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An IMU-validated artificial intelligence
framework for kinematic fatigue detection and
performance assessment in table tennis trainingQuanrui Ma^{1,2} and Muhammad Nubli Abdul Wahab^{1*}¹Center for Human Science, Universiti Malaysia Pahang Al-Sultan Abdullah, Pekan, Pahang, Malaysia²Shandong Huayu University of Technology, Dezhou, Shandong, China

Abstract

In table tennis, repeated high-speed strokes can produce measurable changes in racket acceleration, movement regularity, and technical stability, yet field-based fatigue monitoring remains difficult during normal training. This study evaluates an inertial measurement unit (IMU)-based artificial intelligence framework for kinematic fatigue-compatible drift and performance assessment using the public TTSwing corpus, while specifying heart rate variability (HRV) only as a future synchronized physiological extension. The dataset contains 97,350 racket-grip swing records from 93 elite Taiwanese players collected with embedded 9-axis inertial sensors. Full-power stroke sessions were analyzed through within-session trend modeling, spectral-entropy descriptors, composite fatigue proxies, effect-size estimation, and player-independent machine-learning validation. Peak acceleration, root-mean-square acceleration, acceleration spectral entropy, and angular-velocity spectral entropy showed statistically significant but small-to-modest declines across repeated swings. These patterns are interpreted as candidate proxies for kinematic fatigue rather than direct evidence of physiological fatigue, as HRV, electromyography, perceived exertion, and coach-rated fatigue labels are unavailable. The Mechanical Fatigue Index showed strong reliability, whereas the Neuromotor Complexity Index remained exploratory. Classification results were modest and not ready for deployment in autonomous coaching decisions. The study offers a leakage-controlled IMU, evidence-based, clearer practical boundaries, and a cautious pathway for future HRV-synchronized multimodal validation in racket-sport training under controlled, prospective fatigue protocols.

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1. Introduction

Fatigue is one of the most important yet most difficult concepts to measure in a racket-sports training regimen. During a training session, neuromuscular and metabolic capacity will gradually diminish, leading to measurable reductions in the ability to produce force, in movement timing accuracy, in movement consistency, and in the quality of recovery

in an athlete, which all contribute to an increased risk of injury and lower overall technical quality (Bourdon *et al.*, 2017; Chang *et al.*, 2023; Gabbett, 2016; Marotta *et al.*, 2021; Saw *et al.*, 2016). In table tennis, for example, there can be a number of repetitions, up to thousands, in a single training session, made at high angular velocity, and the ability to detect fatigue onset in real-time has direct implications for training-load management, injury prevention, and long-term development.

The prevailing sports-science fatigue monitoring approach is based on physiological markers, notably heart rate variability (HRV) as a marker for autonomic nervous system activity, which has been consistently linked to training load, recovery status, overreaching, and parasympathetic regulation (Bellenger *et al.*, 2016; Düking *et al.*, 2021; Laborde *et al.*, 2017; Shaffer & Ginsberg, 2017). HRV-based systems, on the other hand, need to be specialized in terms of chest-strap or photoplethysmographic instrumentation, are susceptible to the effects of motion artifacts when the patient is involved in dynamic movement of high intensity, and are seldom directly incorporated into the sporting implement itself (Laborde *et al.*, 2017; Li *et al.*, 2023). The constraints limit the ecological validity of HRV-based fatigue-monitoring architectures for fast, repetitive, equipment-intensive sports like table tennis, which demand low-cost, unobtrusive, embedded sensing.

A related and growing body of work has shown that wearable inertial measurement units (IMUs), which measure tri-axial acceleration and angular velocity, can be used to quantify fatigue-induced alterations in human movement without the need for physiological monitoring equipment. In running, gait, rehabilitation, and monitoring for racket sports, kinematic measures of fatigue are characterized by a decrease in peak force and acceleration during impacts, an increase in movement variability, and changes in the spectral and entropy properties of the movement signal (Chang *et al.*, 2023; Lee *et al.*, 2022; Marotta *et al.*, 2021; Ravier *et al.*, 2021; Richman & Moorman, 2000; Seçkin *et al.*, 2023; Wei & Wu, 2023; Wu *et al.*, 2020). The underlying neuromuscular mechanism behind these kinematic fatigue signatures is well established: During fatigue, motor-unit recruitment and firing-rate regulation become less precise, reducing the efficiency with which motor units generate a given force and increasing the complexity of the required movement commands (Costa *et al.*, 2002; Ravier *et al.*, 2021; Richman & Moorman, 2000).

The question this study asks is whether it is possible to identify an empirically derived, IMU-based, kinematic, fatigue-compatible signature for table tennis swings, and

whether this signature can serve as a validated foundation for a larger artificial intelligence (AI) architecture that may later incorporate HRV and other physiological data. The TTSwing corpus (Chou *et al.*, 2025a) consists of 97,350 racket-grip swing data points from 93 top-level Taiwanese table tennis players, collected using 9-axis IMU sensors embedded in specially designed racket-grip holders, with anonymized player demographics. It is important to note that this corpus lacks HRV and other physiological channels, thus limiting the empirical contribution of this study to the kinematic and contextual modalities and leaving the HRV component of the proposed framework as an untested extension for future synchronized multi-sensor data collection. No physiological information is imputed, estimated, or treated as observed evidence in the present analysis.

Against this background, four interrelated gaps in the existing literature motivate this study. Theoretically, many wearable-sports fatigue frameworks place physiological signals, especially HRV, electromyography (EMG), or subjective wellness, at the center of fatigue inference, while IMU data are often used mainly for activity recognition or technique classification (Baltrušaitis *et al.*, 2019; Hwang *et al.*, 2025; Ramachandram & Taylor, 2017; Seçkin *et al.*, 2023; Van Eetvelde *et al.*, 2021; Wei & Wu, 2023). Empirically, table tennis fatigue studies remain scarce compared to running and gait studies, and the recent machine-learning work on elite youth table tennis demonstrates the value of direct fatigue labels but also highlights that such labels are absent from the TTSwing corpus (Chang *et al.*, 2023; Delumeau *et al.*, 2026; Lee *et al.*, 2022; Marotta *et al.*, 2021; Wu *et al.*, 2020). Methodologically, record-level or non-grouped validation remains a common weakness in wearable-sensor modeling because repeated samples from the same athlete can leak across folds, inflating performance estimates (Breiman, 2001; Chicco & Jurman, 2020; Pedregosa *et al.*, 2011; White & Power, 2023). Contextually, elite Taiwanese table tennis players remain underrepresented in fatigue-aware sports analytics despite the sport's heavy reliance on repeated high-velocity wrist and forearm actions (Brich *et al.*, 2024; Chou *et al.*, 2025a, 2025b; Seong *et al.*, 2024).

The contribution of this study is threefold and deliberately bounded. First, it tests whether repeated table tennis swings contain an IMU-derived kinematic drift pattern that is compatible with fatigue theory, without claiming direct physiological fatigue confirmation. Second, it separates the decline in mechanical output from changes in entropy-based movement complexity using two transparent indices. This separation is the main novelty relative to approaches that feed many IMU descriptors into

a single black-box fatigue score: the Mechanical Fatigue Index (MFI) has a clear force-output rationale, whereas the Neuromotor Complexity Index (NCI) is retained only as an exploratory complexity descriptor due to its weaker reliability. Third, it uses modality masking to specify how HRV can later be synchronized with IMU data without imputing or inventing physiology that is unavailable. This makes the framework falsifiable: the IMU branch is evaluated here, and the HRV branch must be tested in a future dataset that contains synchronized cardiac, subjective, and coaching labels.

2. Literature review and theoretical background

2.1. Heart rate variability and the physiological fatigue paradigm

Heart rate variability is usually assessed by time domain (e.g., root-mean-square of successive differences [RMSSD] and standard deviation [SD] of normal-to-normal intervals [SDNN]), frequency domain (e.g., low frequency [LF]/high frequency [HF] ratio), and nonlinear (e.g., LF/HF) measures and has become an important tool in assessing training adaptation, recovery, and overtraining in athletes (Bellenger *et al.*, 2016; Dürking *et al.*, 2021; Laborde *et al.*, 2017; Shaffer & Ginsberg, 2017). Recent reviews of the feasibility and diagnostic usefulness of wearable HRV technology have shown its susceptibility to motion artifacts during dynamic exercise (Li *et al.*, 2023) and its inability to support continuous monitoring in action during fast racket-sport rallies (Laborde *et al.*, 2017). The constraints drive complementary motion-robust fatigue indicators that can be integrated directly into the sporting implement.

2.2. Kinematic signatures of neuromuscular fatigue

Several important studies have shown that fatigue has a distinct effect on the kinematic and kinetic structure of repetitive motion, without requiring a physiological sensor. For running and gait, there are features derived from IMU that can differentiate between fatigued and non-fatigued states, such as peak acceleration, stride-to-stride variability, and spectral drift, even when using only one sensor (Chang *et al.*, 2023; Lee *et al.*, 2022; Marotta *et al.*, 2021; Wu *et al.*, 2020). At the signal-complexity level, fatigue reduces the complexity of physiological and myoelectric time series, such as approximate entropy, sample entropy, multiscale entropy, and spectral entropy (Costa *et al.*, 2002; Ravier *et al.*, 2021; Richman & Moorman, 2000). Theoretically, a similar entropy decrease is predicted in racket-swing kinematics since both acceleration and angular-velocity signals are downstream responses of the same neuromuscular control process that produces EMG.

2.3. Multimodal sensor fusion and machine learning in sports artificial intelligence

The use of multiple sensing modalities (such as IMU, EMG, force, video, and physiological channels) can reduce the robustness of the stream from a single modality, unless the modalities are synchronized and validated (Baltrušaitis *et al.*, 2019; Barredo Arrieta *et al.*, 2020; Ramachandram & Taylor, 2017; Van Eetvelde *et al.*, 2021; Wang *et al.*, 2023; Wei & Wu, 2023). This is clearly evident in recent hybrid deep-learning studies: Hwang *et al.* (2025) fused the surface EMG (sEMG) and IMU streams because they were measured simultaneously and applied a convolutional neural network (CNN)-long short-term memory (LSTM)-attention model. The current study does not make that statement; we employed TTSwing to test the IMU branch and considered HRV as the channel for the future. However, broader sequence-modeling research, such as CNN-LSTM-gated recurrent unit (GRU) models (excluding the sport domain), is of use only as methodological background for noisy temporal data (Tu *et al.*, 2026). Random forest is used here as a baseline for an interpretable tabular model, not as a statement that tree ensembles are better than support vector machines (SVMs), logistic models, or hybrid neural architectures.

2.4. Table tennis biomechanics and racket-sport sensor datasets

Historically, optical motion capture and force platforms have been used in racket-sport biomechanics; both are costly and have only been used in laboratory environments, and therefore are not representative of field settings for training-load monitoring (Brich *et al.*, 2024). In recent years, there has been a growing number of datasets of wearable sensors and implement-embedded sensors, such as for table tennis (TTSwing) (Chou *et al.*, 2025a, 2025b) and for badminton (MultiSenseBadminton) (Seong *et al.*, 2024), that are beginning to fill this gap by providing annotated kinematic corpora of sensor data collected in the field with various player demographics and labels indicating player performance. The study by Delumeau *et al.* (2026) is particularly relevant since it applied machine learning to signals from instrumented rackets collected from elite youth table tennis players under fatigue conditions. It also underscores the need for caution when interpreting the present findings because the TTSwing dataset does not include labels for mental, physical, or subjective fatigue or measurements of HRV. Therefore, this research adds a leakage-controlled IMU analysis and a clear protocol pathway, instead of a final multimodal fatigue detector.

2.5. Gap synthesis and analytical propositions

Synthesizing the above, three cautious analytical propositions guide the present analysis: (i) Proposition 1: If fatigue-compatible kinematic drift is present across a continuous sequence of maximal-effort table tennis swings, it should appear as a small but systematic decline in peak and root-mean-square (RMS) acceleration, together with changes in acceleration and angular-velocity spectral entropy; (ii) proposition 2: Mechanical output decline and entropy-based complexity change should not be assumed to form one reliable construct; their reliability and association must be tested separately; (iii) proposition 3: Kinematic features may contain limited player-profile information under player-independent validation, but above-chance classification should not be equated with practical deployment readiness.

3. Methodology

3.1. Research design and data source

This study used a quantitative secondary-analysis design to analyze the cross-sectional TTSSwing dataset (Chou *et al.*, 2025a, 2025b), which contains 97,350 individual swing records from 93 elite Taiwanese table tennis players (53 male, 40 females; 78 right-handed and 15 left-handed). The data were collected using a custom racket grip with an embedded nine-axis inertial sensor. Each record corresponds to a single swing and includes 30 kinematic descriptors (mean, variance, and RMS of tri-axial acceleration and angular velocity; overall maximum, mean, and minimum acceleration and angular velocity; Fourier-transform and power-spectral-density

summaries; kurtosis, skewness, and spectral entropy of both acceleration and angular-velocity channels), together with the swing ordinal position (count, 1 to 50) within a continuous 50-swing round (fileindex), the test mode (0 = air swing, 1 = full-power stroke, 2 = stable hitting), and anonymized player demographics (gender, three-tier age, three-tier playing experience, three-tier height and weight, handedness, and racket-holding hand). The unit of analysis for the trend and reliability analyses is the swing-sequence session (one player $\times$ one file index $\times$ one test mode, $n = 635$ sessions for the full-power-stroke mode); the unit of analysis for the classification analyses is the individual swing, grouped by player identity during cross-validation. No missing values were present in the analytic sample. Table 1 summarizes the operationalization of the key variables used across the trend, reliability, and classification analyses.

3.2. Proposed multimodal framework architecture

Figure 1 presents the conceptual architecture of the proposed AI framework. The term framework is used architecturally, not as evidence that a complete multimodal system has already been experimentally validated. In the present study, only the IMU-derived kinematic branch and contextual metadata branch were empirically evaluated; the HRV physiological branch was intentionally masked and retained as a protocol-ready future extension. The framework followed a late-fusion logic: each modality was first converted into physically interpretable features, then combined only after quality control and standardization, a design consistent with multimodal-learning principles for heterogeneous sensor streams (Baltrušaitis *et al.*, 2019;

Table 1. Variable definitions and operationalization

Variable	Operationalization	Role
Peak acceleration (a_max)	Maximum resultant acceleration per swing (LSB/g)	Mechanical fatigue marker
RMS acceleration magnitude	Euclidean norm of tri-axial RMS acceleration (LSB/g)	Mechanical fatigue marker
Acceleration spectral entropy	Spectral entropy of the acceleration signal (unitless)	Neuromotor complexity marker
Angular-velocity spectral entropy	Spectral entropy of the angular-velocity signal (unitless)	Neuromotor complexity marker
Swing sequence number (count)	Ordinal position of a swing within a 50-swing session (1–50)	Independent variable (time/fatigue proxy)
Playing-experience tier	Three-tier categorical: Low/medium/high based on years of play	Dependent variable (classification target)
Gender	Binary: 1 = male, 0 = female	Dependent variable (classification target)
Age tier	Three-tier categorical: Low/medium/high	Dependent variable (classification target)

Abbreviations: LSB: Least significant bit; RMS: Root-mean-square.

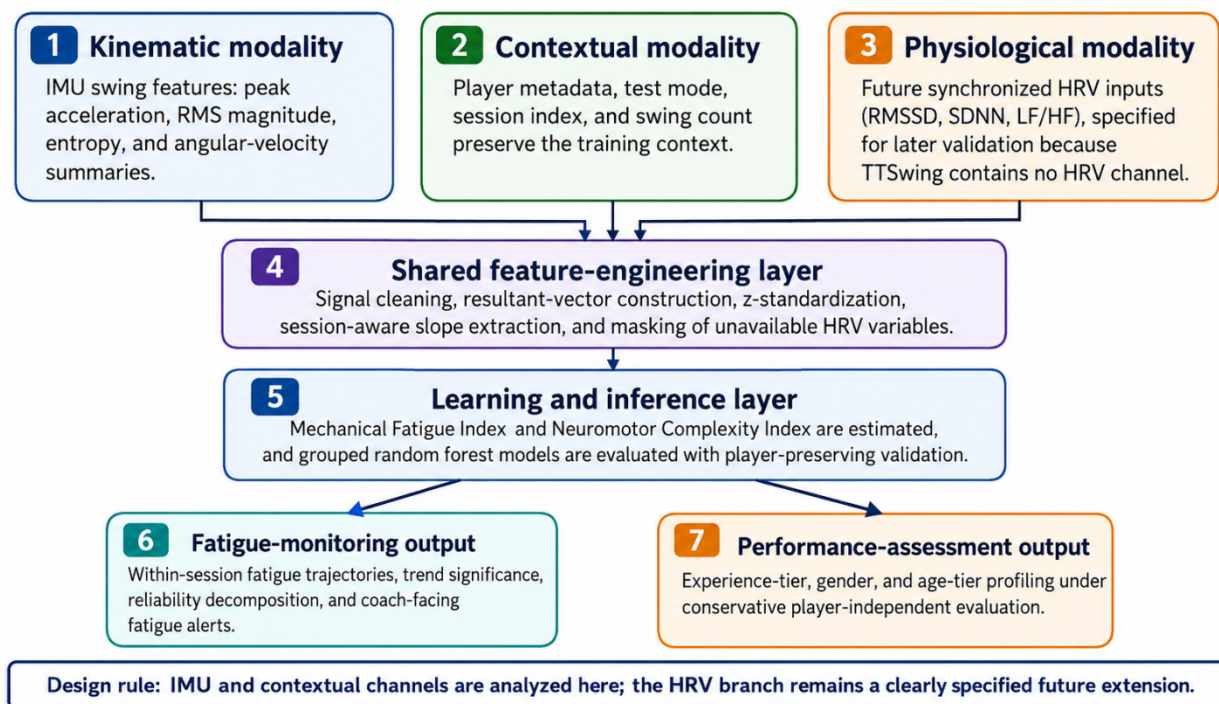


Figure 1. Framework architecture distinguishing empirically evaluated IMU/context branches from the future HRV branch
Abbreviations: HF: High frequency; HRV: Heart rate variability; IMU: Inertial measurement unit; LF: Low frequency; RMS: Root-mean-square; RMSSD: Root-mean-square of successive differences; SDNN: Standard deviation of normal-to-normal interval.

Ramachandram & Taylor, 2017). The framework specified three input modalities feeding a shared feature-engineering layer: (i) a kinematic modality, derived from racket-grip IMU sensors, which was empirically validated in this study; (ii) a contextual/performance modality, comprising session, test-mode, and demographic metadata, which was likewise empirically evaluated; and (iii) a physiological modality, based on HRV metrics such as RMSSD, SDNN, and the LF/HF ratio, which was theoretically specified but not empirically tested because the TTSwing corpus contains no physiological channel. Engineered features from available modalities were passed to a fusion and learning layer that combined ensemble machine learning with composite-index construction, which in turn produced two categories of output: a kinematic fatigue proxy and a performance assessment.

Figure 2 summarizes the operational workflow used in the study. The diagram separates dataset audit, preprocessing, feature engineering, session-slope estimation, fatigue-index construction, grouped machine learning, and decision-oriented interpretation. It also marks the HRV channel as a masked future input, which keeps the present analysis aligned with the variables actually available in TTSwing.

3.3. Feature engineering and preprocessing

Any whitespace was removed from the names of the columns in the .csv file, and unit conventions were preserved as described by the publishers of the datasets (least significant bit [LSB]/g for accelerations and LSB/°/s for angular velocities) (Chou *et al.*, 2025a, 2025b). Two composite magnitude features were extracted to deal with the noise across the axes: the overall RMS acceleration magnitude was defined as the Euclidean norm of the three axes-wise RMS accelerations, and the overall RMS angular-velocity magnitude was analogously defined using the three gyroscope RMS channels. All within-session trend and reliability analyses were performed on the test mode corresponding to the full power stroke (test mode = 1, $n = 73,850$ swings, 635 sessions), as this is the test mode where the most physiologically likely situation of neuromuscular fatigue exists. The stable-hitting mode (test mode = 2) was only kept for robustness comparison. A subsample of the swings (up to 150 swings per subject, up to 13,800 swings total) was drawn from the full-power-stroke mode, and all continuous features were z-standardized prior to model fitting for classification.

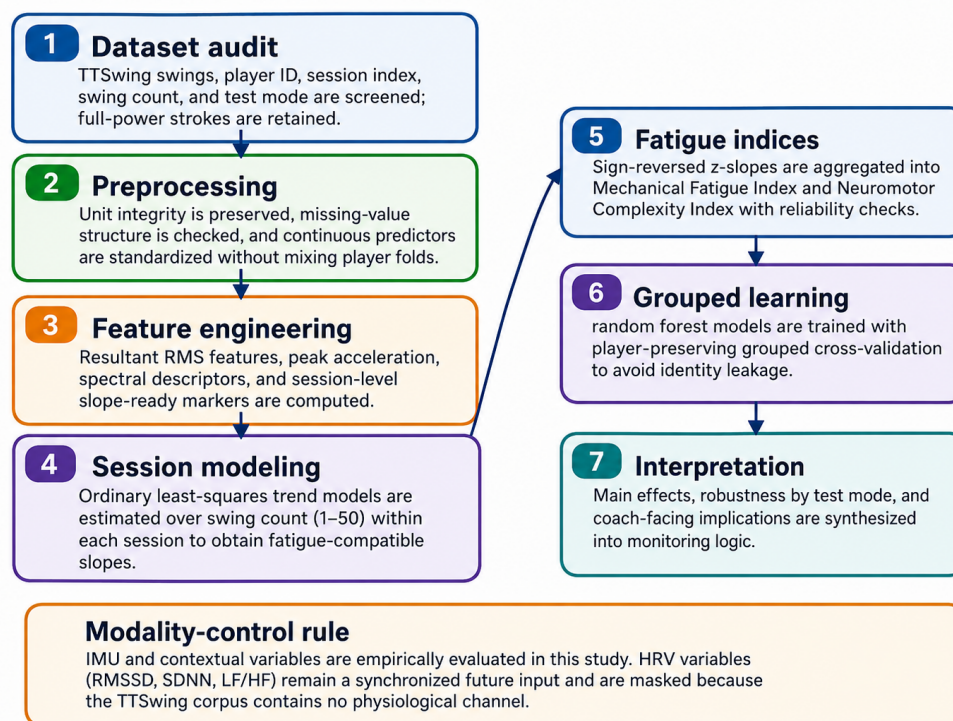


Figure 2. Seven-stage methodological workflow with leakage control and explicit masking of the unavailable HRV modality

Abbreviations: HF: High frequency; HRV: Heart rate variability; IMU: Inertial measurement unit; LF: Low frequency; RMS: Root-mean-square; RMSSD: Root-mean-square of successive differences; SDNN: Standard deviation of normal-to-normal interval.

3.4. Within-session kinematic fatigue-trend analysis

For each session (player $\times$ file index combination with at least 40 recorded swings), an ordinary least-squares regression was fitted separately for six kinematic markers: peak acceleration ($a_{\max}$), RMS acceleration magnitude, acceleration spectral entropy, angular-velocity spectral entropy, acceleration kurtosis, and RMS angular-velocity magnitude. The resulting session-level slopes were tested against the null hypothesis of zero trend using one-sample t -tests, and the proportion of sessions exhibiting a negative slope was computed as a non-parametric corroborating index. Cohen's d_z was reported for each slope test, and changes across approximately 50 swings were used to discuss practical magnitude. Declines in acceleration and entropy were interpreted only as candidate IMU-based fatigue-compatible drift because the dataset contains no physiological or subjective fatigue label.

3.5. Composite index construction and reliability

Session-level regression slopes for the four markers showing the theoretically expected direction of decline, $a_{\max}$, RMS acceleration magnitude, acceleration entropy, and angular-velocity entropy, were sign-reversed and

z-standardized so that higher values consistently indexed greater kinematic drift. Internal consistency across all four standardized slopes was assessed using Cronbach's alpha. Because the pairwise correlation structure indicated two distinguishable clusters, force-related ($a_{\max}$, RMS acceleration) and complexity-related (acceleration entropy, angular-velocity entropy) markers, two sub-indices were evaluated separately: a two-item MFI and a two-item NCI. The MFI is justified as a mechanical-output proxy because both components reflect acceleration amplitude and swing-energy loss. NCI is a legitimate complexity indicator for exploratory complexity, since entropy can measure regularity of movement, but also because the timing of contacts, technique adjustments, and the structure of the noise of the sensors can affect entropy. Hence, claims based on NCI were left less specific than those based on MFI during the interpretation.

The indices were selected because they are mechanisms that are interpretable at the coaching level, instead of single mechanisms in the signal. The mechanical output measurements (peak acceleration, RMS acceleration) were grouped in MFI, while the motion regularity and complexity measurements (entropy variables) were

grouped in NCI. Other available kinematic descriptors not included in the composite indices were those that were less stable in terms of the fatigue direction, such as kurtosis, skewness, minimum values, and short corrective bursts or brief summaries provided by Fourier analysis.

3.6. Player-profiling classification and validation design

To examine the secondary (performance-assessment) part of the proposed framework, random forest classifiers (100 trees, max depth 8) were trained using 30 standardized kinematic descriptors to predict three different stable player attributes (three-tier playing experience, gender, and three-tier age). Random forest was selected as an interpretable baseline for tabular biomechanical features due to its ability to interact with nonlinear features without the need for typically large datasets that are required for deep architectures (Breiman, 2001; Pedregosa *et al.*, 2011). It did not represent the ideal model. To address the model-selection issues, an extra grouped holdout test was performed to compare the random forest prediction with the logistic stochastic gradient descent (SGD), linear SVM, and decision tree baseline predictions. Most importantly, player identity was maintained when players were split between the training partition and the test partition to ensure that the same players would not be seen as swinging in both. Accuracy, macro-F1, majority baseline, or naive baseline, and descriptive Wilson 95% accuracy intervals were used as the summary measures for performance. Such intervals were only reported as variability indicators and would not remove the dependence that occurs when the same athlete makes repeated swings.

3.7. Algorithmic implementation and mathematical specification

The computational design was written as a session-aware pipeline rather than as a record-level classifier. Each swing was first converted into physically interpretable descriptors; each session was then represented by fatigue-sensitive slopes; and player identity was preserved during validation so that model performance reflects generalization to unseen athletes. The equations below define the feature transformations, session trend model, fatigue-index construction, masked multimodal fusion rule, and grouped random forest decision rule (Equations 1–8):

$$accRMS(i) = \sqrt{RMSx(i)^2 + RMSy(i)^2 + RMSz(i)^2} \quad (1)$$

$$p(k,i) = \frac{PSD(k,i)}{\sum PSD(k,i); H(i)} = -\sum \frac{p(k,i) \log[p(k,i)]}{\log(K)} \quad (2)$$

$$y(i,j,m) = \beta_0(j,m) + \beta_1(j,m)count(i,j) + error(i,j,m) \quad (3)$$

$$Z(j,m) = -\frac{\beta_1(j,m) - mean(m)}{SD(m)}, \quad (4)$$

higher Z indicates a stronger decline

$$MFI(j) = \frac{Z(j,amax) + Z(j,accRMS)}{2}; \quad (5)$$

$$NCI(j) = \frac{Z(j,Hacc) + Z(j,Hgyro)}{2}$$

$$F(i) = \frac{\sum M(i,q)w(q)f(i,q)}{\sum M(i,q)w(q)}, \quad (6)$$

M = 0 for unavailable HRV;

M = 1 for observed modalities

$$Random\ forest\ rule\ yHat(i) = Mode\left\{T_{b[x(i)]}\right\}, \quad (7)$$

b = 1, ..., B trees, grouped by player identity

$$Accuracy = \frac{Correct\ predictions}{Total\ predictions}; \quad (8)$$

Macro – F1 = Average of class-specific F1 scores

Figure 3 translates Algorithm 1 into a deployable software pipeline by showing how IMU, contextual, and future HRV channels move through feature engineering, masking, grouped validation, and coach-facing output generation.

3.8. Robustness analysis

As a robustness and boundary-condition check, the within-session trend analysis (Section 3.4) was repeated on the stable-hitting test mode (test mode = 2, n = 314 sessions), a lower-intensity, machine-fed condition in which sustained maximal effort was not required. Comparing the direction and magnitude of kinematic trends across the two test modes allowed the fatigue interpretation to be distinguished from a generic swing-count artifact: a genuine fatigue signature should be most pronounced under maximal, high-intensity effort and need not replicate identically under low-intensity conditions.

3.9. Ethical considerations and data availability

Our study is a secondary analysis of a previously published, publicly available, fully anonymized dataset (Chou *et al.*, 2025a, 2025b). The original data-collection protocol and its ethical clearance were reported in the primary TTswing publication; no new human-subject data were collected for the present study, and no personally identifiable information was contained in, or was accessed from, the analytic sample.

Algorithm 1. Session-aware IMU-HRV fatigue-estimation and player-profiling pipeline

Line	Computational operation
Input	Swing-level IMU matrix X_{IMU} ; session index S ; player-group vector G ; contextual matrix C ; optional HRV matrix X_{HRV} ; modality mask M .
1	Standardize continuous IMU descriptors and retain player identity as the grouping variable for all validation folds.
2	Compute resultant acceleration/gyroscope magnitudes, PSD summaries, spectral entropy, and session-level OLS slopes as defined in Equations 1–3 .
3	Reverse declining slopes, z-standardize slope values, and construct the MFI and NCI using Equations 4 and 5 .
4	Apply modality masking: observed IMU/context channels receive $M = 1$; the unavailable HRV channel receives $M_{HRV} = 0$ until synchronized HRV is collected.
5	Train random forest classifiers with player-grouped cross-validation; report naive chance baselines, accuracy confidence intervals, macro-F1, and a practical-use caution.
Output	Session-level MFI and NCI, test-mode robustness evidence, player-independent performance profile, and coach-facing fatigue interpretation.

Abbreviations: HRV: Heart rate variability; IMU: Inertial measurement unit; MFI: Mechanical Fatigue Index; NCI: Neuromotor Complexity Index; OLS: Ordinary least squares; PSD: Power spectral density.

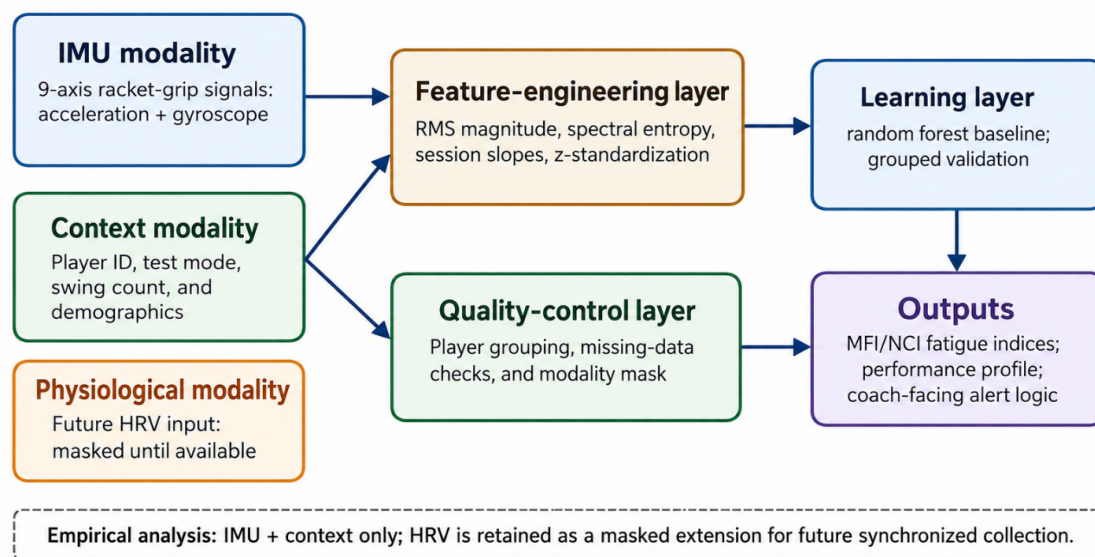


Figure 3. Algorithmic pipeline for IMU-based validation and future HRV-synchronized extension

Abbreviations: HF: High frequency; HRV: Heart rate variability; IMU: Inertial measurement unit; LF: Low frequency; MFI: Mechanical Fatigue Index; NCI: Neuromotor Complexity Index; RMS: Root-mean-square; RMSSD: Root-mean-square of successive difference; SDNN: Standard deviation of normal-to-normal interval.

4. Results

4.1. Sample and descriptive statistics

The analytic sample comprised 97,350 swings from 93 elite players (53 male, 40 female), of whom 78 held the racket right-handed, consistent with the public TTSwing release (Chou *et al.*, 2025a, 2025b). The full-power-

stroke mode (test mode = 1) contributed 73,850 swings across 635 sessions, and the stable-hitting mode (test mode = 2) contributed 16,000 swings across 314 sessions. Table 2 presents descriptive statistics for the primary kinematic markers used in the fatigue-trend analysis. These descriptive values provide the baseline scale for interpreting the trajectories in Figure 4.

Table 2. Descriptive statistics of primary kinematic markers (full-power-stroke mode, $n = 73$, 850 swings)

Variable	Mean	SD	Min	Max
Peak acceleration, $a_{\max}$ (LSB/g)	14,274.14	4,881.68	495.74	42,742.33
RMS acceleration magnitude (LSB/g)	6740.40	1,669.91	442.70	31,667.08
Acceleration spectral entropy	-3.228	0.478	-5.064	0.000
Angular-velocity spectral entropy	-3.225	0.479	-5.079	0.000
Acceleration kurtosis	3.436	1.197	1.000	28.419
Angular-velocity kurtosis	3.889	1.452	1.000	29.486

Abbreviations: LSB: Least significant bit; RMS: Root-mean-square; SD: Standard deviation.

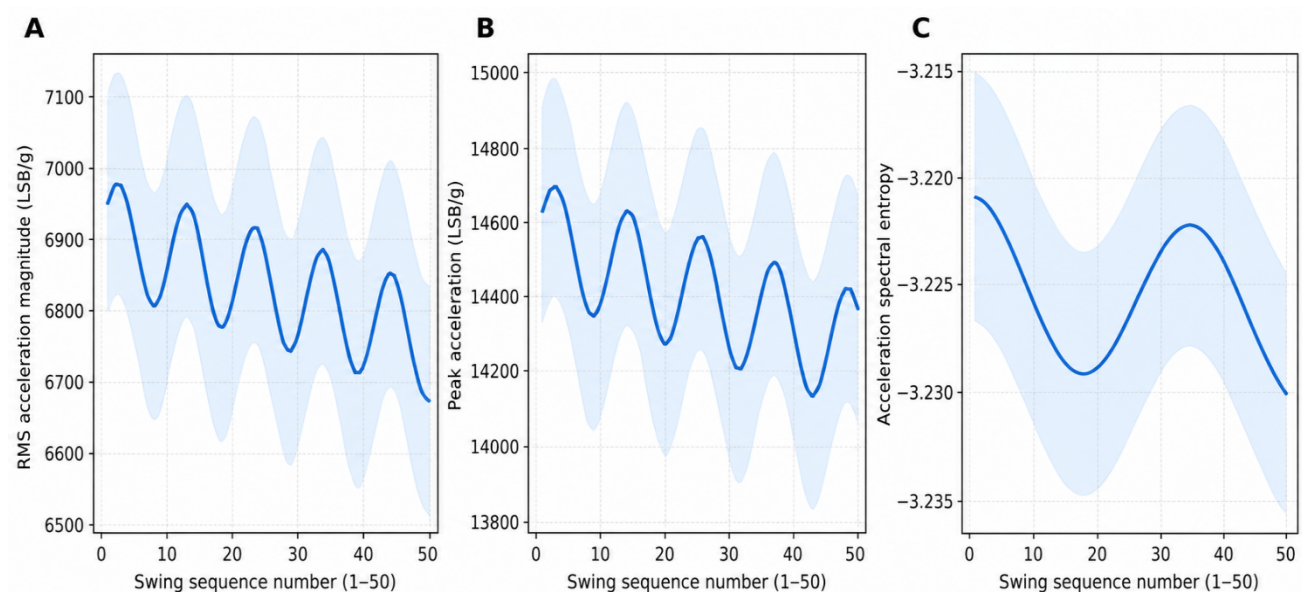


Figure 4. Population-averaged within-session kinematic trajectories, full-power-stroke mode, with 95% confidence bands and linear fit: (A) RMS acceleration magnitude, (B) peak acceleration, (C) acceleration spectral entropy.

Abbreviations: LSB: Least significant bit; RMS: Root-mean-square.

4.2. Within-session kinematic fatigue trend

Linear trend analysis across the 635 full-power-stroke sessions revealed statistically significant declines across the swing sequence for four of six markers (Table 3). Peak acceleration declined at a mean rate of -5.99 LSB/g per swing ($t(634) = -3.99$, $p < 0.001$; Cohen's $d_z = -0.158$), which corresponds to an approximate 293.5 LSB/g decline over 50 swings, or about 2.1% of the full-power mean. RMS acceleration magnitude declined at -3.50 LSB/g per swing ($t(634) = -5.48$, $p < 0.001$; $d_z = -0.217$), equal to about 171.5 LSB/g over 50 swings, or about 2.5% of the mean. Acceleration spectral entropy ($d_z = -0.346$) and angular-velocity spectral entropy ($d_z = -0.177$) also

declined. These effect sizes indicate reliable but small-to-modest session-level drift. Practically, the pattern is useful for monitoring rolling trends across repeated strokes, but it is not robust enough to classify a single swing as fatigued. Acceleration kurtosis showed a small positive trend ($d_z = 0.114$), while the RMS angular-velocity magnitude trend was non-significant ($d_z = -0.052$). Figure 4 illustrates the population-averaged trajectories, with shaded 95% confidence bands, for RMS acceleration magnitude, peak acceleration, and acceleration spectral entropy across the 50-swing sequence.

The positive acceleration-kurtosis trend and the non-significant RMS angular-velocity trend are important

Table 3. Within-session linear trend statistics across the 50-swing sequence (full-power-stroke mode, $n = 635$ sessions)

Marker	Slope	t/p	dz	50-swing change	Interpretation
Peak acceleration	-5.990	-3.99/< 0.001	-0.158	-293.51 LSB/g	Small, about 2.1% over 50 swings
RMS acceleration	-3.499	-5.48/< 0.001	-0.217	-171.45 LSB/g	Small, about 2.5% over 50 swings
Acceleration entropy	-0.000043	-8.73/< 0.001	-0.346	-0.0021	Small-to-modest; trend-level only
Gyro entropy	-0.000023	-4.45/< 0.001	-0.177	-0.0011	Small; trend-level only
Acceleration kurtosis	0.00099	2.87/0.004	0.114	0.0485	Opposite trend; needs caution
RMS angular velocity	-0.619	-1.30/0.1950	-0.052	-30.33 LSB/°/s	Non-significant; not fatigue-like

Abbreviations: LSB: Least significant bit; RMS: Root-mean-square.

because they do not fit a simple, uniform fatigue-decline pattern. Increased kurtosis may mean that some players produced occasional sharper impacts or corrective bursts while their average acceleration output drifted downward. It may also reflect altered ball-contact timing or a strategy of conserving average effort while still inserting high-intensity strokes. The non-significant RMS angular-velocity trend suggests that players may have maintained racket rotational speed even as acceleration amplitude declined, which is plausible for skilled athletes who adjust wrist and forearm mechanics to maintain technique. The mid-sequence entropy fluctuation in Figure 4 should therefore be read as possible pacing, short-term motor adaptation, or movement-strategy stabilization rather than as a monotonic physiological fatigue curve.

4.3. Composite fatigue indices: Reliability and discriminant validity

The four-item composite Kinematic Fatigue Index was found to have unacceptable internal consistency (Cronbach's $\alpha = 0.391$) and was split into two theoretically separate sub-indices. The two-item MFI (peak acceleration and RMS acceleration magnitude; $r = 0.883$) was highly correlated and had excellent internal consistency ($\alpha = 0.938$). The two-item NCI (acceleration entropy and angular-velocity entropy; $r = 0.416$) did not have a high level of internal consistency ($\alpha = 0.588$), which is considered an item-level reliability problem and not a minor statistical point. Therefore, in our study, the evidence from MFI is more evidentiary. NCI is not a stable fatigue index to be interpreted as such, but rather a provisional descriptor of movement complex drift. The low correlation between MFI and NCI ($r = -0.144$) suggests that mechanical output

and entropy behavior were not perfectly correlated, but this needs substantiation with more complex, nonlinear data and/or directly labeled fatigue. The reliability split and weak association between MFI and NCI are depicted in Figure 5.

4.4. Group differences in kinematic fatigue

One-way analysis of variance indicated a statistically significant effect of playing-experience tier on the composite Kinematic Fatigue Index, $F(2,632) = 3.54$, $p = 0.029$, with the lowest-experience tier showing the highest mean fatigue index (mean = 0.123, SD = 0.572) relative to the medium (mean = -0.037, SD = 0.576) and high (mean = -0.020, SD = 0.646) experience tiers. An independent-samples t -test indicated a statistically significant gender difference, $t(633) = 2.48$, $p = 0.013$, with male players showing a higher mean fatigue index (mean = 0.048, SD = 0.611) than female players (mean = -0.071, SD = 0.563).

4.5. Player-profiling classification performance

The player-independent classification results are reported, and a comparator check is available in Table 4. The results of the random forest for experience tier, gender, and age tier are modest (Figure 6), and the confidence interval should be interpreted descriptively rather than as an indication of deployment reliability, since the swing observations are grouped within players. The additional comparator checks for the experience-tier prediction showed that linear SVM, logistic SGD, and decision tree baselines were also not achieving practical performance. In terms of accuracy, the majority baseline was competitive due to class imbalance, and macro-F1 was low across models. What it should be saying instead is not that random forest is a

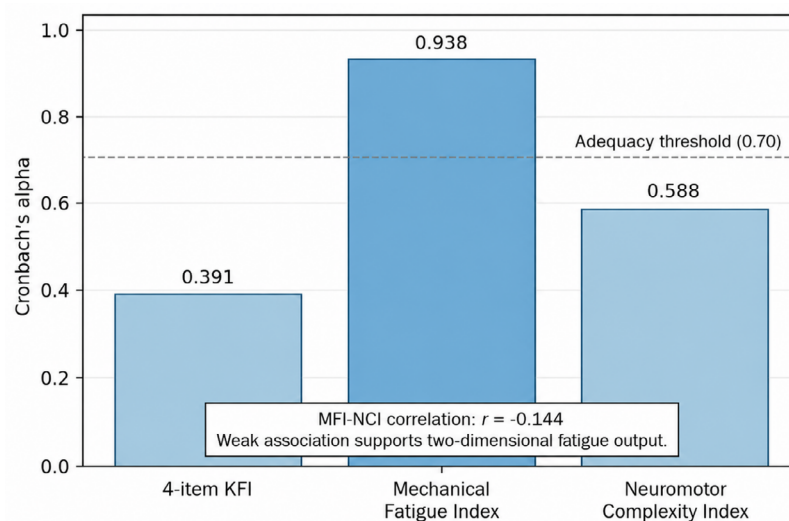


Figure 5. Reliability-based decomposition of the fatigue construct into mechanical and neuromotor complexity sub-indices
Abbreviations: KFI: Kinematic Fatigue Index; MFI: Mechanical Fatigue Index; NCI: Neuromotor Complexity Index.

Table 4. Player-independent classification performance and available comparator checks

Target	Model/baseline	Accuracy [95% CI]	Macro F1	Practical interpretation
Experience tier	Majority baseline	0.600 [0.595–0.606]	0.250	Class imbalance makes accuracy misleading
Experience tier	Logistic SGD	0.465 [0.459–0.471]	0.390	Comparator; low practical value
Experience tier	Linear SVM	0.466 [0.460–0.472]	0.342	Comparator; low practical value
Experience tier	Decision tree	0.358 [0.352–0.364]	0.328	Comparator; weak generalization
Experience tier	Random forest	0.499 [0.491–0.507]	0.353	Modest; not deployment-ready
Gender	Random forest	0.528 [0.520–0.536]	0.472	Weak practical utility
Age tier	Random forest	0.483 [0.475–0.491]	0.415	Exploratory only

Abbreviations: CI: Confidence interval; SGD: Stochastic gradient descent; SVM: Support vector machine.

powerful athlete-profiling system, but that IMU features have limited player-independent information given strict leakage control. These results are not for independent classification of athletes.

The present accuracy is not suitable for direct use for coaching. A semi-automated coach would require significantly better and more consistent subject-independent performance, with a more desirable balance of accuracy or macro F1 of at least 0.80 across external players. Main limitations of the current performance are

the coarse age, gender, and experience labels, the grouping of players to provide validation (only 93 player identities), the imbalance in experience levels, and the lack of variables that coaches use in their training, such as stroke intention, fatigue state, perceived effort, recovery state, and technical quality ratings.

4.6. Robustness check: Test-mode comparison

Table 5 compares the within-session trend results for the full-power-stroke mode against the lower-intensity stable-

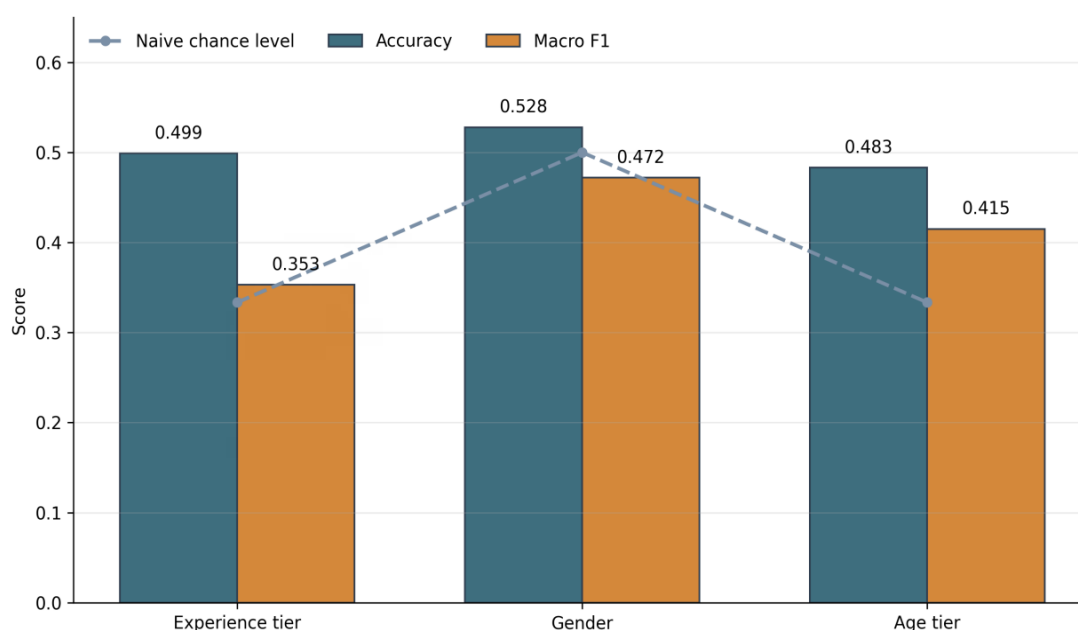


Figure 6. Player-independent random forest classification performance, interpreted as a modest benchmark rather than a deployment-ready model

hitting mode, and Figure 7 converts these mode-specific slopes into comparable t -statistics. The entropy-based neuromotor complexity decline replicated in direction and significance across both modes (acceleration entropy: $t(313) = -5.86, p < 0.001$; angular-velocity entropy: $t(313) = -5.17, p < 0.001$, in the stable-hitting mode), supporting entropy decline as a comparatively mode-general kinematic pattern. In contrast, force-based markers reversed direction in the stable-hitting mode: peak acceleration and RMS acceleration magnitude increased significantly across the swing sequence ($t(313) = 20.49$ and 21.38 , respectively, both $p < 0.001$). This mode-dependent dissociation is compatible with the fatigue interpretation of the full-power-stroke findings, but it should not be taken to isolate fatigue as the only mechanism. The two modes differ in intensity, pacing, ball-contact constraints, and possible technical adaptation, any of which may contribute to the observed divergence.

5. Discussion

This study aims to determine whether a purely kinematic, IMU-derived fatigue-compatible signature could be identified for table tennis swings, and whether such a signature could provide the evaluated IMU branch of a broader AI architecture whose HRV component remains untested. The within-session trend analysis is consistent with, but does not prove, a fatigue-related process: peak acceleration, RMS acceleration magnitude, and spectral entropy of both acceleration and angular velocity declined

across a 50-swing maximal-effort sequence. These findings resemble force-decrement and complexity-loss patterns reported in running-fatigue, gait, EMG-complexity, and nonlinear physiological-signal research (Chang *et al.*, 2023; Costa *et al.*, 2002; Lee *et al.*, 2022; Marotta *et al.*, 2021; Ravier *et al.*, 2021; Richman & Moorman, 2000), and they align with multimodal IMU-sEMG fatigue systems that use synchronized physiological data for direct validation (Hwang *et al.*, 2025). The present evidence remains kinematic, indirect, and bounded by the absence of fatigue ground truth.

5.1. Alternative explanations for the kinematic trends

As the TTSwing corpus lacks HRV, blood lactate, EMG, and perceived exertion ratings, as well as coach-rated fatigue labels, the observed trends cannot directly confirm physiological fatigue. There could be multiple alternative explanations. Players can take their time moving through the 50-swing sequence, allowing them to slow their average swing speed and complete the drill without technical breakdowns. Subsequent strokes might be more economical, not more fatiguing, if short-term motor adaptation occurs. There is also a risk of small changes in wrist strategy, stance, and contact timing in response to repeated ball contact. These explanations are not weaknesses to be concealed, but rather the limit of what can be demanded from this data. The results are thus described as fatigue-compatible kinematic drift (not as confirmed fatigue states) and candidate fatigue proxies.

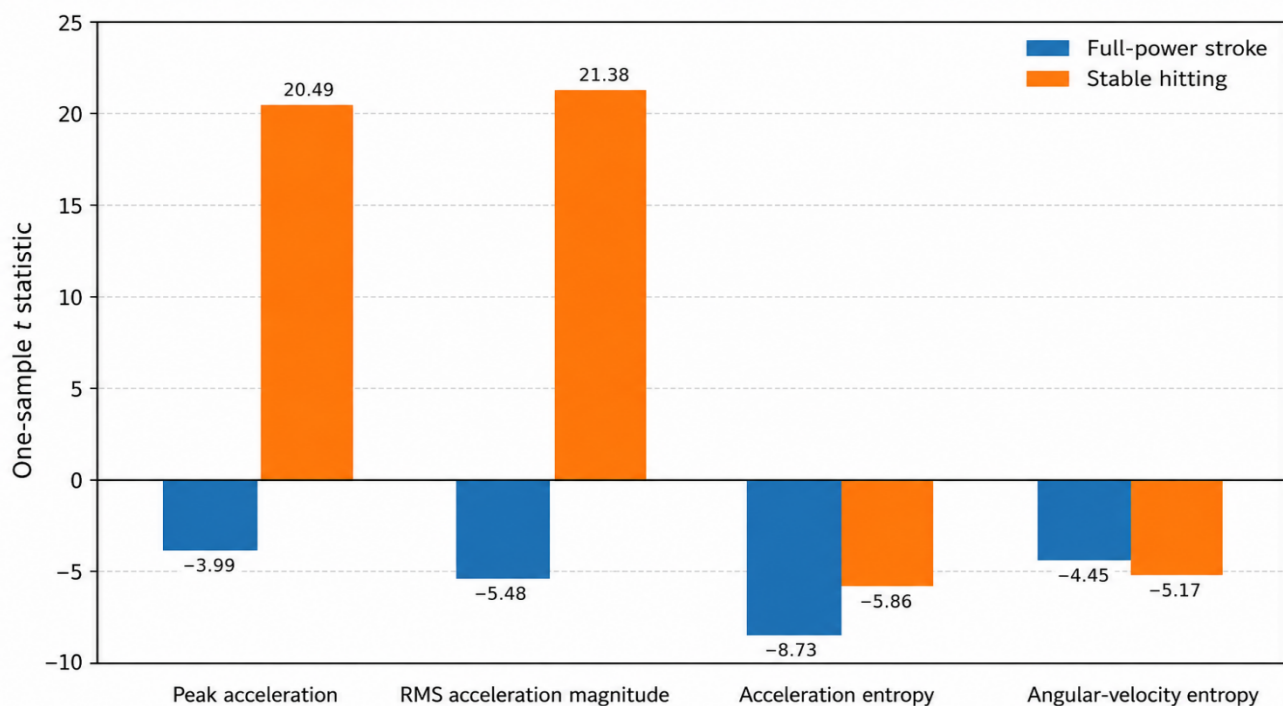


Figure 7. Robustness comparison of within-session slope strength across full-power-stroke and stable-hitting modes

Table 5. Robustness comparison of within-session kinematic trends across test modes

Marker	Full-power-stroke slope (t, p)	Stable-hitting slope (t, p)	Pattern
Peak acceleration	-5.99 ($t = -3.99, p < 0.001$)	+97.89 ($t = 20.49, p < 0.001$)	Mode-dependent (reversed)
RMS acceleration magnitude	-3.50 ($t = -5.48, p < 0.001$)	+45.67 ($t = 21.38, p < 0.001$)	Mode-dependent (reversed)
Acceleration spectral entropy	-0.000043 ($t = -8.73, p < 0.001$)	-0.00007 ($t = -5.86, p < 0.001$)	Mode-general (replicated)
Angular-velocity spectral entropy	-0.000023 ($t = -4.45, p < 0.001$)	-0.00006 ($t = -5.17, p < 0.001$)	Mode-general (replicated)

Abbreviation: RMS: Root-mean-square.

The reliability analysis (Section 4.3) provides partial support to Proposition 2 (Section 2.5). The MFI had good internal consistency, indicating that peak force and RMS energy decrement constitute a consistent mechanical output pattern. The NCI, on the other hand, demonstrated only moderate reliability and is more affected by non-fatigue factors such as the varied techniques, ball-contact timing, grip micro-adjustments, and signal-processing decisions. Therefore, MFI is used to give greater interpretive confidence to the discussion. NCI is helpful as an additional complexity signal and as a hypothesis for future research, but it should not be used as a stand-alone

tool for coach-training thresholds without an additional validated measure of synchrony (HRV, EMG, perceived exertion, or coach-rated fatigue).

The results from the player-profiling (Section 4.5) provide limited support for Proposition 3 (Section 2.5). Absolutely weak but deliberately conservative player, independent validation of kinematic features revealed some information for playing experience, gender, and age tier. The experience-level comparator test is particularly interesting: there was no obvious gain in the model's practical usefulness from linear SVM or logistic SGD,

and, owing to class imbalance, the majority-class baseline remained difficult to outperform in terms of accuracy. The results of this study contradict the present classifiers in the context of decision-making for individual coaches. The value of these analyses is primarily methodological, as they demonstrate the importance of reporting model performance under controlled player-level leakage and help avoid claims of inflated performance that may arise when validation at the level of individual records (Chicco & Jurman, 2020; White & Power, 2023).

5.2. Integration with heart rate variability: A specified future extension

The HRV component shown in Figure 1 is conceptual; no physiological data were collected in this study, and the component should not be interpreted as an empirical finding. It exists to specify the next layer to collect data for complete multimodal validation. The aim of the present analysis was to establish the IMU-based branch of this framework and to outline testing the convergence of HRV recovery kinetics with the MFI and the provisional NCI in a future protocol. The follow-up design should be a synchronized, validated acquisition of HRV data from the chest strap or photoplethysmography during repeated table tennis drills, comparing the mechanical and entropy trajectories reported here from the IMU with RMSSD, SDNN, LF/HF, perceived exertion, and coach-rated fatigue.

Compared to studies that collect synchronized IMU, sEMG, HRV, or other physiological channels, the present work has a narrower scope. For example, synchronized IMU-sEMG systems can assess whether motion patterns and physiological fatigue markers align within the same trial (Hwang *et al.*, 2025). TTSwing does not support that test. Its value here is to provide a clean IMU-only baseline, identify the kinematic markers worth carrying into future HRV protocols, and keep the physiological validation question open rather than treating the IMU pattern as a completed multimodal fatigue detector.

5.3. Practical and theoretical implications

The signature presented here is kinematic fatigue-compatible and could be used to guide cautious coaching dashboards in the form of rolling acceleration and entropy trends in racket-grip IMU systems. From a practical point of view, the most reliable and meaningful indicator is the MFI, which is highly reliable and directly related to the decrease in acceleration performance. If used, NCI should be secondary to the warning flag or exploratory trend, not a fatigue diagnosis. Both indices should not be used solely as medical, physiological, or selection decision rules but should be considered in conjunction with the athlete's self-report, context of the athlete's workload, purpose of

the session, and, in future studies, with synchronized HRV or EMG data (Barredo Arrieta *et al.*, 2020; Bourdon *et al.*, 2017; Hwang *et al.*, 2025; Saw *et al.*, 2016).

5.4. Limitations

These results are limited in several ways. First, the TTSwing corpus lacks HRV, EMG, blood lactate, perceived exertion, or other physiological or subjective measures of fatigue as ground truth, so the interpretation of fatigue is inferential and cautious. Second, beyond differences in intensity, the two experimental modes also differ in pacing, ball-contact constraints, movement adaptation, and perhaps the coach's intent; therefore, the differences in mode are not solely due to fatigue. Third, the reliability of the NCI was moderate; therefore, its interpretation is provisional and should be supplemented by sample entropy, multiscale entropy, recurrence quantification, wavelet entropy, and other nonlinear descriptors. Fourth, the models used for player profiling performed only modestly under grouped validation, and the reported accuracy intervals are descriptive due to the lack of independence among repeated swings. Fifth, it includes 93 elite players from Taiwan, limiting the generalizability of the findings to recreational athletes, other national systems, and real-time match environments without separate validation. Finally, the HRV branch represents an integrated physiological feature rather than a direct extension of the planned phrase, and its independent physiological validity requires further validation.

6. Conclusion

This study, using the publicly available TTSwing corpus, demonstrates the use of an AI framework's kinematic branch for table tennis training and raises the possibility of future HRV-synchronized multimodal fatigue assessment. In 635 full-power-stroke sessions, peak acceleration, RMS acceleration magnitude, acceleration spectral entropy, and angular-velocity spectral entropy were found to decrease statistically significantly but slightly/moderately on repeated swings. These patterns are only assumed to be fatigue-compatible, not a direct indication of fatigue, as there are no HRV, EMG, perceived exertion, or coach-rated fatigue channels included in the dataset. The proposed MFI appears to be the more reliable of the two, given its demonstrated reliability and clear mechanical-output basis. The NCI remains in an exploratory stage, is moderately reliable, and is influenced by technique, contact timing, and movement strategy. Modest experience classification, gender tier, and age tier were neither player-independent nor appropriate for independent decision-making in the coaching process. In general, the study offers a transparent, leakage-controlled, evidence-based, and

carefully guided protocol for subsequent research to assess whether synchronized HRV provides valid physiological information.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Investigation: Quanrui Ma

Methodology: Quanrui Ma

Visualization: Quanrui Ma

Writing—original draft: Quanrui Ma

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Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

This study used the publicly available TTSwing dataset, which can be accessed through the GitHub repository (<https://github.com/DEPhantom/TTSWING>), Dryad-linked release, and Zenodo software record reported by the dataset authors (Chou *et al.*, 2025a, 2025b). No new data were generated. Analysis code is available from the corresponding author upon reasonable request.

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