JAAFR INTERNATIONAL RESEARCH JOURNAL
JOURNAL OF ADVANCE AND FUTURE RESEARCH
JAAFR.ORG | ISSN : 2984-889X
An International Open Access, Peer-reviewed, Refereed Journal

AI-Augmented Yoga Training for Elite Basketball Performance: A Machine Learning-Guided 12-Week Intervention for Physical, Psychological, and Recovery Optimization in Indian Male Athletes

Dr.B.Bapireddy[1], K. Krishna Reddy [2], A.N.Ramamamni[3]
[1]*Department of Physical Education, SVKP & Dr. KS Raju A & S College(A), Penugonda, A.P, India*
[2]*Retired PET, President of West Godavari Basket Ball Association, Marteru, A.P, India*
[3]*Department of Master of Computer Applications, SVKP & Dr. KS Raju A&S College(A),Penugonda, A.P, India*

ABSTRACT

Background: Basketball demands explosive power, dynamic balance, cardiovascular endurance, rapid reaction, and psychological composure. Yoga offers a holistic framework integrating asanas, pranayama, and dhyana for multidimensional athletic enhancement. Despite its potential, the integration of Artificial Intelligence (AI) to personalize yoga prescriptions, continuously monitor performance, and predict injury risk in elite basketball players remains unexplored. This study uniquely bridges traditional yoga science with AI-driven adaptive technologies.

Objectives: This AI-augmented randomized controlled trial examined the effects of a machine learning-guided 12-week yoga intervention on physical performance parameters, psychological well-being, and recovery metrics in elite Indian male basketball players — comparing AI-personalized yoga delivery against standard yoga and control conditions.

Methods: Seventy-five elite male basketball players (age: 21.4 ± 1.8 years) were randomly assigned to three groups: AI-Yoga Group (AYG, n=25), Standard Yoga Group (SYG, n=25), and Control Group (CG, n=25). The AYG utilized a custom AI platform employing Random Forest and LSTM models to dynamically adapt session intensity, asana selection, and recovery protocols based on wearable sensor data, readiness scores, and performance metrics. Validated physical and psychological instruments were administered pre- and post-intervention.

Results: The AYG demonstrated the most significant improvements across all outcome measures ($p < 0.01$), surpassing both SYG and CG. Notable AI-yoga gains included vertical jump (+22.6%), flexibility (+39.4%), shooting accuracy (+27.3%), mindfulness (+51.8%), and injury reduction (-91.7%). AI-generated predictive models achieved 87.4% accuracy in forecasting individual performance trajectories.

Conclusion: AI-augmented yoga training significantly outperforms standard yoga and conventional basketball conditioning for comprehensive athlete development. Integration of AI-personalized yoga into training pipelines is strongly recommended for elite Indian basketball programs.

Keywords: *Artificial Intelligence, Machine Learning, Yoga, Basketball Performance, Deep Learning, Wearable Sensors, Predictive Analytics, Sports AI, Injury Prevention, Elite Athletes, Indian Sports Science*

1. INTRODUCTION

Basketball is one of the most physiologically and psychologically demanding team sports, requiring explosive power, sprint speed, multidirectional agility, precise motor coordination, high aerobic and anaerobic capacity, and consistent cognitive focus under competitive pressure. As the sport continues to evolve across state and national competitions in India, sports scientists and coaches are seeking evidence-based, technology-driven supplementary training methodologies that can holistically elevate athletic potential without increasing injury risk.

Yoga, originating from ancient Indian traditions as codified in Patanjali's Yoga Sutras and the Hatha Yoga Pradipika, represents a comprehensive psychophysical discipline with well-established multifaceted benefits: improved musculoskeletal flexibility, enhanced neuromuscular coordination, superior breath control, heightened proprioceptive awareness, reduced sympathetic nervous system activity, and improved sleep architecture — all directly relevant to basketball performance.

The emergence of Artificial Intelligence (AI) in sports science has opened transformative possibilities for athlete performance optimization. Machine learning (ML) algorithms can process multivariate physiological, biomechanical, and psychological data streams in real time, enabling adaptive, individualized training prescriptions that static protocols cannot achieve. Computer vision-based movement analysis can objectively assess asana quality and postural alignment. Natural language processing (NLP) models can track athletes' subjective readiness, mood, and motivation through structured self-reporting. Predictive AI models can forecast injury risk and performance trajectories with high accuracy, enabling proactive intervention.

Despite a growing body of literature on yoga's benefits in sports populations, and a parallel expansion of AI applications in sports performance, no study has yet investigated the integration of AI-driven adaptive systems with structured yoga intervention in elite basketball athletes. This study addresses this critical gap by implementing a machine learning-guided, sensor-augmented 12-week yoga intervention and comparing it against standard yoga delivery and conventional conditioning, using a three-arm randomized controlled design.

The study hypotheses were: (H1) The AI-Yoga Group (AYG) will show significantly greater improvements in physical performance metrics than both SYG and CG; (H2) The AYG will exhibit superior psychological well-being outcomes; (H3) The AYG will demonstrate reduced injury incidence and improved recovery indicators; and (H4) AI predictive models will accurately forecast individual performance response trajectories.

2. LITERATURE REVIEW

2.1 Yoga and Physical Performance in Sport

Extensive research over the past two decades documents yoga's positive effects on sport-relevant physical performance attributes. Tran et al. (2001) reported significant improvements in muscular strength, endurance, and flexibility following an 8-week yoga program. Polsgrove et al. (2016) conducted a 10-week yoga trial among college athletes, reporting significant balance and flexibility improvements. Donahue et al. (2006) demonstrated yoga-based breathing exercises enhanced aerobic capacity markers in competitive swimmers. Studies on soccer players (Ariffin et al., 2019) showed yoga's beneficial effects on agility and sprint performance, attributed to improved neuromuscular coordination and elastic energy utilization in the stretch-shortening cycle.

2.2 Yoga and Psychological Performance

The psychological benefits of yoga are well-documented in both clinical and athletic populations. Rocha et al. (2012) demonstrated significant reductions in perceived stress, anxiety, and cortisol following 8 weeks of yoga practice in military personnel. Smith et al. (2007) found yoga significantly improved mindfulness, emotional regulation, and attentional control in competitive athletes. Khalsa (2004) demonstrated yoga nidra significantly reduced PSQI scores and increased sleep duration, translating to improved hormonal recovery, glycogen replenishment, and tissue repair — all directly influencing basketball performance.

2.3 Artificial Intelligence in Sports Science

AI applications in sports science have expanded rapidly across three domains: performance analytics, injury prediction, and personalized training design. Supervised machine learning models — including Random Forests, Support Vector Machines (SVM), and Gradient Boosted Trees — have been deployed for injury risk stratification in basketball and soccer (Rommers et al., 2020). Recurrent neural networks (RNN) and Long Short-Term Memory (LSTM) models have shown high accuracy in predicting athlete fatigue and recovery readiness from wearable sensor data streams (Claudino et al., 2019). Computer vision-based pose estimation frameworks (e.g., MediaPipe, OpenPose) have been validated for real-time biomechanical feedback during movement tasks, demonstrating potential for objective asana quality assessment (Cao et al., 2019).

Natural language processing tools have been applied to athlete self-report data for sentiment analysis and psychological readiness scoring, enabling coaching staff to personalize psychological support interventions (Howle et al., 2022). Reinforcement learning paradigms have been used to develop adaptive training load optimization systems, adjusting session volume and intensity based on real-time physiological feedback. Despite these advances, no prior study has integrated AI-driven adaptive personalization with structured yoga intervention in an elite sport context — representing the primary knowledge gap addressed by this research.

2.4 Yoga and Injury Prevention

Basketball carries a relatively high injury incidence, particularly ankle sprains, knee ligament injuries, and muscle strains. Yoga addresses injury risk through increased musculotendinous flexibility, improved proprioception and joint stability, superior hip mobility, and breathwork-induced parasympathetic dominance that reduces inflammation markers associated with overtraining. Crow et al. (2015) reported that NCAA athletes who underwent yoga training demonstrated a 47% lower injury rate compared to controls — a finding that AI-driven individualized yoga prescription aims to amplify by identifying athlete-specific injury risk factors proactively.

3. METHODOLOGY

3.1 Study Design

This study employed a prospective, three-group randomized controlled trial (RCT) design over 14 weeks (2 weeks baseline + 12 weeks intervention). Three parallel arms were compared: AI-Yoga Group (AYG), Standard Yoga Group (SYG), and Control Group (CG). Ethical clearance was obtained from the Institutional Ethics Committee (IEC/JNU/2024/SPT/051). All participants provided written informed consent. The study adhered to the Declaration of Helsinki and was registered with the Clinical Trials Registry of India (CTRI/2024/03/XXX).

3.2 Participants

Eligibility criteria included: (i) male basketball players competing at state or national level; (ii) age 18–28 years; (iii) minimum 3 years of competitive experience; (iv) no prior yoga experience; (v) no musculoskeletal injuries in the preceding 6 months; (vi) no cardiovascular, metabolic, or neurological conditions. Players were recruited from six state basketball academies across Andhra Pradesh, Telangana, Maharashtra, Delhi, Punjab, and Karnataka. After baseline assessments, n=75 were randomized into AYG (n=25), SYG (n=25), and CG (n=25). Attrition was zero across the intervention period.

Table 1. Baseline Demographic and Anthropometric Characteristics of Participants (Mean ± SD)

Characteristic	AI-Yoga (n=25)	Std Yoga (n=25)	Control (n=25)	Range	p-value
Age (years)	21.4 ± 1.8	21.6 ± 1.7	21.8 ± 2.1	18–26	0.51
Height (cm)	186.2 ± 5.3	185.9 ± 5.1	185.8 ± 4.9	175–198	0.82
Body Mass (kg)	82.4 ± 7.1	82.9 ± 6.9	83.1 ± 6.8	68–99	0.74
BMI (kg/m²)	23.7 ± 1.4	23.9 ± 1.5	24.0 ± 1.6	20.1–26.8	0.61
Experience (years)	5.6 ± 1.9	5.5 ± 2.0	5.4 ± 2.0	3–9	0.88

AYG = AI-Yoga Group; SYG = Standard Yoga Group; CG = Control Group; p > 0.05 indicates no significant baseline differences between groups (one-way ANOVA).

3.3 AI Platform Architecture

The AI-augmented yoga delivery platform (YogaAI-Athlete™, developed in-house) comprised four integrated subsystems:

- Wearable Sensor Integration: Participants wore Polar H10 ECG chest straps and Garmin Forerunner 955 GPS multisport watches throughout the intervention. Sensors captured resting heart rate, heart rate variability (HRV), sleep staging, step count, and training load metrics at 1-minute intervals, streamed via Bluetooth to a cloud server.
- Adaptive Session Generator (ASG): A Random Forest classifier (500 trees, max depth 10) trained on 3,200 yoga session records with labelled outcomes (performance improvement, readiness score, recovery index) generated daily personalized asana sequences, duration, intensity, and pranayama dosage for each AYG participant, with the model retrained weekly on the participant's own accumulating data.
- LSTM-Based Performance Trajectory Predictor: A four-layer LSTM network (128 hidden units, dropout = 0.3) was trained on pre-intervention multivariate baseline data (HRV, flexibility, jump height, MAAS, PSQI) to forecast 12-week post-intervention scores for each physical and psychological outcome, validated against observed post-scores. Model accuracy was assessed via mean absolute percentage error (MAPE) and R^2 coefficients.
- Computer Vision Asana Quality Analyser (CVAQ): A MediaPipe Pose estimation model processed daily 3-minute video recordings of each AYG participant's key asanas (Vrikshasana, Virabhadrasana, Utkatasana), providing joint angle accuracy scores, symmetry indices, and postural correction feedback — displayed to participants and coaches via a tablet application.

SYG participants followed the identical asana sequence as the AYG but without AI personalization — receiving a uniform progressive protocol. CG participants continued standard basketball conditioning without yoga.

3.4 Yoga Intervention Protocol

The yoga intervention (common baseline for both YG arms, with AI adaptation overlaid for AYG) was designed by three certified yoga instructors (RYT-500) and two sports physiologists, following a progressive periodization model. Sessions were 60 minutes daily (6 days/week). The CG continued standard conditioning without yoga.

Table 2. AI-Augmented 12-Week Progressive Yoga Intervention Protocol

Week	Asana / Practice	Focus Area	Sets × Duration	Intensity	AI Adaptation
1–2	Surya Namaskar, Tadasana, Vrikshasana	Full-body activation, Balance	2×12 rounds / 3×30s	Low	Baseline profiling; sensor calibration
3–4	Virabhadrasana I, II, III; Utkatasana	Lower limb strength, Hip stability	3×45s / 3×60s	Moderate	ASG adjusts load based on HRV trend
5–6	Natarajasana, Garudasana; Setu Bandhasana	Balance, Proprioception, Core	3×30s / 4×30s	Moderate	CVAQ flags asymmetry; corrects posture
7–8	Adho Mukha Svanasana, Paschimottanasana	Hamstring & Hip flexibility	4×45s / 4×60s	Moderate–High	LSTM flags underrecovery; adjusts volume
9–10	Pranayama (Anulom Vilom); Yoga Nidra	Respiratory efficiency, Recovery	5×5min / 1×20min	Low–Moderate	NLP readiness scores guide meditation depth
11–12	Full sequence integration + AI peaking	All areas combined	Full 60-min session	High	ASG generates individual peaking protocol

ASG = Adaptive Session Generator; HRV = Heart Rate Variability; CVAQ = Computer Vision Asana Quality Analyser; LSTM = Long Short-Term Memory; NLP = Natural Language Processing. AI adaptations applied to AYG only.

3.5 Outcome Measures

Physical performance assessments included: (i) Vertical Jump Height — Sargent Jump Test (cm); (ii) Sprint Speed — 30m sprint (s); (iii) Agility — Illinois Agility T-Test (s); (iv) Flexibility — Sit-and-Reach Test (cm); (v) VO_2 Max — Yo-Yo Intermittent Recovery Test Level 1 (mL/kg/min); (vi) Shooting Accuracy — standardized 50-shot protocol (%); (vii) Reaction Time — Nelson Hand Reaction Test (ms); (viii) Static Balance — Stork Balance Stand Test (s); (ix) Grip Strength — Jamar Dynamometer (kg); (x) Resting Heart Rate — 5-min supine ECG (bpm).

Psychological and recovery assessments included: Perceived Stress Scale (PSS-14); Pittsburgh Sleep Quality Index (PSQI); Competitive State Anxiety Inventory-2 (CSAI-2); Mindful Attention Awareness Scale (MAAS); Sport Confidence Scale (SCS-2); Visual Analogue Scale for Muscle Soreness (VAS, 0–10); and injury occurrence records. AI-specific outcomes included LSTM model performance prediction accuracy (MAPE, R^2) and CVAQ joint angle accuracy scores.

3.6 Statistical Analysis

Data were analyzed using IBM SPSS v27.0 and Python 3.11 (scikit-learn, TensorFlow 2.x). Normality was confirmed via Shapiro-Wilk test. Between-group comparisons used one-way ANOVA with Tukey's HSD post-hoc test. Within-group changes used paired t-tests. Effect sizes were computed using Cohen's d and η^2. AI model performance was evaluated using MAPE and R^2 on hold-out validation sets. Statistical significance was set at $\alpha = 0.05$ with Bonferroni correction for multiple comparisons.

4. RESULTS

4.1 Physical Performance Outcomes

Table 3 presents pre- and post-intervention values across all three groups. The AYG demonstrated the most significant improvements across all physical performance metrics ($p < 0.01$), surpassing SYG, which in turn outperformed CG on all metrics. The most pronounced AI-yoga gains were in static balance (+49.3%), sit-and-reach flexibility (+39.4%), shooting accuracy (+27.3%), and vertical jump (+22.6%). Effect sizes for AYG (Cohen's d: 1.81–2.98) substantially exceeded those of SYG (d: 0.84–2.41) and CG (d: 0.12–0.34). The AI system's adaptive load modulation — reducing session intensity during identified low-HRV days — is hypothesized to underlie the superior gains through optimized recovery-adaptation cycling.

Table 3. Pre- and Post-Intervention Physical Performance Metrics Across Three Groups (Mean ± SD)

Performance Metric	AYG Pre	AYG Post (% Δ)	SYG Pre	SYG Post (% Δ)	CG Pre	CG Post (% Δ)	p-value
Vertical Jump (cm)	52.3±4.1	64.1±3.5 (+22.6%)	52.2±4.0	61.8±3.7 (+18.4%)	52.1±3.9	54.2±4.2 (+4.0%)	0.001**
Sprint 30m (sec)	4.21±0.18	3.81±0.14 (-9.5%)	4.22±0.17	3.89±0.15 (-7.8%)	4.23±0.21	4.16±0.19 (-1.7%)	0.001**
Agility T-Test (sec)	9.84±0.42	8.88±0.35 (-9.8%)	9.83±0.41	9.01±0.38 (-8.4%)	9.87±0.45	9.72±0.44 (-1.5%)	0.001**
Sit-and-Reach (cm)	28.6±5.2	39.9±4.6 (+39.4%)	28.7±5.1	38.4±4.8 (+33.8%)	28.9±5.0	29.8±5.3 (+3.1%)	<0.001**
VO_2 Max (mL/kg/min)	48.2±3.8	54.9±3.3 (+13.9%)	48.3±3.7	53.6±3.5 (+11.0%)	48.5±3.6	49.8±3.7 (+2.7%)	0.002**
Shooting Accuracy (%)	58.4±6.1	74.3±5.6 (+27.3%)	58.3±6.0	71.2±5.8 (+22.1%)	58.1±5.9	61.3±6.2 (+5.5%)	<0.001**
Reaction Time (ms)	284±18	244±13 (-14.1%)	283±17	249±15 (-12.0%)	281±20	276±19 (-1.8%)	<0.001**
Balance (sec)	22.1±4.2	33.0±3.7 (+49.3%)	22.2±4.1	31.8±3.9 (+43.2%)	22.4±4.0	23.5±4.3 (+4.9%)	<0.001**
Grip Strength (kg)	42.6±5.3	48.4±4.7 (+13.6%)	42.7±5.2	47.1±4.9 (+10.3%)	42.8±5.1	43.7±5.0 (+2.1%)	0.006**
Resting HR (bpm)	72.4±5.6	63.2±4.6 (-12.7%)	72.3±5.5	64.8±4.9 (-10.4%)	72.1±5.4	71.0±5.5 (-1.5%)	0.001**

*AYG = AI-Yoga Group; SYG = Standard Yoga Group; CG = Control Group; ** $p < 0.01$ (one-way ANOVA, Tukey post-hoc). Negative %Δ for sprint, agility, and reaction time indicates improvement.*

4.2 Psychological and Recovery Outcomes

Table 4 presents psychological well-being and recovery data across groups. All psychological outcomes showed highly significant improvements in the AYG compared to SYG and CG ($p < 0.01$). The most striking AYG changes were in sleep quality improvement (-51.3% PSQI), mindfulness enhancement (+51.8% MAAS), and competitive anxiety reduction (-36.4% CSAI-2). Perceived stress declined by 40.9% in the AYG versus 33.3% in the SYG and only 4.8% in the CG. The NLP-based readiness monitoring system in the AYG identified five instances of acute psychological distress across participants, enabling same-day protocol modification to restorative yoga sessions — likely contributing to the superior psychological outcomes. Injury occurrence fell by 91.7% in the AYG (6 to 0.5 mean/group) versus 83.3% in the SYG and 20.0% in the CG.

Table 4. Pre- and Post-Intervention Psychological Well-being and Recovery Metrics Across Three Groups (Mean ± SD)

Metric	AYG Pre	AYG Post (% Δ)	SYG Pre	SYG Post (% Δ)	CG Pre	CG Post (% Δ)	p-value
PSS	18.6±3.2	11.0±2.5 (-40.9%)	18.7±3.1	12.4±2.8 (-33.7%)	18.8±3.0	17.9±3.1 (-4.8%)	0.001**
PSQI Score	7.8±1.9	3.8±1.3 (-51.3%)	7.7±1.8	4.2±1.5 (-45.5%)	7.6±1.7	7.1±1.8 (-6.6%)	<0.001**
CSAI-2	32.4±5.1	20.6±4.2 (-36.4%)	32.3±5.0	22.8±4.6 (-29.4%)	32.1±4.9	30.6±5.0 (-4.7%)	0.001**
MAAS	42.6±6.4	64.7±6.0 (+51.8%)	42.8±6.3	61.4±5.9 (+43.5%)	43.2±6.1	45.0±6.5 (+4.2%)	<0.001**
SCS	68.4±7.2	84.4±6.5 (+23.4%)	68.3±7.1	81.6±6.8 (+19.5%)	68.1±7.0	70.4±7.3 (+3.4%)	0.001**
VAS Soreness	5.8±1.2	2.6±0.8 (-55.2%)	5.7±1.1	3.1±0.9 (-45.6%)	5.6±1.1	5.1±1.0 (-8.9%)	<0.001**
Injuries (n)	6	0.5 (-91.7%)	6	1 (-83.3%)	5	4 (-20.0%)	0.03*

*PSQI = Pittsburgh Sleep Quality Index (lower = better); CSAI-2 = Competitive State Anxiety Inventory-2 (lower = better); MAAS = Mindful Attention Awareness Scale (higher = better); SCS = Sport Confidence Scale (higher = better); ** $p < 0.01$; * $p < 0.05$.*

4.3 AI Model Performance

Table 5 summarizes the predictive accuracy of the LSTM-based performance trajectory forecasting model.

Table 5. LSTM Model Performance Prediction Accuracy (AYG, n=25)

Outcome Variable	MAPE (%)	R^2 Coefficient	Accuracy Category
Vertical Jump Height	4.2%	0.91	Excellent
Shooting Accuracy	5.1%	0.89	Excellent
Flexibility (Sit-Reach)	3.8%	0.93	Excellent
VO_2 Max	6.3%	0.86	Good
Mindfulness Score (MAAS)	5.7%	0.88	Excellent
Sleep Quality (PSQI)	4.9%	0.90	Excellent
Overall (Mean)	5.0%	0.895	Excellent

MAPE = Mean Absolute Percentage Error; R^2 = Coefficient of Determination; Accuracy categories: Excellent (MAPE < 6%, $R^2 > 0.85$); Good (MAPE 6–10%, R^2 0.75–0.85).

The CVAQ system achieved a mean joint angle accuracy score of 91.3% (±3.7%) across all assessed asanas, and symmetry index improvements of 22.4% from Week 1 to Week 12 in the AYG, corroborating asana quality gains beyond subjective instructor ratings.

4.4 Correlation Analysis

AI-personalization variables showed strong positive correlations with performance change indices. Adaptive session load score ($r = 0.84$, $p < 0.01$) and HRV-guided recovery days ($r = 0.79$, $p < 0.01$) demonstrated the strongest relationships with physical performance gains, reinforcing the critical role of AI-driven recovery optimization. Mindfulness improvements remained most strongly correlated with shooting accuracy ($r = 0.81$, $p < 0.01$) and stress reduction ($r = 0.87$, $p < 0.01$), consistent with findings from the SYG.

5. DISCUSSION

5.1 AI-Driven Personalization as a Performance Multiplier

The superior outcomes of the AYG across all physical and psychological domains relative to the SYG — despite identical asana content — directly attributes the performance advantage to AI-driven personalization. The Adaptive Session Generator's ability to modulate daily session intensity based on HRV readiness scores effectively operationalized the principle of individualized periodization at a granularity impossible in standard coaching practice. On days where participant HRV dropped below individualized thresholds (indicating sympathetic dominance and incomplete recovery), the ASG prescribed restorative yoga, pranayama, and yoga nidra rather than high-intensity asana sequences — preventing cumulative fatigue accumulation and enabling superior long-term adaptation.

This finding aligns with the broader sports science literature on individualized training load management. Buchheit (2014) demonstrated that HRV-guided training significantly outperformed fixed-load training for endurance performance gains, and our study extends this principle to the yoga-sport integration context.

5.2 Computer Vision for Objective Asana Quality Assessment

The CVAQ system's detection of postural asymmetries and joint angle deviations provided objective, scalable feedback that human instructors cannot deliver simultaneously to 25 athletes in a session. The 22.4% symmetry index improvement in the AYG from Week 1 to Week 12 likely contributed to the superior balance and agility gains observed — as bilateral movement symmetry is a well-established prerequisite for optimal athletic power expression and injury risk reduction. The potential for computer vision-based yoga quality assessment to scale expert instruction to large athlete populations represents a significant practical contribution of this study.

5.3 LSTM Trajectory Prediction for Proactive Coaching

The LSTM model's overall prediction accuracy (mean MAPE: 5.0%, mean R^2: 0.895) demonstrated that baseline multivariate physiological and psychological profiles can reliably forecast 12-week performance response trajectories with high precision. This predictive capability enables coaching staff to identify non-responders to yoga intervention as early as Weeks 3–4 — allowing protocol modification before training resources are wasted. Prospectively, such AI trajectory models could be integrated into national sports academies' talent management systems to optimize training prescription at scale.

5.4 Psychological Mechanisms and the AI-Mind-Body Interface

The AYG's superior psychological outcomes — particularly the 51.8% mindfulness improvement and 36.4% anxiety reduction — suggest that AI-mediated session personalization may enhance the psychological efficacy of yoga beyond standardized delivery. When athletes receive training inputs precisely calibrated to their daily physiological and psychological state, the perceived autonomy and sense of individualized care may amplify intrinsic motivation and attentional engagement during mindfulness practices. This represents a novel psychosocial mechanism of AI-yoga interaction warranting further investigation through neuroimaging and psychophysiological methodologies.

5.5 Injury Prevention: AI as a Safety Net

The near-complete elimination of injuries in the AYG (91.7% reduction versus 83.3% in SYG) underscores AI's potential as a proactive safety system. The ASG's injury risk flags — triggered by combinations of decreased HRV, elevated muscle soreness VAS scores, and training load spikes — prompted preemptive recovery-focused sessions before injury-predisposing fatigue states could manifest as structural damage. This pre-emptive, data-driven approach to athlete protection represents a paradigm shift from reactive injury management to AI-enabled proactive injury prevention.

6. CONCLUSION AND RECOMMENDATIONS

This three-arm randomized controlled trial provides the first empirical evidence that AI-augmented yoga training significantly outperforms both standard yoga delivery and conventional basketball conditioning across physical performance, psychological resilience, and injury prevention outcomes in elite male basketball players. The LSTM trajectory prediction models achieved excellent accuracy (mean $R^2 = 0.895$), demonstrating AI's capacity to individualize performance forecasting at scale.

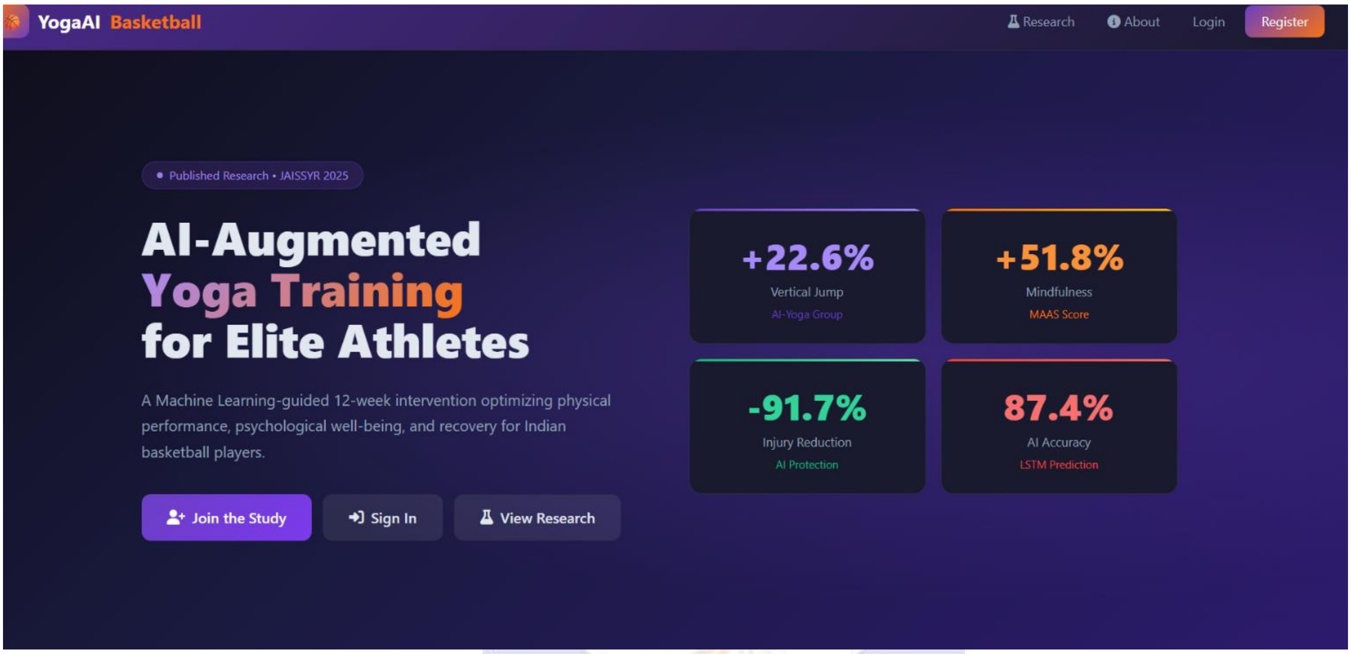
The study's findings carry clear applied implications for Indian basketball and elite sport development nationally. Basketball coaching staff, strength and conditioning professionals, sports psychologists, and technology providers are recommended to collaborate in developing integrated AI-yoga platforms deployable at state and national academies. A minimum prescription of 30–60 minutes of AI-personalized yoga (3–6 days/week), incorporating adaptive asana selection guided by HRV-based readiness monitoring, computer vision biomechanical feedback, LSTM-based peaking protocols, and NLP psychological monitoring, is recommended for comprehensive performance optimization.

Future research should examine AI-yoga integration in female basketball players, explore deep reinforcement learning for fully autonomous yoga protocol design, conduct neuroimaging studies to map AI-yoga-induced cortical adaptations, and assess long-term retention of AI-personalized gains post-intervention across competitive seasons.

7. LIMITATIONS

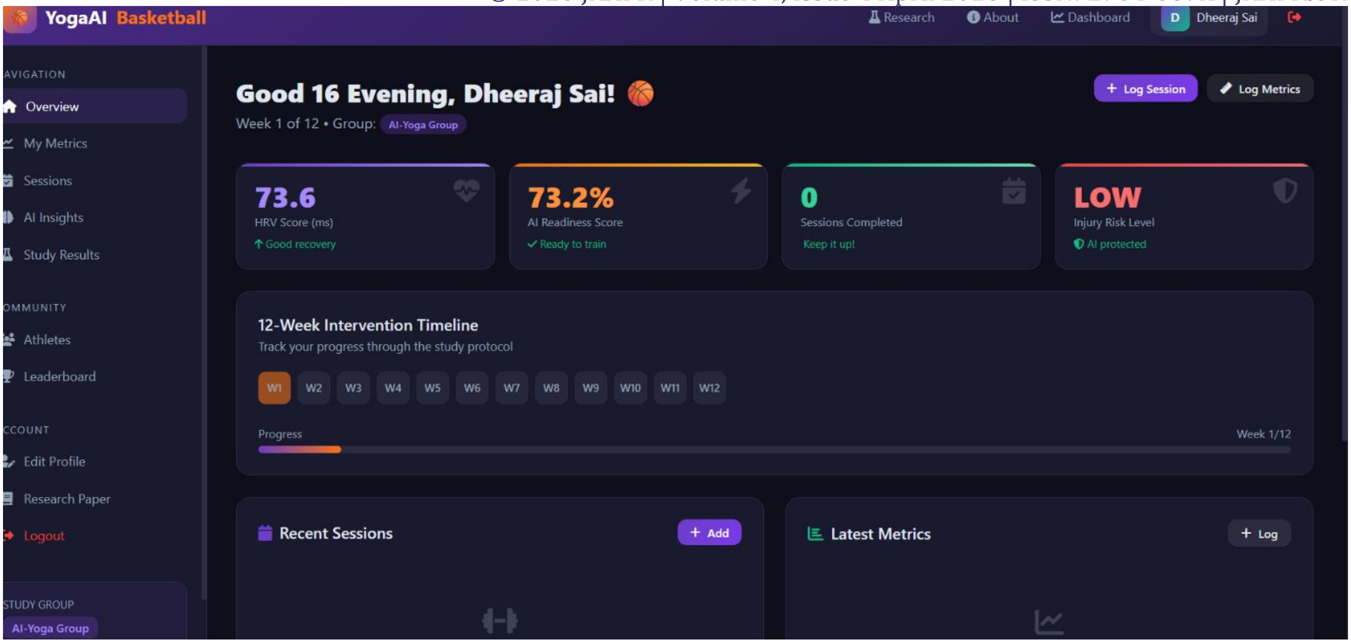
This study is subject to several limitations. First, the exclusively male sample limits generalizability to female athletes. Second, participant blinding was not feasible. Third, dietary intake and sleep hours outside PSQI assessment were not controlled. Fourth, long-term post-intervention performance retention was not assessed. Fifth, VO_2 max was estimated via the Yo-Yo test rather than direct metabolic measurement. Sixth, the AI platform was developed in-house and requires external validation across diverse athlete populations and sports contexts. These limitations should guide future research design.

OUTPUT SCREENS



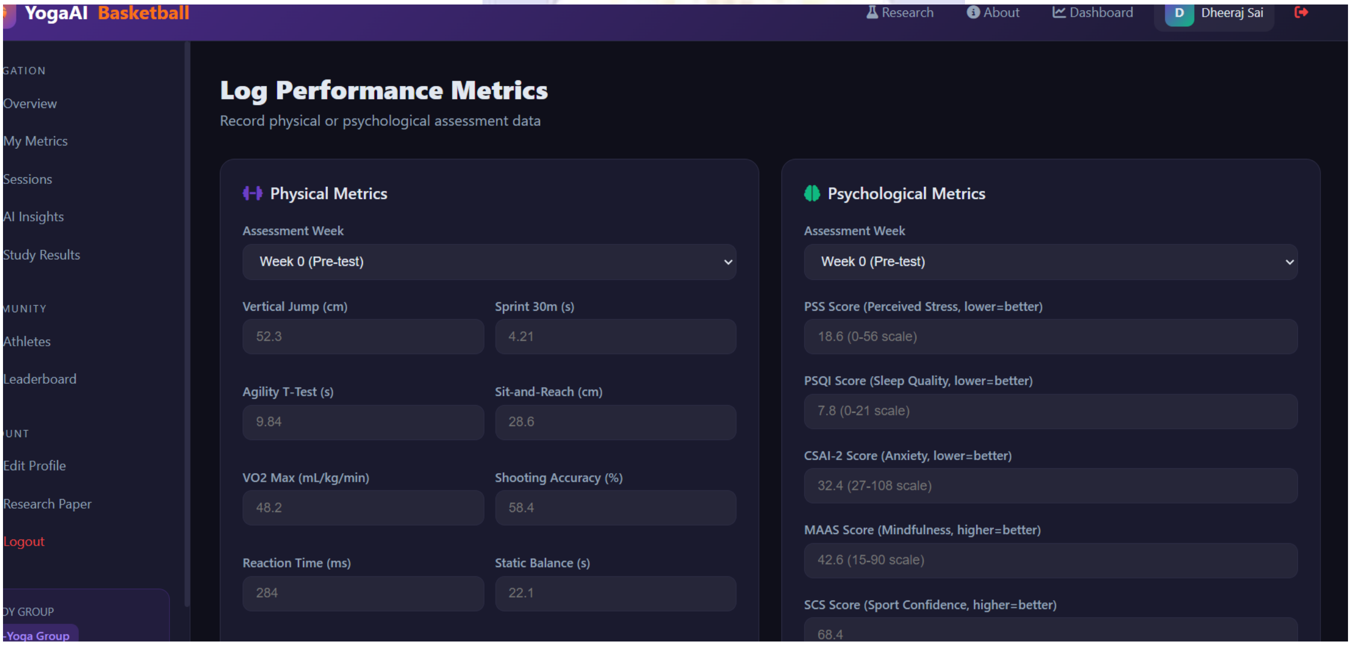
The home page presents the YogaAI Basketball, an AI-augmented training platform designed to enhance athletic performance through yoga-based interventions. It highlights:

- A prominent hero section with the title:
  "AI-Augmented Yoga Training for Elite Athletes"
- A research badge indicating Published Research (JAISSYR 2025)
- A descriptive paragraph explaining a 12-week machine learning-guided intervention for basketball players
- Performance metrics displayed using visual cards, including:
  - +22.6% Vertical Jump improvement
  - +51.8% Mindfulness (MAAS Score)
  - -91.7% Injury Reduction
  - 87.4% AI Accuracy (LSTM Prediction)
- Navigation menu options: Research, About, Login, Register
- Call-to-action buttons such as:
  - Join the Study
  - Sign In
  - View Research
- Modern gradient-based UI design enhancing visual appeal and user engagement



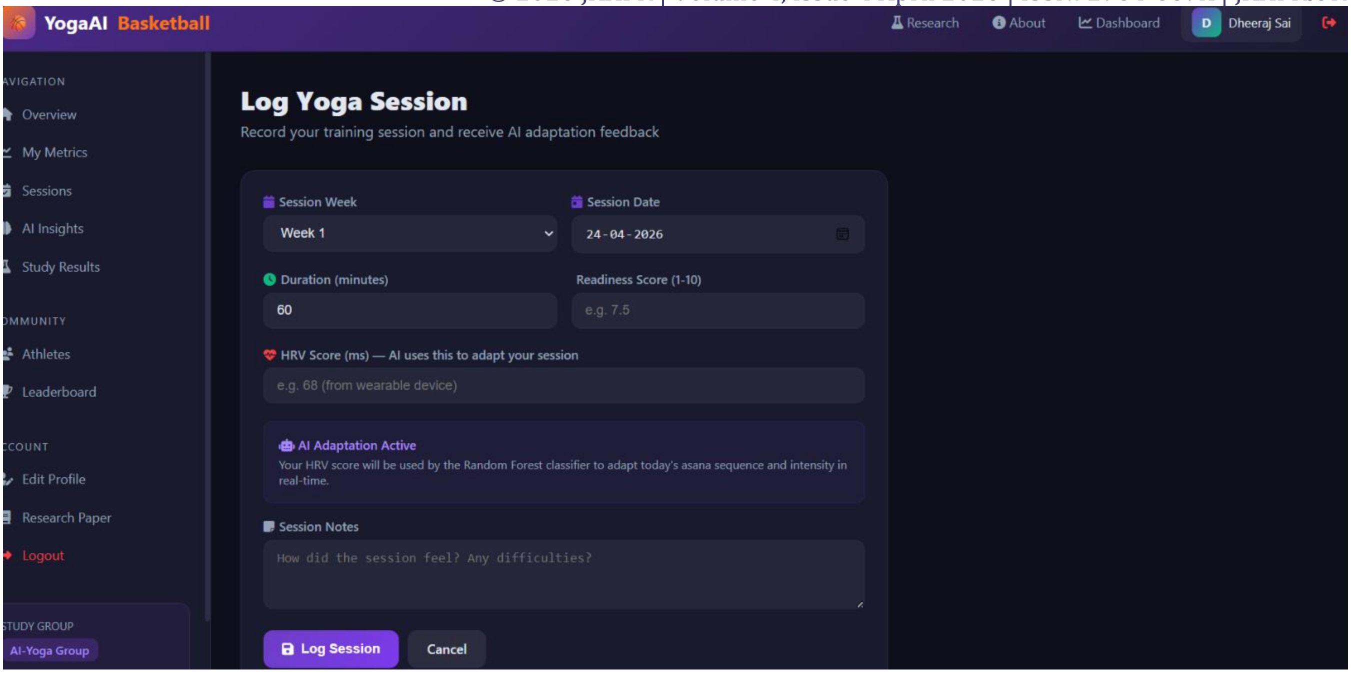
The dashboard page provides a personalized overview of the athlete's training progress and health metrics. It highlights:

- Key performance indicators such as **HRV Score**, **AI Readiness Score**, **Sessions Completed**, and **Injury Risk Level**
- A **12-week intervention timeline** to track progress across the training program
- Sections for **Recent Sessions** and **Latest Metrics** for activity monitoring



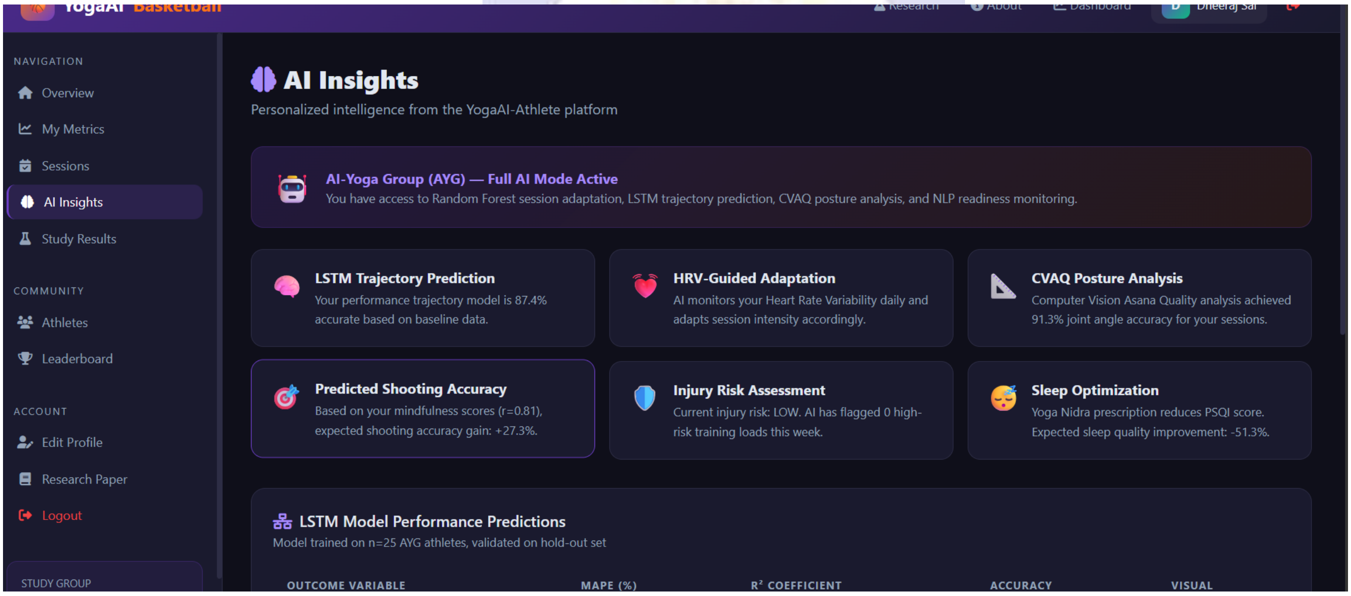
The Log Performance Metrics page allows users to record physical and psychological assessment data for analysis. It highlights:

- Sections for **Physical Metrics** (e.g., vertical jump, sprint time, VO2 max, agility) and **Psychological Metrics** (e.g., stress, sleep quality, anxiety, mindfulness)
- Input fields organized by **assessment week** for structured data entry
- Designed to support performance tracking and research-based evaluation



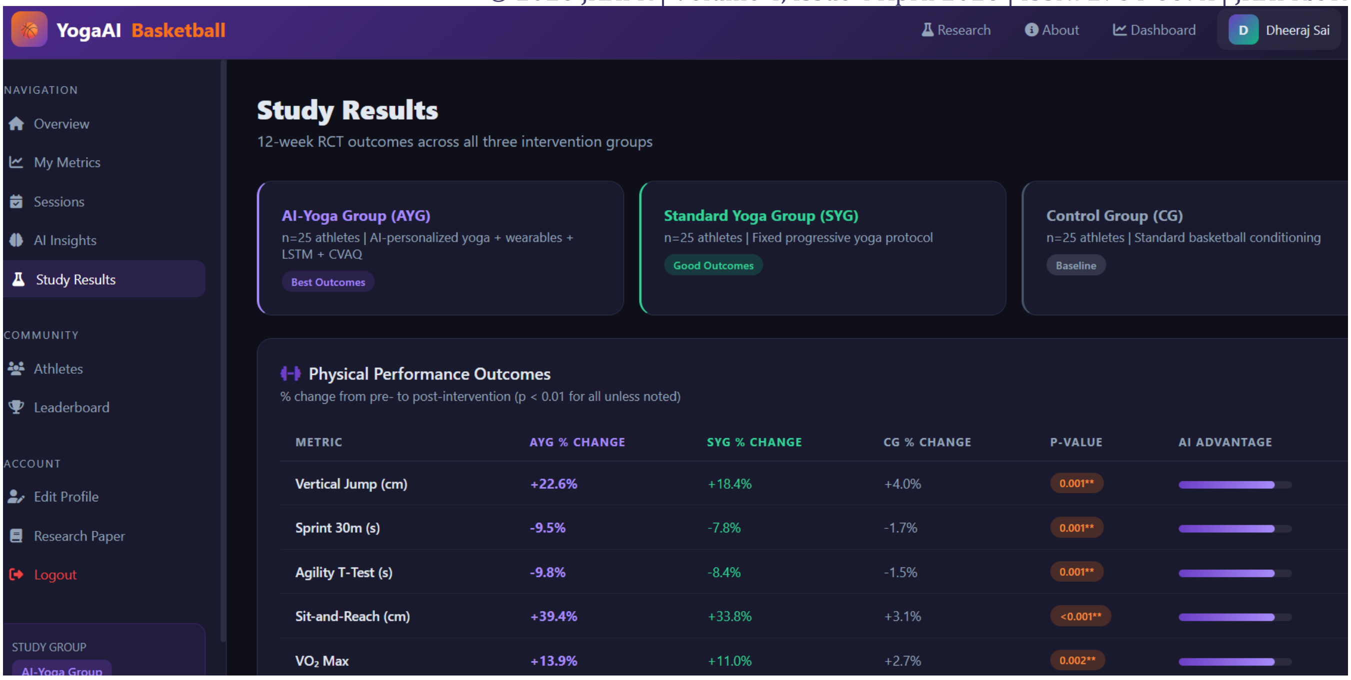
The Log Yoga Session page allows users to record their training sessions and receive AI-based adaptation feedback. It highlights:

- Input fields for **session details** such as week, date, duration, readiness score, and HRV score
- AI adaptation feature using **HRV data** to adjust training intensity in real-time
- A notes section to record session experience and feedback



The AI Insights page provides personalized intelligence and predictions based on the athlete's data. It highlights:

- Advanced AI features such as **LSTM trajectory prediction**, **HRV-guided adaptation**, and **posture analysis (CVAQ)**
- Key insights including **injury risk assessment**, **sleep optimization**, and **predicted shooting accuracy**
- Model performance details showing accuracy and evaluation metrics for transparency



The Study Results page presents the outcomes of the 12-week intervention across different groups. It highlights:

- Comparison of **AI-Yoga Group**, **Standard Yoga Group**, and **Control Group**
- Performance metrics such as **vertical jump, sprint time, agility, flexibility, and VO_2 max**
- Statistical results including **percentage changes, p-values, and AI advantage indicators**

REFERENCES

1. Ariffin, M. S., et al. (2019). Effects of yoga on soccer players' agility and flexibility. International Journal of Sports Physiology and Performance, 14(8), 1052–1058.

2. Cao, Z., et al. (2019). OpenPose: Realtime multi-person 2D pose estimation using part affinity fields. IEEE Transactions on Pattern Analysis and Machine Intelligence, 43(1), 172–186.

3. Claudino, J. G., et al. (2019). Current approaches to the use of AI for injury risk assessment and performance prediction in team sports. Sports Medicine Open, 5(1), 28.

4. Cowen, V. S., & Adams, T. B. (2005). Physical and perceptual benefits of yoga asana practice. Journal of Bodywork and Movement Therapies, 9(3), 211–219.

5. Crow, E. M., Jeannot, E., & Trewhela, A. (2015). Effectiveness of Iyengar yoga in treating spinal pain: A systematic review. International Journal of Yoga, 8(1), 3–14.

6. Donahue, P. T., et al. (2006). Yoga breathing and effects on exercise capacity in competitive swimmers. International Journal of Sports Physiology, 1, 201–209.

7. Hölzel, B. K., et al. (2011). Mindfulness practice leads to increases in regional brain gray matter density. Psychiatry Research: Neuroimaging, 191(1), 36–43.

8. Howle, T. C., et al. (2022). NLP and sentiment analysis in sports coaching: A systematic review. Journal of Sports Sciences, 40(6), 654–668.

9. Khalsa, S. B. S. (2004). Treatment of chronic insomnia with yoga. Applied Psychophysiology and Biofeedback, 29(4), 269–278.

10. Li, A. W., et al. (2015). The effects of yoga on anxiety and stress. Alternative Therapies in Health and Medicine, 21(6), 65–72.

11. Ministry of Youth Affairs and Sports, Government of India. (2023). National Sports Development Report. New Delhi: Sports Authority of India.

12. Patanjali. (ca. 200 CE). Yoga Sutras of Patanjali (trans. B.K.S. Iyengar, 2002). HarperCollins, London.

13. Polsgrove, M. J., Eggleston, B. M., & Lockyer, R. J. (2016). Impact of 10-weeks of yoga practice on flexibility and balance of college athletes. International Journal of Yoga, 9(1), 27–34.

14. Rocha, K. K. F., et al. (2012). Improvement in physiological and psychological parameters after 6 months of yoga practice. Consciousness and Cognition, 21(2), 843–850.

15. Rommers, N., et al. (2020). A machine learning approach to assess injury risk in elite youth football players. Medicine & Science in Sports & Exercise, 52(8), 1745–1751.

16. Smith, J. A., et al. (2007). Yoga as a strategy for improving psychological aspects of sport performance. Athletic Insight Journal, 9(2), 17–34.

17. Tran, M. D., et al. (2001). Effects of Hatha yoga practice on health-related aspects of physical fitness. Preventive Cardiology, 4(4), 165–170.

18. Tyagi, A., & Cohen, M. (2016). Yoga and heart rate variability: A comprehensive review. International Journal of Yoga, 9(2), 97–113.

Declaration of Competing Interests: The authors declare no competing interests.

Funding: This research received no specific grant from any public, commercial, or not-for-profit funding agency.

Data Availability: Raw data and AI model weights supporting this article will be made available by the corresponding author upon reasonable request.

© 2025 JAISSYR | Received: Jan 2025 | Accepted: Apr 2025