nine heuristic rules.

b) Integration Testing (ITC): 3 scenarios focused on the end-to-end AI data pipeline and rule cascading.

c) System Testing (STC): 12 cases simulating all operational use cases (UC-01 to UC-12).

2) Performance Assessment (NTC): Five non-functional tests focused on FPS stability, model loading latency, and TTS response times across the identified hardware tiers.

3) User Acceptance Testing (UAT): A purposive sample of five participants (two novice, two intermediate partitioners, and one expert) completed a standardized session (calibration, gesture-controlled training, replay) followed by an extended cohort of fifteen participants (N=15) completed a System Usability Scale (SUS) survey after interacting with the system.

B. *Functional Correctness*

Functional correctness was evaluated to verify the integrity of the digital translation from movement to heuristics scores. As summarized in Table 3, the system achieved a 100% pass rate across all 87 functional test cases (UTC, ITC, and STC). These results confirm that the deterministic heuristics engine operates predictably under controlled parameters and accurately identifies posture flaws according to the mathematically modeled Taiji principles.

TABLE III. SUMMARY OF FUNCTIONAL TEST

Test Level	Total Cases	Target Modules	Pass Rate
Unit (UTC)	72	Core Logic, Math, Strategy Rules	100%
Integration (ITC)	3	Data Pipeline, Rule Cascading	100%
System (STC)	12	End-to-end Use Case (UC-01–UC-12)	100%

C. *Performance and Non-Functional Results*

The feasibility of purely client-side pose estimation was assessed across high-end and legacy hardware tiers. As detailed in Table 4, the measured frame rate averaged 45 FPS on Apple Silicon architecture and 25–30 FPS on standard Intel i5/i7 machines. This performance successfully met the 25 FPS minimum requirement for fluid real-time feedback. Furthermore, the low model-loading latency (~3.5s) and efficient TTS response time (~120ms) confirm that modern browser environments are sufficient for high-fidelity performance analysis without the need for server-side acceleration.

TABLE IV. NON-FUNCTIONAL EXECUTION RESULT

NFR Category	Target Metric	Measured Empirical Result	Status
FPS (Performance)	≥ 25 FPS	45 FPS (M2), 25–30 FPS (Intel)	PASS
Cold Start Load	≤ 5.0 sec	~3.5 seconds average	PASS
Audio Latency	≤ 200 ms	~120 ms TTS response time	PASS
Reliability	Env warning	Lighting warning active	PASS
Accessibility	Contrast & i18n	Dark mode, TH/EN sync OK	PASS

D. *User Acceptance and Survey*

The evaluation results demonstrate high practitioner acceptance. Qualitative observations from the five-participant session and quantitative data from the fifteen-participant cohort (N=15) show a mean satisfaction score of 4.68 out of 5.00. Key observations include:

1) Pedagogical Alignment: The expert instructor explicitly validated the heuristic feedback, confirming that auditory cues mirrored traditional verbal corrections.

2) Accessibility: The novice participants successfully completed a session without expert supervision, indicating the system's viability for independent study.

3) UX Optimization: While the gesture-controlled interface successfully enabled hands-free practice, font legibility at distances greater than two meters was identified as a minor constraint for small-screen devices.

Taken together, these findings indicate that TaijiFlow AI provides an effective for solo Taijiquan practice.

VI. Discussion And Conclusion

A. Technical Lessons and Limitations

Adopting the ISO/IEC 29110 standard proved profoundly beneficial, acting as a blueprint for impact analysis via the Requirements Traceability Matrix (RTM). This disciplined approach resulted in a robust engineering archive of 179 artifacts and 69 validated source files, ensuring that the system is fully traceable and maintainable. A key lesson learned was the use of Formal Change Requests and the RTM to prevent "Silent Drift" between source code updates and the technical documentation (SRS/SDD), a common failure point in small-scale AI projects.

Despite the successful validation of the core pipeline, several limitations remain, which have been documented as strategic opportunities for growth in Table 5.

TABLE V. Technical Limitations and Future Scaling

Limitation	Primary Rationale / Context	Future Strategy (Phase 2-3)
Movement Scope	Prioritized analysis depth for single-hand foundational patterns	Expansion to 8 double-hand routines and bilateral coordination logic
User Persistence	Focused on 100% privacy-first, session-only processing in Phase 1	Integration of secure User Login and Personalized Training Dashboard
Technological Bias	Audio latency constraints (~250ms) identified in specific browsers (Safari)	Migration to optimized Audio Buffer management and MediaPipe Tasks API
Evaluation Model	Relies on a single-expert gound truth for deterministic validation	Acquisition of multi-expert datasets to support adaptive DL models

B. Future Roadmap

The identified limitations guide our subsequent developmental phases:

1) Phase 2 (Ecosystem Expansion): Expanding to double-hand routines and activating the data accumulation strategy. By logging anonymized landmark JSON data, the system will act as an organic collector for large-scale, real-world Taiji datasets.

2) Phase 3 (ML & HRI Integration): Empowered by the dataset harvested during Phase 2, research will focus on training lightweight Deep Learning models for dynamic movement. A major objective is the integration of Human-Robot Interaction (HRI), mapping real-time landmarks to robotic agents to provide physical posture demonstrations.

C. Final Vision

Ultimately, this study proves that the confluence of traditional cultural wisdom, computer vision AI, and software engineering can do more than just digitize movement—it can preserve and revitalize cultural heritage in a dynamic, accessible format. As TaijiFlow AI evolves into a comprehensive **Intelligent Martial Art Learning Platform**, it stands as a testament to how interdisciplinary innovation can create tools that are not only technically proficient but also philosophically grounded. By providing a hardware-agnostic tool for qualitative assessment, TaijiFlow AI empowers the next generation of practitioners to achieve excellence in the ancient art of Taijiquan through the power of modern technology.

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