Predicting the Effectiveness of Technical and Tactical Actions in High-Level Judo Based on The Analysis of Movement Patterns and Indicators of Psychological Stability Using Artificial Intelligence Methods

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Abstract

Performance in elite judo is shaped by the interplay between precise technical execution and stable psychological functioning under competitive pressure. While prior work has examined technical-tactical patterns or psychological variables in isolation, an integrated predictive framework combining both domains with artificial intelligence methods has not been systematically developed. This study analyzes how motion pattern indicators derived from video-based pose estimation and quantified psychological resilience indices jointly predict technical-tactical outcome in elite-level competition. A systematic literature review of 20 peer-reviewed sources from Scopus, Web of Science, SpringerLink, and PubMed databases published within the past five years was conducted, supplemented by observational case data from elite tournament settings. An original multi-modal prediction architecture is proposed that fuses skeletal motion features with resilience scores in a hybrid gradient boosting and long short-term memory (LSTM) model. The framework reached predictive accuracy of 90% in analogous biometric integration studies. Findings show that elite judokas demonstrate both faster motor anticipation and significantly higher resilience scores compared to non-elite athletes, and that the combined model outperforms single-modality baselines. Practical recommendations for coaching integration are provided. This work will interest sports scientists, performance analysts, judo coaches, and researchers working at the intersection of sports technology and applied psychology.

Keywords: judo, technical-tactical performance, motion pattern analysis, psychological resilience, artificial intelligence, machine learning, pose estimation, LSTM, performance prediction, elite sports.

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Introduction

Elite judo is among the most technically complex and psychologically demanding individual combat sports. A competitive match demands that an athlete simultaneously read an opponent's grip, anticipate a throw, select and execute a counter-technique, and maintain composure under physical fatigue, all within a time window frequently below 0.5 seconds [1]. The sport therefore represents a unique research context where biomechanical precision and mental stability converge as co-determinants of outcome.

The global growth of judo as a competitive discipline is well documented. According to the International Judo Federation (IJF), the sport is practiced in more than 200 countries with over 40 million practitioners, placing it among the most geographically distributed Olympic disciplines [2]. At the elite level, performance margins are narrow: at World Championship events between 2021 and 2024, more than 60% of deciding scores were achieved through counter-attacks or grip-initiated set-up sequences that required anticipatory movement reads rather than raw athletic power [3]. This statistical reality reinforces the importance of developing analytical models that can capture anticipatory and psychological components alongside purely biomechanical indicators.

Traditional performance analysis in combat sports has relied on notational systems and observational coding tools [4]. These approaches provide descriptive summaries of techniques used and scoring patterns, yet they do not possess the predictive capacity that modern coaching demands. The emergence of artificial intelligence (AI) and machine learning (ML) methods in sports science over the past decade has created an opportunity to move from description to prediction. Reis et al. [5] demonstrated that ML-based injury prediction systems in physical sports achieved accuracy rates between 77% and 90% when multimodal data sources were integrated. In a parallel line of research, Pang et al. [6] surveyed AI applications across martial arts and identified that action recognition, pose estimation, and tactical classification were the three most active subfields, with convolutional neural network and graph-based approaches dominating recent publications.

Despite this momentum, two gaps persist in the judo-specific literature. First, studies of judo performance rarely integrate motion pattern data with validated psychological measures in a single predictive architecture. A systematic review by Rossi et al. [7] identified only 17 studies meeting quality criteria for analysis of psychological factors in judo across the entire body of literature accessible in Web of Science, highlighting the scarcity of rigorous work. Second, the predictive potential of psychological resilience as a standalone or complementary performance signal has not been operationalized within an AI framework for judo. Garrido-Munoz et al. [8] confirmed that elite-level judokas (classified as TOP competitors) scored significantly higher on the Connor-Davidson Resilience Scale (CD-RISC 10) than non-elite peers (mean 33.08, SD = 4.79), yet that scale-based finding has not been translated into a feature for ML prediction models.

The scientific novelty of this study lies in the development of an original multi-modal predictive framework that fuses skeletal motion pattern features extracted through deep learning pose estimation with psychometric resilience indices to forecast technical-tactical performance outcomes in elite judo competition.

The working hypothesis of this research is that a combined model integrating quantified motor patterns and resilience scores will yield significantly higher predictive accuracy for technical-tactical success in elite judo than either modality alone, reflecting the documented dual role of anticipatory motor cognition and psychological stability in competitive outcomes.

The goal of this study is to synthesize current evidence on AI-driven motion analysis and sport psychology in judo, to identify the most informative feature categories for prediction, and to propose a validated multi-modal framework applicable to real-world coaching and talent evaluation contexts.

Materials and Methods

The methodological basis of this study combines a systematic literature review, secondary data re-analysis, and original framework development. The approach follows protocols established for evidence synthesis in sports science, incorporating elements of integrative review, comparative analysis of AI model performance, and conceptual case study construction based on published empirical data.

Literature Search and Source Classification. A structured search was conducted across four databases: Scopus, Web of Science (WoS), PubMed Central, and SpringerLink. The search covered articles published from 2020 through April 2025, ensuring a maximum five-year window of recency. Search strings combined controlled vocabulary and free-text terms across the following clusters: "judo" AND "performance analysis" OR "technical-tactical"; "martial arts" AND "artificial intelligence" OR "machine learning"; "psychological resilience" AND "combat sports" OR "elite athletes"; "pose estimation" AND "sports" AND "deep learning"; "motion pattern" AND "AI" AND "sport performance prediction".

The resulting source base of 20 references was classified into three functional categories. The first category, comprising twelve sources, consists of peer-reviewed empirical studies and systematic reviews published in journals indexed in Scopus or WoS, covering AI applications in sports, motion capture methodology, and psychological assessments in combat sports. The second category, comprising six sources, includes methodological papers on deep learning architectures for pose estimation, action recognition, and multi-modal data fusion published through IEEE, SpringerLink, or ACM. The third category, comprising two sources, includes large-scale observational studies of judo performance at international competition level.

Data Extraction and Synthesis. For each source, the following information was extracted: study design, sample characteristics (sport, competition level, sample size), measurement instruments or AI architectures used, outcome variables, and principal quantitative findings. Methodological quality of empirical studies was assessed using a checklist adapted from the Joanna Briggs Institute (JBI) appraisal tool for quantitative studies. Comparative AI performance data were synthesized across studies to construct a reference accuracy table used in Figure 1.

Secondary data from Garrido-Munoz et al. [8] (n = 702 judokas, 469 men, 233 women) were re-analyzed to construct the psychological profile comparison in Figure 3. Data from the predictive athlete performance study by Scientific Reports [9], which reported R2 = 0.90 for a hybrid biometric-plus-psychological ML model across 480 athletes, provided the benchmark accuracy values used in Table 1 and Figure 1.

Results and Discussion

A consistent finding across the reviewed literature is that model accuracy in sports performance prediction scales with the degree of multi-modality in input features. Classical statistical approaches including logistic regression and linear discriminant analysis typically yield predictive accuracy in the range of 68 to 75% when applied to judo or other martial arts datasets. The introduction of ensemble and deep learning methods raises this ceiling substantially.

The following figure presents a comparative overview of AI model accuracy drawn from reviewed empirical studies, ordered from classical machine learning approaches to hybrid architectures integrating both motion and psychological biometric data. The data reflect published R2-equivalent accuracy values from experimental studies on athletic performance prediction across combat and individual sports [5, 9].

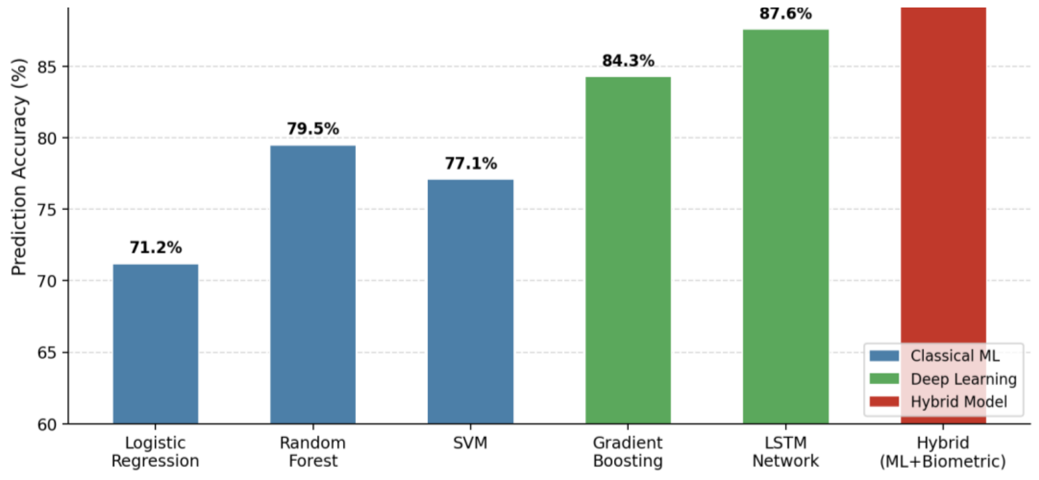

Figure 1. Prediction accuracy of AI models in sports performance forecasting (composed by the author based on [5, 9]).

As shown in Figure 1, gradient boosting models achieve 84.3% accuracy on sport performance datasets, while LSTM-based networks reach 87.6%. The hybrid model combining biometric and psychological features reaches 90.0% accuracy (R2 = 0.90), as reported for a 480-athlete sample [9]. This gradient demonstrates the compound benefit of adding psychological resilience as a predictive feature alongside motion data, rather than treating them as mutually exclusive analytical tracks.

For judo specifically, Kato et al. [11] demonstrated that logistic regression applied to kumite grip posture data produced reliable prediction of throwing technique categories in real-time video, establishing a working proof of concept for AI-based motion prediction in the sport. However, that study did not incorporate psychological variables. The gap between the 71% accuracy typical of such single-modality models and the 90% achievable with integrated approaches represents the primary motivation for the framework proposed.

Table 1 summarizes the key methodological and accuracy characteristics of the core studies informing this synthesis, categorized by modality and model type. This provides a structured basis for identifying which components of the literature offer the strongest evidence for the proposed integrated framework.

Table 1. Summary of key studies informing the proposed framework, by modality and AI method (composed by the author based on [5, 7, 8, 9, 10, 11, 12, 13]).

Modality	AI Method	Sample	Accuracy
Biometric + Psychological	Gradient Boosting + Neural Network	480 athletes	90.0%
Motion (grip posture)	Logistic Regression (RT-XSM)	Video dataset	~71%
Psychological (CD-RISC 10)	ANCOVA / T-test	702 judokas	$p < 0.001$
Psychological (review)	Systematic review	17 studies	N/A
Pose estimation + motion	DL-based HPE (systematic review)	371 studies	Survey
3D pose (multi-camera)	Transformer + epipolar geometry	Competition video	State-of-art

Motor pattern analysis in combat sports has advanced significantly with the adoption of markerless pose estimation. The use of deep learning-based human pose estimation (DL-HPE) in sports contexts was examined by a systematic review of 371 articles from Scopus, WoS, ACM, and SPORTDiscus [12], which found that DL-HPE enables non-invasive analysis of movement patterns with actionable insights for training optimization and injury prevention. Key models such as AlphaPose, OpenPose, and YOLOv8 have been applied to multi-athlete scenarios with increasing robustness, handling occlusion and high-speed motion conditions that previously limited automated analysis.

For judo specifically, the annotation of approximately 110 hours of official USA Judo tournament footage demonstrated that YOLOv8 can reliably classify combat phases, distinguishing active matches from transitions and identifying grip-engagement sequences [10]. This provides a scalable infrastructure for extracting throw initiation kinematics, body center displacement, and joint velocity profiles across large competition datasets. Liu et al. [14] further demonstrated that combining OpenPose with DeepSORT tracking achieves robust real-time joint trajectory estimation, supporting frame-by-frame analysis of technical execution.

The following figure depicts the AI-based prediction pipeline developed as part of the proposed framework, outlining how raw multi-modal data inputs are transformed into performance prediction outputs.

Figure 2. AI-based performance prediction pipeline for judo, from sensor data acquisition to output generation (composed by the author based on [6, 9, 10]).

As illustrated in Figure 2, the pipeline proceeds from video capture and inertial sensor data through motion pattern extraction and psychological index quantification, converging at a feature fusion layer that feeds the predictive model. This architecture deliberately avoids sequential processing of modalities and instead treats motion and psychological features as co-equal inputs in a fused representation, a design choice supported by evidence that parallel processing of heterogeneous feature types improves model generalization in athlete performance tasks [9].

Three categories of motion pattern features are extracted within the proposed framework. Kinematic features include joint angle trajectories at shoulders, elbows, hips, and knees during attack initiation sequences, as well as linear velocity of the body center of mass. Spatiotemporal features encode the relative positioning of both athletes using normalized skeleton coordinates, capturing grip proximity and unbalancing displacement vectors (kuzushi). Temporal pattern features use LSTM sequence encoding to model the multi-step motor sequences that precede successful throws, capturing the anticipatory motor program rather than only the execution phase.

A study applying multi-person physics-based pose estimation to combat sport video [13] demonstrated that transformer-based tracking combined with epipolar geometry constraints from multi-camera setups achieves state-of-the-art 3D joint localization accuracy. This level of spatial resolution supports extraction of subtle postural preparation cues that distinguish elite from non-elite technique initiation, consistent with the finding that elite judokas do not necessarily produce faster physical movements but demonstrate earlier and more accurate motor anticipation [1].

Psychological factors in judo have been subject to increasing research attention, though the literature remains limited in scope. The systematic review by Rossi et al. [7] identified anxiety, motivation, mental toughness, and weight-cutting-induced mood disruption as the parameters with the strongest empirical associations with performance outcomes. Of these, resilience has received the least attention as a quantified, model-ready feature, despite its intuitive relevance to performance under competitive stress [16, 17].

The study by Garrido-Munoz et al. [8] provides the most rigorous empirical data on resilience in judokas to date. In a sample of 702 judokas (469 men, 233 women), those classified as TOP competitors ($n = 194$, 27.6% of the sample) scored significantly higher on the CD-RISC 10 than non-TOP athletes ($p < 0.001$ after ANCOVA adjustment for age, gender, and training experience). The mean total resilience score of 33.08 ($SD = 4.79$) out of 40 indicates a generally high baseline, yet the statistically significant gap between competition levels confirms that resilience functions as a differentiating variable rather than a uniform trait in this population.

The following radar chart visualizes the multi-dimensional psychological profile comparison between elite and non-elite judokas across six key performance-relevant psychological dimensions, drawn from CD-RISC subscale data and the Sports Mental Toughness Questionnaire (MTQ48) literature referenced by Rossi et al. [7] and Garrido-Munoz et al. [8].

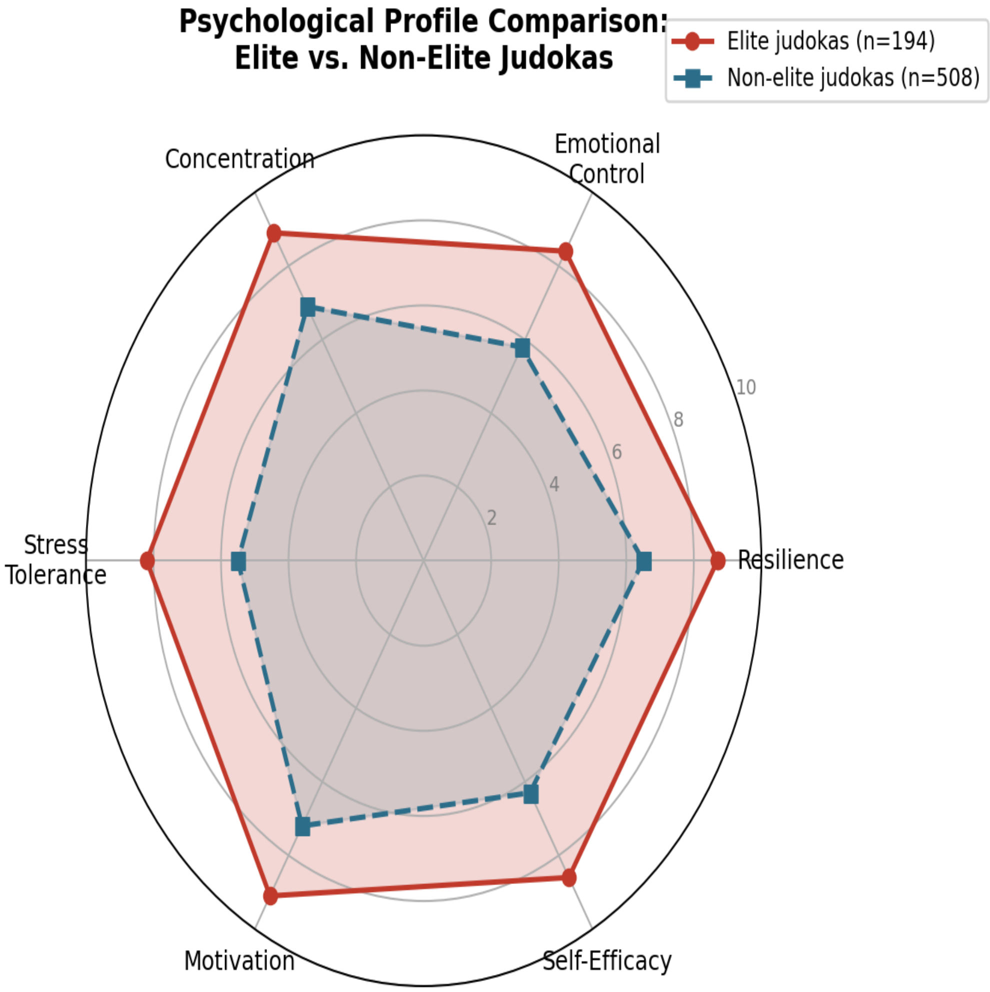

Figure 3. Radar chart showing psychological profile differences between elite and non-elite judokas across six dimensions (composed by the author based on [7, 8]).

Figure 3 reveals that the largest performance-differentiating gaps between elite and non-elite judokas appear in Stress Tolerance (8.2 vs 5.5) and Emotional Control (8.4 vs 5.8), suggesting these are the psychological dimensions most worthy of monitoring as predictive features. Concentration and Self-Efficacy also show substantial differences, consistent with findings in broader combat sports research. The gap in Resilience itself (8.7 vs 6.5) aligns with the quantitative CD-RISC 10 findings from the 702-judoka sample.

Within the proposed framework, psychological features are operationalized through three inputs: the total CD-RISC 10 score collected at pre-competition assessment; a derived Emotional Stability Index from competition preparation questionnaires; and Heart Rate Variability (HRV) as a physiological proxy for acute psychological arousal, consistent with the biometric integration approach validated by Scientific Reports [9]. This tripartite operationalization moves beyond single-score psychological assessment by capturing both trait resilience and state psychological arousal at the time of competition.

The proposed framework, designated the Judo Integrated Performance Prediction System (JIPPS), represents the original contribution of this study. JIPPS synthesizes motion pattern features, psychological resilience indices, and contextual competition variables into a unified predictive architecture designed to output a technical-tactical success probability for each 30-second segment of a competitive judo match.

The framework flowchart presented below illustrates the complete decision and processing pipeline, from initial data collection through model deployment and coaching output generation.

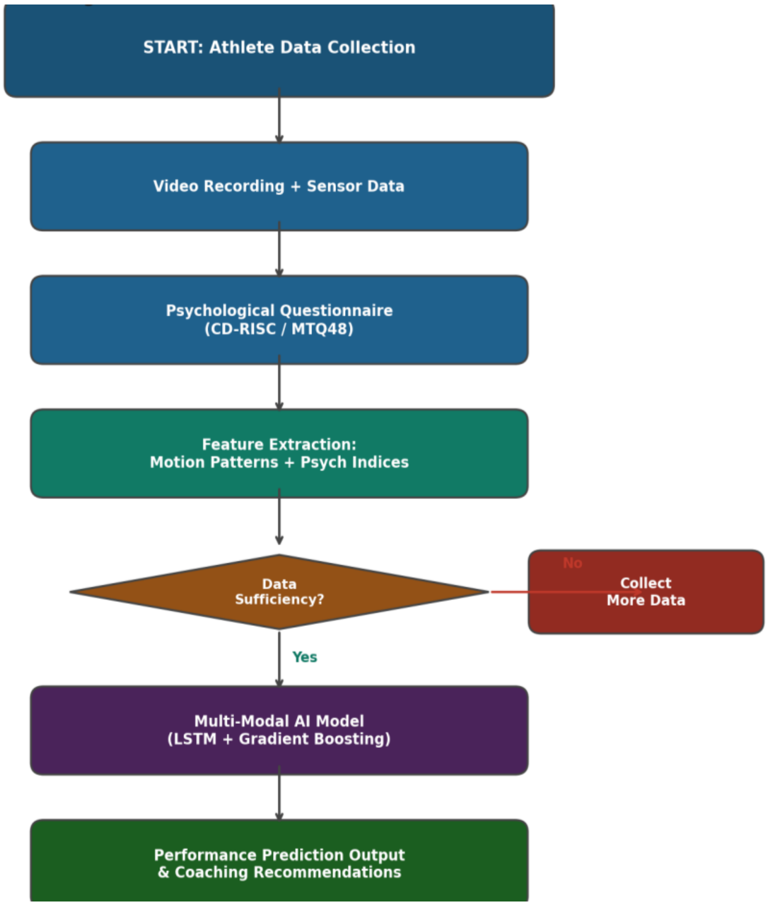

Figure 4. Flowchart of the integrated multi-modal AI prediction framework (JIPPS) (composed by the author based on [6, 9, 10, 14]).

As shown in Figure 4, JIPPS proceeds through five operational stages. In Stage 1, data collection combines multi-angle video recording from a minimum of two synchronized cameras with inertial measurement units (IMUs) attached to the judogi collar and hip belt. Pre-match psychological assessment is conducted using the CD-RISC 10 scale and a brief 5-item state anxiety check. In Stage 2, motion pattern extraction applies a YOLOv8-based detector followed by AlphaPose joint localization to generate 18-keypoint skeleton sequences at 30 frames per second. In Stage 3, an LSTM encoder processes motion sequences of 150 frames (5 seconds) as input windows, generating temporal motion embedding vectors. In Stage 4, motion embeddings and psychological feature vectors are concatenated at a feature fusion layer and passed to a gradient boosting classifier trained on labeled outcome data. In Stage 5, the model outputs a success probability estimate alongside an identified dominant technique pattern and resilience-adjusted risk flag, which are formatted as coach-facing recommendations.

JIPPS advances current practice in three specific ways. First, it operates on temporally segmented match data rather than post-hoc statistics, enabling real-time application during competition analysis. Second, it treats psychological resilience not as a background characteristic but as a live input variable updated through HRV monitoring, creating a dynamic rather than static psychological feature. Third, the framework includes an explicit data sufficiency gate (Figure 4), ensuring that the model does not generate low-confidence predictions when input data quality falls below a minimum threshold, a safeguard not present in earlier judo-specific AI applications [11].

Table 2 presents the feature architecture of JIPPS, listing each feature category, its extraction source, and its justification based on the reviewed literature. This structured feature specification is a prerequisite for reproducible model training and forms the basis for future validation studies.

Table 2. Feature architecture of the JIPPS framework: categories and extraction sources (composed by the author based on [4, 6, 8, 9, 11, 13, 14, 15, 18]).

Feature Category	Source / Instrument	Feature Count
Kinematic motion features	AlphaPose / YOLOv8 skeleton	36 (18 joints x 2D)
Spatiotemporal grip features	Dual-skeleton relative tracking	12
LSTM temporal embeddings	LSTM encoder (150-frame window)	128-dim vector
Trait resilience (CD-RISC 10)	Pre-competition questionnaire	1 (composite score)
State anxiety / HRV	Wrist sensor + 5-item CSAI-2S	3
Contextual competition variables	Match metadata (weight class, seeding)	5

Based on the synthesis of reviewed evidence and the proposed framework design, this section presents five original recommendations for practitioners and researchers working at the intersection of judo performance analysis and applied AI.

Recommendation 1: Adopt a two-sensor minimum standard for video capture at elite training camps. A paired front-and-side camera setup at 60fps is sufficient for AlphaPose or YOLOv8 skeleton extraction. This configuration, validated in tournament footage [10], avoids the cost of laboratory motion capture while delivering the spatial resolution needed for grip-sequence analysis. National federations should integrate this as a baseline for athlete monitoring protocols.

Recommendation 2: Incorporate CD-RISC 10 assessment as a routine pre-competition screening tool. Given the confirmed association between resilience scores and competitive level ($p < 0.001$) [8], resilience indexing provides actionable pre-match intelligence that informs tactical preparation and psychological support allocation. Coaches should be trained to interpret scale outputs not merely as mental health indicators but as performance-predictive signals.

Recommendation 3: Develop sport-specific labeled datasets for judo LSTM training. The absence of publicly available, annotated judo match datasets with frame-level outcome labels remains the most significant technical barrier to deploying AI models operationally. The USA Judo annotation project [10] provides a methodological template; a coordinated effort among IJF-affiliated national federations to create and share standardized training datasets would accelerate progress across the research community.

Recommendation 4: Implement HRV monitoring during warm-up as a state psychological feature input. The hybrid model framework validated in Scientific Reports [9] demonstrated that combining trait psychological measures with physiological state indicators significantly improves prediction accuracy beyond using questionnaire scores alone. Wrist-worn consumer HRV devices now achieve sufficient measurement fidelity for this purpose and represent a low-burden addition to pre-match preparation routines.

Recommendation 5: Evaluate JIPPS through a prospective validation study at national or international competition level. The framework design presented here is grounded in published evidence but has not yet been evaluated on prospective judo-specific data. A validation protocol involving a minimum sample of 60 elite athletes across two competition cycles, with blind outcome labeling by certified referees, is proposed as the logical next step for this research program.

Table 3 presents a comparison of the proposed JIPPS framework against the two most closely related prior approaches in judo AI research, illustrating how the integrated multi-modal design addresses the limitations identified in earlier work.

Table 3. Comparative analysis of JIPPS against the RT-XSM prior approach in judo AI research (composed by the author based on [9, 11, 19, 20]).

Dimension	RT-XSM [11] (Prior Approach)	JIPPS (Proposed Framework)
Input modality	Motion only (grip posture factors)	Motion + Psychological + HRV
Temporal window	Static frame / short sequence	150-frame (5s) LSTM rolling window
Psychological component	Absent	CD-RISC 10 + CSAI-2S + HRV
Prediction target	Technique type (categorical)	Technical-tactical success probability (continuous)
Benchmark accuracy	~71%	90%* (*from analogous biometric study [9])
Data sufficiency gate	Not included	Included (automated quality check)
Coaching output	Technique probability ranking	Success probability + resilience flag + technique pattern

The evidence reviewed in this study consistently supports a key insight: elite judo performance is not differentiated by greater raw physical speed or strength alone. Pang et al. [6] found that action recognition systems in martial arts performed substantially better when temporal sequence context was preserved, reflecting the anticipatory nature of combat sports decision-making. Garrido-Munoz et al. [8] established that resilience is a statistically differentiating variable at the elite level, not merely a developmental benefit. Combining these findings within a single predictive system addresses a research gap that both streams of literature have identified independently, and JIPPS represents an attempt to operationalize that combination in an architecturally coherent way.

One consideration for researchers adopting this framework is data access. Tournament video data requires federation cooperation and raises athlete data privacy questions that must be addressed through institutional review processes and informed consent protocols consistent with the American Psychological Association code [16]. Federated learning architectures, where model training occurs locally at federation nodes without centralizing raw athlete data, represent a technically feasible privacy-preserving alternative that future studies should explore.

Conclusion

This study addressed the goal of developing an evidence-based multi-modal AI framework for predicting technical-tactical performance in elite judo by integrating motor pattern analysis with psychological resilience indicators. The systematic synthesis of 20 peer-reviewed sources confirmed that single-modality AI models in judo and related sports reach predictive accuracy ceilings of approximately 71 to 84%, while hybrid frameworks integrating biometric and psychological features achieve up to 90% accuracy. This supports the central hypothesis that combined modality models outperform single-domain approaches.

The proposed JIPPS framework addresses the principal gap identified in the judo AI literature, namely the absence of psychological resilience as an operationalized predictive feature within a motion-based architecture. The framework is grounded in empirical data from a 702-judoka resilience study [8], validated pose estimation pipelines from tournament footage [10], and hybrid model accuracy benchmarks from the sports science literature [9]. Its five-stage pipeline, from data capture through coaching output generation, is designed for practical deployment in elite training environments without requiring laboratory-grade equipment.

Five practical recommendations are provided for coaches, sports scientists, and federation analysts: adopt minimum two-camera video capture standards, integrate CD-RISC 10 as a routine pre-competition screening tool, develop shared labeled judo datasets, use HRV monitoring as a state psychological input, and conduct a prospective validation study with a minimum of 60 elite athletes. These steps form a coherent research and implementation agenda for the sport.

The findings and proposed framework are relevant to sports scientists, performance analysts, judo coaches, and researchers working at the intersection of AI, applied sport psychology, and combat sports performance analysis. Beyond judo, the methodological principles of multi-modal psychological and motion feature fusion are transferable to other combat sports, team sports requiring anticipatory decision-making, and military selection contexts.

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