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Artificial Intelligence (AI)-Predicted Joint Stress Indices and Overuse Injuries in Martial Arts Training Among Martial Arts Athletes

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Abstract: Artificial intelligence offers a paradigm shift from reactive to proactive injury prevention in sports, yet its practical acceptance and accuracy in high-impact disciplines like martial arts require empirical validation. This study investigated martial arts athletes' perceptions of AI-predicted joint stress indices and their correlation with overuse injuries, guided by the Human-AI Teaming framework. Employing a descriptive-comparative-correlational design, 355 martial arts athletes from a university setting completed a validated questionnaire assessing AI-predicted indices across five dimensions: stability, symmetry, alignment, variability, and reproducibility. Descriptive and inferential statistics analyzed the data.Results indicated a uniform, moderate perception of the AI system's accuracy, with an overall mean rating of 1.91 (SD=0.79) on a 4-point Likert scale, interpreted as "Slightly Accurate." Reproducibility of feedback was the highest-rated dimension (Mean=1.94), while stability, symmetry, and alignment were rated lowest (Mean=1.90). Statistical analyses revealed no significant differences in these perceptions based on athlete sex, age, martial arts discipline, or years of experience. The findings suggest that while AI is recognized as a potentially valuable tool for longitudinal monitoring, its current application is perceived as lacking the nuanced accuracy required for detailed biomechanical feedback and immediate technical correction. The study concludes that AI-predicted joint stress indices hold promise as a supplementary tool for injury prevention but require significant algorithmic refinement to improve biomechanical fidelity and athlete trust before achieving full integration into personalized training frameworks.
Keywords: Artificial Intelligence, Joint Stress Indices, Overuse Injuries, Martial Arts Training, Injury Prevention, Biomechanical Monitoring, Sports Technology

I. Introduction

Artificial intelligence has become a transformative force in sports science, providing advanced tools for optimizing performance and preventing injury. In martial arts, athletes routinely endure high-impact, repetitive movements that place cumulative strain on joints, leading to a high prevalence of overuse injuries that can hinder development and shorten careers. Traditional injury prevention methods, relying on subjective feedback and generalized modifications, often fail to address the dynamic and individualized nature of biomechanical stress. AI, particularly through predictive analytics, enables a paradigm shift toward a proactive and personalized approach to safeguarding athlete health. The repetitive techniques of punching, kicking, and grappling generate substantial stress on joints such as the knees, shoulders, and ankles. Current monitoring often only identifies injuries after they occur, making rehabilitation reactive. In contrast, AI systems can analyze data from motion capture, force plates, and wearable sensors to model and predict joint stress in real time. Research by Liu et al. (2025) has used deep learning to identify biomechanical precursors to injury in martial artists, while Chen and Tang (2025) and Bakirtzis et al. (2024) demonstrated convolutional neural networks effectively assess muscle and joint load, offering actionable feedback to reduce risks.

These technologies move beyond one-size-fits-all training. AI can offer individualized insights, recommending adjustments in intensity, volume, and technique to balance performance and joint health. This study therefore investigates the relationship between AI-predicted joint stress indices and overuse injury incidence in martial arts. The objective is to validate AI models within a data-driven injury prevention framework, contributing to safer and more sustainable training methodologies for athletes.

To guide this investigation, the study seeks to answer the following research questions:

1. What is the demographic profile of the athlete respondents in terms of sex, age, type of martial arts practiced, and number of years as a martial arts athlete?
2. What is the self-assessment of athlete respondents of their AI-predicted joint stress indices in terms of stability of stress levels across sessions, symmetry of joint loading, alignment with actual movement patterns, variability in stress distribution, and reproducibility of AI feedback?
3. Is there a significant difference in the self-assessment of athlete respondents of their AI-predicted joint stress indices when they are grouped according to their profile?

II. Literature Review

This review examines biomechanical foundations, injury epidemiology, and AI applications in martial arts injury

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prevention, highlighting opportunities for data-driven approaches to address overuse injuries [1-3].

A. Biomechanical Foundations

Biomechanics provides the foundation for analyzing martial arts techniques through kinematic and kinetic assessment [4]. Movement analysis enables optimization of performance while identifying injury-risk patterns in techniques like kicking and punching [5,6]. Biomechanical modeling facilitates individualized training programs through workload monitoring and recovery assessment [7,8]. Current limitations include motion capture costs and ecological validity challenges in laboratory settings [9,10].

B. Injury Epidemiology

Martial arts injury epidemiology shows distinct patterns across demographics and disciplines [11]. Research indicates higher injury incidence among male practitioners, particularly adolescents, with upper extremity injuries being most prevalent [12-14]. Shoulder injuries from repetitive impact and improper technique represent significant concerns that can lead to chronic conditions [15,16]. The field requires increased focus on preventive approaches rather than treatment-oriented solutions [17,18].

C. AI in Injury Prediction

Artificial intelligence enables advanced pattern recognition in biomechanical data analysis [19]. Machine learning applications demonstrate capabilities in predicting joint stress and identifying injury-risk movement patterns [20,21]. Multi-modal data integration from wearable sensors and video systems enhances predictive accuracy for personalized interventions [22,23]. Implementation challenges include technical barriers, data privacy concerns, and integration with existing training methodologies [24,25].

III. Theoretical Framework

This study is grounded in the theoretical perspective of Human-AI Teaming (HAT), which conceptualizes artificial intelligence not as a passive tool but as an active, collaborative teammate within the coach-athlete dynamic. The core premise of HAT is that effective outcomes depend on shared situation awareness, calibrated trust, and clear role definition between human and artificial agents. In the context of martial arts training, the AI teammate's role is to sense and predict joint stress indices from biomechanical data, while the human coach interprets these predictions within the broader training context and the athlete's condition. Together, this team decides on interventions, such as adjusting training load or technique, to mitigate the risk of overuse injuries.

The framework posits that the successful application of AI-predicted joint stress indices to prevent injuries is contingent upon several factors derived from HAT principles. First, the AI's predictive validity and its explainability—the ability to clarify why a specific stress level is predicted—are critical for building appropriate human trust and enabling informed decision-making. Second, the framework incorporates the calibration of trust, where coaches must learn to rely on AI outputs without succumbing to automation bias or unjustified rejection. Finally, effective workflow integration is essential, ensuring that AI-generated alerts and recommendations are presented in a way that augments, rather than disrupts, the coaching process, with humans retaining final authority over training adjustments. Thus, this framework theorizes that a reduction in overuse injuries will be achieved not by the AI's predictions alone, but through the quality of the human-AI teaming process.

IV. Methodology

This study employed a descriptive-comparative-correlational research design. It was conducted at Jiaozuo University in China with a purposive sample of 150 martial arts athletes who had at least one year of training and competitive experience. This sampling ensured participants had sufficient background to provide meaningful assessments of joint stress and injury patterns.

Data were collected using a researcher-made questionnaire containing three sections: demographic profile, self-assessment of AI-predicted joint stress indices (stability, symmetry, alignment, variability, reproducibility), and self-assessment of overuse injuries. Responses were recorded on a 4-point Likert scale. The instrument was validated by experts and pilot-tested, with reliability confirmed via Cronbach's Alpha in SPSS.

Data analysis utilized descriptive statistics to summarize profiles and assessments. Comparative analyses used t-tests and ANOVA to examine differences across demographic groups, while Pearson's r correlation analyzed the relationship between stress indices and injuries. All analyses were performed in SPSS with significance at $p < 0.05$. The study adhered to strict ethical protocols, including informed consent, confidentiality, and voluntary participation.

V. Results And Discussions

Table 1 presents the demographic profile of the 355 martial arts athlete respondents. The data reveals a significant gender disparity, with males constituting the overwhelming majority (83.7%) of the sample. This substantial imbalance is consistent with broader trends in many traditional and competitive martial arts disciplines, which have historically been male-dominated. The high concentration of young adults, particularly those aged 18 and above (98.6% of the sample), accurately reflects the typical demographic of university-level athletes. This age group represents individuals who are physically mature and actively engaged in structured training programs, making their experiences highly relevant to the study's focus on joint stress and overuse injuries.

Regarding the types of martial arts practiced, Tai Chi emerges as the predominant discipline (74.9%), which is a notable finding. Unlike more high-impact martial arts, Tai Chi is characterized by slow, controlled movements and is often practiced for its health benefits. This prevalence may influence the overall patterns of joint stress and injury reported in the study, potentially skewing results towards a lower incidence of acute or high-impact overuse injuries. Furthermore, the data on experience shows that a significant majority of respondents (74.9%) have been practicing for less than three years, indicating a sample largely composed of novice to intermediate-level athletes. This inexperience is a critical factor, as less seasoned athletes may have different biomechanics and higher susceptibility to overuse injuries compared to their more experienced counterparts.

Table 1 Frequency Distribution of the Respondents' Demographic Profile

Profile	Frequency	Percentage
Sex		
Male	**297**	**83.7%**
Female	58	16.3%
Total	355	100%
Age		
Below 17 years old	1	0.3%
17 years old	4	1.1%
18 years old	149	42.0%
More than 18 years old	201	56.6%
Total	355	100%
Types of Martial Arts Practiced		
Shaolin	39	11.0%
Tai Chi	266	74.9%
Wing Chun	2	0.6%
Xingyiquan	7	2.0%
Baguazhang	4	1.1%
Others	37	10.4%
Total	355	100%
Number of Years as Martial Arts Athlete		
Less than 3 years	266	74.9%
3-5 years	27	7.6%
More than 5 years	62	17.5%
Total	355	100%

Table 2 reveals that athletes perceive the stability of the AI-predicted joint stress indices as only "Slightly Accurate," with a composite mean of 1.90. The highest-ranked indicators suggest the AI system shows a modest ability to maintain consistent readings despite variations in training intensity and minor movement errors, both scoring 1.93. This indicates a foundational level of robustness that is perceptible to users. However, the lowest-ranked item, concerning the absence of unexpected fluctuations between sessions (mean=1.88), highlights a significant user concern regarding the system's reliability over time. The overall low scores across all indicators, clustered tightly together, suggest that while the AI demonstrates a basic level of functional stability, it is not yet perceived as a dependable or predictable tool for tracking stress session-to-session.

The generally tentative ratings imply that the AI's algorithmic predictions may be susceptible to noise or inconsistencies that undermine athlete confidence. For an injury prevention tool, predictability is paramount; coaches and athletes need to trust that a change in the stress index reflects a genuine change in biomechanical load, not an artifact of the system itself. The current "Slightly Accurate" perception suggests that the AI's output stability requires significant improvement. Enhancing the system's filtering algorithms and validating its predictions against gold-standard biomechanical measurements could be crucial next steps to transition the technology from a novel indicator to a trusted component of daily training monitoring.

Table 2 Respondents' Self-Assessment of their AI-Predicted Joint Stress Indices in Terms of Stability of Stress Levels Across Sessions

Stability of Stress Levels Across Sessions	Mean	SD	Qualitative Description	Interpretation	Rank
The AI predictions show consistent stress levels across multiple training sessions.	1.89	0.89	Slightly True	Slightly Accurate	6.5
The stress indices remain stable even when training intensity varies.	1.93	0.89	Slightly True	Slightly Accurate	1.5
My AI-predicted joint stress indices are not easily influenced by minor movement errors.	1.93	0.87	Slightly True	Slightly Accurate	1.5
Stress values from the AI system show predictable patterns across repeated drills.	1.89	0.85	Slightly True	Slightly Accurate	6.5
The AI consistently reflects stable stress indices from warm-up to cooldown phases.	1.89	0.85	Slightly True	Slightly Accurate	6.5
My AI-predicted stress levels do not fluctuate unexpectedly between sessions.	1.88	0.84	Slightly True	Slightly Accurate	9
The stability of AI predictions increases my trust in the feedback.	1.92	0.86	Slightly True	Slightly Accurate	3
AI outputs for stress indices remain reliable even with different session durations.	1.89	0.84	Slightly True	Slightly Accurate	6.5
The system demonstrates dependable stress monitoring throughout extended practice.	1.91	0.87	Slightly True	Slightly Accurate	4
Composite Mean	1.90	0.81	Slightly True	Slightly Accurate	

Legend: 3.51-4.00 Very True/Very Accurate; 2.51-3.50 True /Accurate;1.51-2.50 Slightly True /Slightly Accurate;1.00-1.1.50 Not True /Not Accurate

The data in Table 3 indicates that athletes view the AI's assessment of joint loading symmetry as "Slightly Accurate" (composite mean=1.90). Notably, the highest-ranked items (mean=1.92) relate to the AI's ability to identify asymmetries and reflect equilibrium, suggesting its primary value lies in detecting imbalances that may not be obvious to the athlete during training. This points to the AI's potential role as an augmentative tool for enhancing body awareness, providing an objective measure to complement subjective physical sensation. However, the lower score for the indicator concerning minimal differences in stress between symmetrical movements (mean=1.88) reveals a critical limitation: users are less convinced of the system's precision in confirming well-executed, balanced technique.

This pattern of results presents a dual narrative. On one hand, the AI shows promise as a diagnostic tool for uncovering hidden asymmetries that are risk factors for overuse injuries. On the other hand, its inability to consistently validate symmetry undermines confidence in its quantitative accuracy. For practical application, coaches need to trust that the system can accurately distinguish between balanced and imbalanced loading, not just flag potential problems. Therefore, refining the system's sensitivity and specificity for bilateral comparison is essential. Improving the calibration of sensors and the biomechanical models used to interpret the data could enhance the perceived accuracy and make the AI a more reliable partner in technique correction and injury prevention.

Table 3 Respondents' Self-Assessment of their AI-Predicted Joint Stress Indices in Terms of Symmetry of Joint Loading

Symmetry of Joint Loading	Mean	SD	Qualitative Description	Interpretation	Rank
The AI indicates balanced stress distribution between left and right joints.	1.90	0.84	Slightly True	Slightly Accurate	6
The predicted indices show minimal differences in stress between symmetrical movements.	1.88	0.84	Slightly True	Slightly Accurate	9
My AI feedback highlights consistent bilateral loading during repetitive kicks.	1.92	0.86	Slightly True	Slightly Accurate	2.5
Stress indices reveal even weight-bearing across both legs.	1.91	0.87	Slightly True	Slightly Accurate	5
The AI detects and reports when one side experiences higher stress than the	1.89	0.85	Slightly True	Slightly Accurate	7.5

Symmetry of Joint Loading	Mean	SD	Qualitative Description	Interpretation	Rank
other.					
Symmetry in predicted joint loading aligns with my actual physical sensations.	1.89	0.84	Slightly True	Slightly Accurate	7.5
AI stress indices reflect equilibrium across joint movements.	1.92	0.86	Slightly True	Slightly Accurate	2.5
The feedback captures asymmetries that I might not notice during training.	1.92	0.85	Slightly True	Slightly Accurate	2.5
The indices are accurate in identifying left-right stress imbalances.	1.92	0.85	Slightly True	Slightly Accurate	2.5
Composite Mean	1.90	0.81	Slightly True	Slightly Accurate	

Legend: 3.51-4.00 Very True/Very Accurate; 2.51-3.50 True /Accurate;1.51-2.50 Slightly True /Slightly Accurate;1.00-1.1.50 Not True /Not Accurate

able 4 shows a composite mean of 1.90, indicating a "Slightly Accurate" perception of the AI's alignment with athletes' actual movement patterns. The highest-rated item (mean=1.93) pertains to the system's ability to reflect stress changes as movement patterns adapt, suggesting it is most responsive to dynamic, gross motor adjustments. Similarly, items relating to movement rhythm, fatigue adjustments, and motor control (mean=1.91) were perceived more favorably, indicating the AI captures broad, perceptible trends in biomechanical output. In contrast, the lowest-ranked items involved aligning with the specific biomechanical phases of kicks and detecting form breakdown (means=1.87 and 1.89), indicating a weakness in analyzing fine-grained, technically precise elements of movement.

This discrepancy suggests that the AI system currently operates effectively at a macro level but lacks the nuanced understanding required for detailed technical feedback. Athletes and coaches may find the general stress trends useful for monitoring overall exertion but are likely to distrust the AI's assessment of specific technique flaws. For the system to evolve from a general indicator to a coaching aid, its algorithms must be refined to better deconstruct complex martial arts movements into their constituent phases. Integrating more sophisticated movement pattern recognition that correlates with expert biomechanical analysis would be necessary to improve alignment and make the feedback actionable for technical refinement.

Table 4 Respondents' Self-Assessment of their AI-Predicted Joint Stress Indices in Terms of Alignment with Actual Movement Patterns

Alignment with Actual Movement Patterns	Mean	SD	Qualitative Description	Interpretation	Rank
The AI stress predictions correspond well with my observed joint movements.	1.92	0.85	Slightly True	Slightly Accurate	2
The indices align with my video analysis of joint mechanics.	1.90	0.84	Slightly True	Slightly Accurate	6.5
AI-predicted stress levels match my coach's assessment of my movements.	1.90	0.85	Slightly True	Slightly Accurate	6.5
The indices reflects changes in stress as my movement patterns adapt.	1.93	0.86	Slightly True	Slightly Accurate	1
My joint stress data mirrors the biomechanical phases of my kicks.	1.87	0.85	Slightly True	Slightly Accurate	9
The AI captures stress changes that occur when my form breaks down.	1.89	0.86	Slightly True	Slightly Accurate	8
My movement rhythm and stress indices are consistent with one another.	1.91	0.86	Slightly True	Slightly Accurate	4
The indices accurately mirror my body's adjustments during fatigue.	1.91	0.84	Slightly True	Slightly Accurate	4
The AI's predicted stress levels are consistent with my actual motor control.	1.91	0.84	Slightly True	Slightly Accurate	4
Composite Mean	1.90	0.81	Slightly True	Slightly Accurate	

Legend: 3.51-4.00 Very True/Very Accurate; 2.51-3.50 True /Accurate;1.51-2.50 Slightly True /Slightly Accurate;1.00-1.1.50 Not True /Not Accurate

The assessment of variability in stress distribution in Table 5 received a composite mean of 1.91 ("Slightly Accurate").

The system scored highest (mean=1.94) in capturing stress fluctuations during transitions between stances, indicating a particular sensitivity to dynamic weight-shifting and changes in base of support. This is a valuable capability, as these transitions are critical moments for joint loading. The AI also performed relatively well in reflecting uneven loading across movement phases and differentiating between speed and power drills (means=1.93 and 1.92), showing an ability to discern stress patterns based on movement intent and phase.

However, the lowest score (mean=1.89) was for detecting subtle variations during complex kicks, revealing a significant limitation in analyzing sophisticated, multi-joint techniques. This suggests the system's models may be better at handling larger, more generalized movement patterns than the intricate mechanics of advanced techniques. For martial artists, understanding stress variability within a single complex movement is crucial. Therefore, enhancing the AI's resolution to map stress distribution withina technique, rather than just between different types of drills, is a key area for development. Improving the granularity of the analysis would make the variability data much more meaningful for technique optimization and targeted injury prevention.

Table 5 Respondents' Self-Assessment of their AI-Predicted Joint Stress Indices in Terms of Variability in Stress Distribution

Variability in Stress Distribution	Mean	SD	Qualitative Description	Interpretation	Rank
The AI detects subtle variations in stress distribution during complex kicks.	1.89	0.86	Slightly True	Slightly Accurate	9
My predicted stress indices reflect uneven loading in different movement phases.	1.93	0.86	Slightly True	Slightly Accurate	2
The AI shows distinct stress patterns during speed versus power drills.	1.92	0.86	Slightly True	Slightly Accurate	4
Variability in stress indices corresponds with my changes in kicking intensity.	1.90	0.84	Slightly True	Slightly Accurate	8
The predictions capture fluctuations in stress during transitions between stances.	1.94	0.85	Slightly True	Slightly Accurate	1
AI outputs differentiate stress loads across upper and lower joints	1.91	0.86	Slightly True	Slightly Accurate	6.5
The variability in stress predictions reflected my dynamic movement adjustments.	1.92	0.87	Slightly True	Slightly Accurate	4
The indices highlight changing stress levels as I switch between offensive and defensive moves.	1.91	0.86	Slightly True	Slightly Accurate	6.5
The variability data helps me adjust to reduce injury risks.	1.92	0.87	Slightly True	Slightly Accurate	4
Composite Mean	1.91	0.82	Slightly True	Slightly Accurate	

Legend: 3.51-4.00 Very True/Very Accurate; 2.51-3.50 True /Accurate;1.51-2.50 Slightly True /Slightly Accurate;1.00-1.1.50 Not True /Not Accurate

Table 6 indicates that reproducibility is the strongest dimension of the AI system, achieving the highest composite mean of 1.94, though it remains in the "Slightly Accurate" range. The highest-ranked item (mean=1.96) confirms that stress predictions are consistent when sessions are repeated on different days, which is fundamental for tracking progress over time. The high scores for items related to confidence in adjustments, reliability in practice versus sparring, and tracking weekly progress (mean=1.95) indicate that this day-to-day consistency is translating into a degree of practical utility and trust for longitudinal monitoring.

Despite being the highest-rated dimension, the scores still indicate only modest reproducibility. The lower scores for consistency in repeating the same drill and across different environments (means=1.91 and 1.92) point to contextual vulnerabilities. This suggests that while the system is stable over a long-term, controlled timeline, it may be influenced by immediate factors like specific drill execution or environmental conditions. For the AI to be fully integrated into training, its outputs must be robust and repeatable in all contexts, not just over time. Enhancing the system's calibration protocols and ensuring its algorithms are insensitive to minor contextual changes are necessary steps to solidify its reputation as a reliable and reproducible tool.

Table 6 Respondents' Self-Assessment of their AI-Predicted Joint Stress Indices in Terms of Reproducibility of AI Feedback

Reproducibility of AI Feedback	Mean	SD	Qualitative Description	Interpretation	Rank
The AI system produces consistent stress indices when the same drill is repeated.	1.91	0.85	Slightly True	Slightly Accurate	9
My predicted indices are reproducible across different practice environments.	1.92	0.85	Slightly True	Slightly Accurate	8
Stress predictions remain consistent even when I repeat sessions on separate days.	1.96	0.86	Slightly True	Slightly Accurate	1
The producibility of feedback increases my confidence in training adjustments.	1.95	0.97	Slightly True	Slightly Accurate	3
AI-predicted stress levels are reliable during both practice and sparring.	1.95	0.85	Slightly True	Slightly Accurate	3
The indices reproduce stable results despite variations in recording conditions.	1.93	0.86	Slightly True	Slightly Accurate	6.5
AI feedback provides repeatable results when tracking progress over weeks.	1.95	0.87	Slightly True	Slightly Accurate	3
My reproducibility scores match those of my teammates using the same system.	1.94	0.85	Slightly True	Slightly Accurate	4
The consistent reproduction of feedback allows me to track long-term stress trends.	1.93	0.85	Slightly True	Slightly Accurate	6.5
Composite Mean	1.94	0.81	Slightly True	Slightly Accurate	

Legend: 3.51-4.00 Very True/Very Accurate; 2.51-3.50 True /Accurate;1.51-2.50 Slightly True /Slightly Accurate;1.00-1.1.50 Not True /Not Accurate

Table 7 provides a crucial overview, showing that all five dimensions of the AI-predicted joint stress indices are perceived as only "Slightly Accurate," with an overall mean of 1.91. Reproducibility of AI feedback is ranked highest (mean=1.94), indicating that consistency over time is the system's most recognized strength. Variability in stress distribution follows closely (mean=1.91), while stability, symmetry, and alignment are tied as the weakest perceived areas (mean=1.90). This tight clustering of means demonstrates that athletes do not perceive any single aspect of the AI's functionality as particularly strong or weak; instead, there is a uniformly moderate level of skepticism across the board.

This summary underscores that the AI system is currently viewed as a promising but unrefined technology. Its highest score in reproducibility suggests a solid foundation for longitudinal data collection, which is positive for research and trend analysis. However, the consistently low scores for core biomechanical assessments like stability, symmetry, and alignment reveal a significant gap between the technology's potential and its current practical utility for immediate training feedback and technical correction. The findings clearly indicate that substantial refinement is needed across all algorithmic domains to improve the system's accuracy, build user trust, and ultimately fulfill its promise as an effective tool for injury prevention and performance enhancement in martial arts.

Table 7 presents the summary of the respondents' self-assessment of their AI-predicted joint stress indices.

Table 7 Summary of the Respondents' Self-Assessment of their AI-Predicted Joint Stress Indices

AI-Predicted Joint Stress Indices	Mean	SD	Qualitative Description	Interpretation	Rank
Stability of Stress Levels Across Sessions	1.90	0.81	Slightly True	Slightly Accurate	4
Symmetry of Joint Loading	1.90	0.81	Slightly True	Slightly Accurate	4
Alignment with Actual Movement Patterns	1.90	0.81	Slightly True	Slightly Accurate	4
Variability in Stress Distribution	1.91	0.82	Slightly True	Slightly Accurate	2
Reproducibility of AI Feedback	1.94	0.81	Slightly True	Slightly Accurate	1
Overall Mean	1.91	0.79	Slightly True	Slightly Accurate	

Legend: 3.51-4.00 Very True/Very Accurate; 2.51-3.50 True /Accurate;1.51-2.50 Slightly True /Slightly Accurate;1.00-1.1.50 Not True /Not Accurate

Differences in the Self-Assessment of Respondents of their AI-Predicted Joint Stress Indices When Grouped According to Profile

Tables 8-11 present the differences in the self-assessment of athlete respondents of their AI-predicted joint stress indices

when they are grouped according to sex, age, type of martial arts practiced, and number of years as martial arts athlete.
On Sex
Table 8 presents the differences in the self-assessment of athlete respondents of their AI-predicted joint stress indices when they are grouped according to sex.
Table 8
Differences in the Self-Assessment of Respondents of their AI-Predicted Joint Stress Indices when Grouped According to Sex

Indicators	Sex	Mean	SD	Computed t-value	Sig	Decision on Ho	Interpretation
Stability of Stress Levels Across Sessions	Male	1.88	0.80	1.37	0.17	Accepted	Not Significant
	Female	2.04	0.87				
Symmetry of Joint Loading	Male	1.88	0.80	1.02	0.31	Accepted	Not Significant
	Female	2.00	0.85				
Alignment with Actual Movement Patterns	Male	1.89	0.81	0.68	0.50	Accepted	Not Significant
	Female	1.97	0.79				
Variability in Stress Distribution	Male	1.90	0.82	0.66	0.51	Accepted	Not Significant
	Female	1.98	0.81				
Reproducibility of AI Feedback	Male	1.92	0.81	0.16	0.38	Accepted	Not Significant
	Female	2.02	0.81				
Over-all	Male	1.90	0.79	0.12	0.34	Accepted	Not Significant
	Female	2.00	0.79				

As shown in Table 8, across all indicators, female respondents consistently reported slightly higher mean scores than male respondents, indicating a marginally more favorable perception of the AI system among females. However, the computed t-value for all dimensions, stability of stress levels across sessions, symmetry of joint loading, alignment with actual movement patterns, variability in stress distribution, and reproducibility of AI feedback, were all statistically non-significant. Consequently, the null hypothesis was accepted for each indicator, indicating no significant sex-based differences in self-assessment. The overall means further support this finding, with males and females both falling within the "slightly true/slightly accurate" range. These results imply that perceptions of the accuracy, consistency, and usefulness of AI-predicted joint stress indices are largely uniform across sexes, and that sex does not meaningfully influence how respondents evaluate the AI system's performance in monitoring joint stress.
Tables 8-11 present the differences in the self-assessment of athlete respondents of their AI-predicted joint stress indices when they are grouped according to sex, age, type of martial arts practiced, and number of years as martial arts athlete.
Table 9 presents the differences in the self-assessment of athlete respondents of their AI-predicted joint stress indices when they are grouped according to age.

Table 9 Differences in the Self-Assessment of Respondents of their AI-Predicted Joint Stress Indices when Grouped According to Age

Indicators	Age	Mean	SD	Computed F-value	Sig	Decision on Ho	Interpretation
Stability of Stress Levels Across Sessions	<17 y/o	3.00	.	0.84	0.47	Accepted	Not Significant
	17 y/o	2.20	0.90				
	18 y/o	1.92	0.78				
	>18 y/o	1.88	0.83				
Symmetry of Joint Loading	<17 y/o	3.00	.	0.86	0.46	Accepted	Not Significant
	17 y/o	2.25	0.96				
	18 y/o	1.89	0.78				
	>18 y/o	1.90	0.84				
Alignment with Actual Movement Patterns	<17 y/o	3.00	.	0.86	0.46	Accepted	Not Significant
	17 y/o	2.25	0.96				
	18 y/o	1.89	0.79				
	>18 y/o	1.90	0.82				
Variability in Stress Distribution	<17 y/o	3.00	.	0.82	0.48	Accepted	Not Significant
	17 y/o	2.25	0.96				

	18 y/o	1.91	0.81				
	>18 y/o	1.90	0.83				
Reproducibility of AI Feedback	<17 y/o	3.00	.	0.82	0.48	Accepted	Not Significant
	17 y/o	2.25	0.96				
	18 y/o	1.91	0.80				
	>18 y/o	1.94	0.82				
Over-all	<17 y/o	3.00	.	0.88	0.45	Accepted	Not Significant
	17 y/o	2.24	0.95				
	18 y/o	1.91	0.77				
	>18 y/o	1.91	0.79				

As shown in Table 9, although there are observable differences in mean scores across age groups, the computed F-values for all indicators range from 0.82 to 0.88, with corresponding significance values between 0.45 and 0.48, all exceeding the 0.05 level of significance. As a result, the null hypothesis was accepted for every dimension, indicating that age does not significantly influence respondents' self-assessment of the AI-predicted joint stress indices. Notably, respondents below 17 years old reported substantially higher mean scores across all indicators, falling within the "True/Accurate" range, while younger adults (17 years old) rated the system lower and older groups (18 and above) consistently reported the lowest means, corresponding to the "Slightly True/Slightly Accurate" range. Despite this apparent downward trend in perceived accuracy with increasing age, the lack of statistical significance indicates that these differences may be due to sample size limitations or variability within groups rather than true age-related effects. Overall, the findings imply that respondents across different age groups generally share similar perceptions of the AI system's performance, with age not emerging as a meaningful factor in shaping evaluations of the accuracy, consistency, or usefulness of AI-predicted joint stress indices.

Table 10 presents the differences in the self-assessment of athlete respondents of their AI-predicted joint stress indices when they are grouped according to type of martial arts practiced.

Table 10 Differences in the Self-Assessment of Respondents of their AI-Predicted Joint Stress Indices when Grouped According to Type of Martial Arts Practiced

Indicators	Type of Martial Arts Practiced	Mean	SD	Computed F-value	Sig	Decision on Ho	Interpretation
Stability of Stress Levels Across Sessions	Shaolin	1.74	0.84	1.97	0.08	Accepted	Not Significant
	Tai Chi	1.89	0.79				
	Wing Chun	1.00	0.00				
	Xingyiquan	2.17	0.90				
	Baguazhang	2.61	0.62				
	Others	2.08	0.86				
Symmetry of Joint Loading	Shaolin	1.85	0.82	1.40	0.23	Accepted	Not Significant
	Tai Chi	1.88	0.80				
	Wing Chun	1.00	0.00				
	Xingyiquan	2.21	0.90				
	Baguazhang	2.36	0.40				
	Others	2.08	0.89				
Alignment with Actual Movement Patterns	Shaolin	1.85	0.83	1.52	0.18	Accepted	Not Significant
	Tai Chi	1.88	0.80				
	Wing Chun	1.00	0.00				
	Xingyiquan	2.17	0.90				
	Baguazhang	2.44	0.42				
	Others	2.09	0.87				
Variability in Stress Distribution	Shaolin	1.81	0.83	1.41	0.22	Accepted	Not Significant
	Tai Chi	1.90	0.82				
	Wing Chun	1.00	0.00				
	Xingyiquan	2.24	0.92				
	Baguazhang	2.31	0.28				
	Others	2.09	0.85				
Reproducibility of AI Feedback	Shaolin	1.85	0.80	1.79	0.11	Accepted	Not Significant
	Tai Chi	1.91	0.81				
	Wing Chun	1.00	0.00				

Indicators	Type of Martial Arts Practiced	Mean	SD	Computed F-value	Sig	Decision on Ho	Interpretation
	Xingyiquan	2.17	0.90				
	Baguazhang	2.39	0.45				
	Others	2.19	0.83				
Over-all	Shaolin	1.82	0.80	1.68	0.14	Accepted	Not Significant
	Tai Chi	1.89	0.78				
	Wing Chun	1.00	0.00				
	Xingyiquan	2.19	0.90				
	Baguazhang	2.42	0.42				
	Others	2.11	0.81				

As shown in Table 10, across all indicators, the computed F-values range from 1.40 to 1.97, with corresponding significance values between 0.08 and 0.23, all of which exceed the 0.05 level of significance. Consequently, the null hypothesis was accepted for every dimension, indicating that there are no statistically significant differences in self-assessment based on the type of martial art practiced. Descriptively, however, some variation in mean scores is evident. Practitioners of Baguazhang and Xingyiquan generally reported higher mean scores across most indicators, indicating a relatively more favorable perception of the AI system's ability to capture joint stress characteristics, while Wing Chun practitioners consistently reported the lowest mean scores, indicating minimal perceived accuracy. Shaolin and Tai Chi practitioners tended to cluster around the overall mean, reflecting "Slightly True/Slightly Accurate" perceptions similar to the broader sample. Despite these observable differences, the lack of statistical significance indicates that the variations may be attributed to small or uneven group sizes rather than genuine differences in how the AI system performs across martial arts styles. Overall, the findings imply that the perceived accuracy, variability, and reproducibility of AI-predicted joint stress indices are generally consistent across different martial arts disciplines, and that the type of martial art practiced does not significantly influence respondents' evaluations of the AI system.

Table 11 presents the differences in the self-assessment of athlete respondents of their AI-predicted joint stress indices when they are grouped according to number of years as martial arts athlete.

Table 11 Differences in the Self-Assessment of Respondents of their AI-Predicted Joint Stress Indices when Grouped According to Number of Years as Martial Arts Athlete

Indicators	Years as Martial Arts Athlete	Mean	SD	Computed F-value	Sig	Decision on Ho	Interpretation
Stability of Stress Levels Across Sessions	<3 years	1.95	0.80	3.07	0.08	Accepted	Not Significant
	3-5 years	1.57	0.72				
	>5 years	1.83	0.86				
Symmetry of Joint Loading	<3 years	1.94	0.80	1.27	0.28	Accepted	Not Significant
	3-5 years	1.73	0.73				
	>5 years	1.82	0.88				
Alignment with Actual Movement Patterns	<3 years	1.93	0.79	0.67	0.51	Accepted	Not Significant
	3-5 years	1.78	0.75				
	>5 years	1.84	0.92				
Variability in Stress Distribution	<3 years	1.94	0.80	0.90	0.41	Accepted	Not Significant
	3-5 years	1.73	0.74				
	>5 years	1.878	0.92				
Reproducibility of AI Feedback	<3 years	1.98	0.80	1.60	0.20	Accepted	Not Significant
	3-5 years	1.72	0.72				
	>5 years	1.86	0.90				
Over-all	<3 years	1.95	0.77	1.46	0.23	Accepted	Not Significant
	3-5 years	1.71	0.69				
	>5 years	1.84	0.87				

As shown in Table 11, Across all indicators, the computed F-values range from 0.67 to 3.07, with corresponding significance values between 0.08 and 0.51, all of which exceed the 0.05 level of significance. As a result, the null hypothesis was accepted for every dimension, indicating that years of experience in martial arts do not significantly influence respondents' self-assessment of the AI-predicted joint stress indices. Descriptively, athletes with less than three years of experience consistently reported the highest mean scores across most indicators, while those with three to five years of experience reported the lowest mean scores, and those with more than five years of experience fell in between. All group means remained within the "Slightly True/Slightly Accurate" range, indicating a generally modest perception of the AI system regardless of experience level. The slightly lower ratings from more experienced practitioners may reflect higher expectations or greater biomechanical awareness, whereas less experienced athletes may perceive the AI feedback as more helpful or informative. However, since these differences are not statistically significant, they should be interpreted with caution. Overall, the findings indicate that the perceived accuracy, stability, variability, and reproducibility of AI-predicted joint stress indices are relatively consistent across different levels of martial arts experience, indicating that the AI system's perceived performance is not meaningfully affected by the length of athletic practice.

VI. Conclusion

This study assessed martial arts athletes' perceptions of AI-predicted joint stress indices. The findings indicate that while athletes acknowledge the technology's potential, they perceive its current accuracy as only moderate. Reproducibility was the strongest dimension, suitable for longitudinal trend monitoring, whereas stability, symmetry, and alignment require significant algorithmic improvement. Perceptions were consistent across all demographic groups, indicating the limitations are fundamental to the technology itself.

For coaches and athletes, these results carry direct practical implications. Coaches should currently treat AI-generated joint stress data as a supplementary screening tool for identifying potential risk trends, not as a definitive diagnostic or technique-correction system. Its best use is in tracking broad load trends over time to inform periodization. Athletes should be educated that the feedback is probabilistic and must be interpreted alongside subjective feelings of pain, fatigue, and coach observation. Trust in the system must be calibrated—neither ignored nor blindly followed.

Successful integration requires a human-in-the-loop model. Coaches remain essential for interpreting AI outputs within the full context of an athlete's condition, making final decisions on training adjustments. Future development must focus on improving real-time biomechanical fidelity and creating intuitive feedback interfaces. When refined, this technology can evolve into a vital component of a data-informed coaching process, helping to balance performance and joint health proactively.

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