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Age-Related Differences in Heart Rate Variability and Physiological Load Among Professional Soccer Players Using a Wrist-Worn Biosensor

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Abstract

Background: Wearable sensing technologies enable continuous monitoring of physiological states in athletes, yet age-related differences in autonomic and mechanical load among professional soccer players remain insufficiently characterized. This study investigated whether heart rate variability (HRV) indices and accelerometry-derived physical load differ between younger and older professional players during routine morning training sessions. Methods: Fourteen male professional soccer players were monitored using a wrist-worn biosensor. Participants were divided into two age groups: Group A (≤23 years, n = 7) and Group B (≥24 years, n = 7). The device was attached at 08:30 and recorded tri-axial acceleration and cardiac signals continuously until 11:30 (≈3 h). Extracted metrics included root mean square of successive differences (RMSSD), percentage of NN intervals differing by more than 50 ms (pNN50), heart rate recovery (HRR), maximum heart rate, and total beat count. Group differences and position-based differences were evaluated. Results: Accelerometry-based physical load showed no significant difference between age groups. In contrast, HRV indices demonstrated age-related divergence: RMSSD was significantly higher in Group A compared to Group B ($p = 0.031$), suggesting greater parasympathetic activity in younger players. Total beat count was significantly higher in Group B ($p = 0.015$). pNN50 showed no group difference ($p = 0.918$). Pre- and post-session HRR did not differ significantly between groups, whereas maximum heart rate was significantly higher in Group A ($p = 0.0017$). Position-based comparisons revealed no consistent differences across metrics. Conclusions: Although mechanical load was comparable between age groups, autonomic markers—particularly RMSSD—indicated higher parasympathetic modulation in younger professional players. These findings align with established sports physiology literature but provide preliminary evidence derived from real-world data collected in professional soccer athletes using a compact wrist-worn biosensor. The results support the utility of wearable HRV monitoring for age-related physiological profiling in elite sports environments.

Keywords: heart rate variability; wearable biosensor; professional soccer players; accelerometry; age-related physiological differences

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1. Introduction

Heart rate variability (HRV) and cardiac autonomic regulation have been widely investigated across exercise science, clinical physiology, and sports performance research. Numerous studies have demonstrated that aerobic and resistance exercise influence resting and post-exercise HRV, blood pressure, and autonomic balance [1–13]. Exercise training has also been shown to improve sleep quality, autonomic modulation, and cardiovascular function in both healthy adults and clinical populations [3,4,8]. Meta-analytic evidence further indicates that exercise frequency, intensity, and modality modulate HRV responses across the lifespan [2,5,6]. Collectively, these findings highlight HRV as a sensitive, non-invasive marker of physiological stress, recovery, and training adaptation [7,10–12].

Beyond general exercise physiology, advanced digital health technologies and wearable systems have enabled continuous HRV monitoring in high-performance athletes. Prior work has examined HRV as a digital biomarker of chronic adaptation [14,15], leveraging mobile and wearable devices for real-time monitoring of training load and recovery [16,17], as well as the detection of overtraining risks [18–29]. Although subjective measures often complement objective load metrics in predicting training responses [18], sensor-based HRV metrics provide a reliable, quantifiable physiological index when interpreted within context. Signal processing applications in endurance athletes, sprinters, handball players, and motorsport athletes have demonstrated that HRV indices and heart rate recovery (HRR) accurately reflect sport-specific stress, autonomic reactivation, and performance capacity [11,19–22,24–28]. In soccer analytics specifically, wearable-derived HRV has been deployed to evaluate overtraining, cardiovascular load, and accumulated training stress [29–31], while complementary sensor research has explored injury risk, playing surface interactions, sprint training, and biomechanical monitoring [32–40].

Age-related differences in autonomic regulation have also been well-documented through various time-domain and frequency-domain analyses. Numerous studies report that aging is associated with reduced parasympathetic activity, decreased HRV complexity, and altered autonomic responsiveness [41–57]. These degradation effects have been observed across resting conditions, exercise responses, sleep, heat exposure, and daily activities [43,56,58]. Young adults typically exhibit higher RMSSD, greater vagal modulation, and more complex heart rate dynamics than older cohorts [45,46,50–54]. Even within physically active populations, age remains a primary determinant of autonomic function and biological signal characteristics [47,58–65].

Despite this extensive body of literature, several critical gaps remain at the intersection of wearable sensor systems and sports analytics. First, few studies have characterized age-related autonomic differences specifically in elite professional soccer players, whose intensive training loads, match demands, and physiological profiles differ substantially from recreational or semi-professional cohorts. Second, although multi-sensor fusion combining accelerometry and electrocardiography/photoplethysmography (ECG/PPG) is commonly proposed, simultaneous comparison of mechanical load (accelerometry-derived) and autonomic markers (RMSSD, pNN50, HRR) across different age groups within the same professional ecosystem is rare. Third, position-specific variations in autonomic regulation remain poorly understood, despite clear positional differences in physical demands during training and competition.

To address these limitations, this study presents an integrated framework evaluating age-related and position-related differences in accelerometry-derived physical load and time-domain HRV indices among 14 professional soccer players, utilizing a continuous wrist-worn biosensor. By extracting and processing real-world physiological and mechanical data collected during routine training, this work provides novel insights into autonomic function and physical load characteristics in elite athletes. Unlike previous research con-

ducted in general populations or via intermittent laboratory assessments, the present study leverages continuous, wearable-based monitoring in a professional sports environment, offering new evidence on how age and positional demands influence parasympathetic activity, heart rate dynamics, and field-based training responses.

2. Materials and Methods

2.1. Participants

Fourteen male professional soccer players belonging to a Japanese professional soccer club voluntarily participated in this study. Participants were divided into two age groups: Group A ($\leq$23 years, n = 7) and Group B ($\geq$24 years, n = 7). Participant characteristics are summarized in Table 1.

Table 1. Participant characteristics.

Variable	Group A ($\leq$23 Years)	Group B ($\geq$24 Years)	Total
n	7	7	14
Age (years)	21.3 $\pm$ 1.3	29.1 $\pm$ 2.1	25.2 $\pm$ 4.4

All participants were actively competing professional athletes and regularly engaged in team training.

Inclusion and exclusion criteria: Because highly trained athletes frequently exhibit physiological adaptations known as "athlete's heart," including sinus bradycardia and cardiac hypertrophy, recent medical evaluations performed by the team physician, including electrocardiography and echocardiography, were reviewed prior to participation. Athletes with clinically significant cardiovascular abnormalities were excluded.

Additional exclusion criteria included the following:

1. Current use of medications affecting autonomic nervous system function, including β-blockers, antiarrhythmic agents, or other cardiovascular medications.
2. Presence of acute illness or injury.
3. Excessive psychological stress or fatigue on the measurement day.
4. Failure to comply with study restrictions.

To minimize factors influencing heart rate variability (HRV), participants were instructed to refrain from consuming caffeine-containing beverages, energy drinks, preworkout supplements, and other stimulants for at least 24 h before measurement. High-dose nutritional supplements potentially affecting cardiovascular regulation were also restricted. To reduce the influence of acute training fatigue and overreaching, measurements were scheduled during a standardized team training period and were not conducted immediately following competitive matches or high-intensity training sessions. Training load during the preceding 24 h was standardized as much as possible through team scheduling. Participants were required to abstain from alcohol consumption on the night before testing, obtain sufficient sleep, and avoid food intake for at least 1–2 h before measurement. Subjective stress and fatigue levels were assessed using a visual analog scale (VAS) immediately before data collection. Only players reporting no substantial stress or fatigue were included in the final analysis.

2.2. Experimental Overview

Physiological monitoring was conducted during a routine morning training session. A wrist-worn biosensor was attached to each participant at approximately 08:30 and continuous measurements were collected until 11:30.

The training session consisted of three phases:

1. Warm-up (~30 min)
2. Main training session (~140 min)
3. Cool-down (~10 min)

Prior to initiating the recording, participants remained at rest until heart rate stabilization was confirmed.

Player positions were classified into four categories; Midfielder (MF), Forward (FW), Defender (DF) and Goalkeeper (GK). Position-specific analyses were conducted to evaluate potential differences in physiological responses (Figure 1).

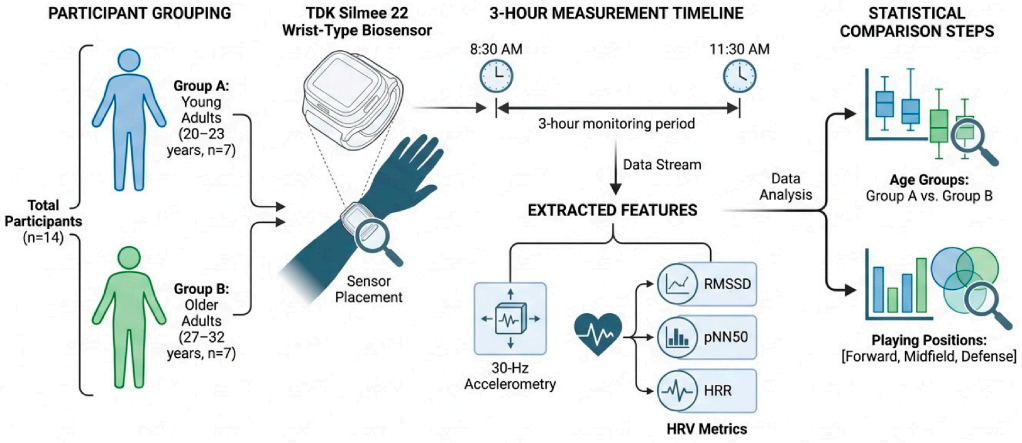


Figure 1. Experimental protocol and wearable biosensor (Silmee™ W22, TDK Corporation, Tokyo, Japan).

2.3. Wearable Biosensor

Physiological and activity data were collected using the Silmee™ W22 wearable biosensor (TDK Corporation, Tokyo, Japan). The device continuously recorded the following: Heart rate (HR), Pulse peak interval (PPI), Tri-axial acceleration, Skin temperature, Step count and Energy expenditure. Tri-axial acceleration signals were sampled at 30 Hz. PPI data were acquired in an event-driven manner at each detected pulse wave peak, resulting in a variable sampling frequency of approximately 25 Hz. The accelerometer-derived activity data were used to estimate physical load during training. Synthetic acceleration (SA) was defined as the vector magnitude of tri-axial acceleration: $SA = \sqrt{(ax^2 + ay^2 + az^2)}$, where ax, ay, az denote the three orthogonal acceleration components sampled at 30 Hz. The mean SA over the full monitoring window was used as a session-level physical load indicator.

2.4. PPI Processing and HRV Analysis

PPI data were treated as equivalent to RR intervals for HRV computation. Time-domain HRV indices were calculated from the cleaned PPI series. The following metrics were extracted: Root Mean Square of Successive Differences (RMSSD), Percentage of successive intervals differing by more than 50 ms (pNN50), Total Beats Count, Maximum Heart Rate (HRmax) and Heart Rate Recovery (HRR). RMSSD reflects parasympathetic nervous system activity, whereas pNN50 quantifies short-term heart rate variability. Beats Count represents the total number of pulse intervals recorded during the analysis period.

The following equations were used to compute the time-domain HRV indices from the cleaned PPI series:

$$RMSSD = \sqrt{\frac{1}{(N-1)}\sum_{i=1}^{n-1}(PPI_{i+1} - PPI_i)^2} \quad (1)$$

$$pNN50 = \left(\frac{\left| \left\{ i : \left| PPI_i^{+1} - PPI_i \right| > 50\ ms \right\} \right|}{(N-1)} \right) \times 100\ (\%) \quad (2)$$

$$Beat\ Count = N\ (total\ number\ of\ valid\ PPI\ values\ in\ the\ analysis\ window) \quad (3)$$

$$HR_{max}\ (bpm) = 60000/min(PPI_i)\ \ [PPI\ in\ ms] \quad (4)$$

where N denotes the total number of valid PPI intervals in the analysis period, and PPI_i represents the i-th inter-pulse interval in milliseconds.

PPI data quality control; a multi-stage artifact correction procedure was implemented in Python (3.14.0). First, physiologically implausible PPI values were removed. Intervals shorter than 300 ms or longer than 2000 ms were considered artifacts and excluded. Second, an adjacent-difference filter was applied. PPI values differing by more than ±30% from the preceding interval were identified as potential noise and removed. Third, a local median filter with a short moving window was applied to suppress transient spike artifacts. Finally, an artifact correction procedure modeled after the Kubios HRV methodology was implemented, including the following: physiological filtering, statistical outlier detection (±3 SD) and automatic interpolation of removed intervals. The cleaned PPI series was then used for HRV computation.

2.5. Ethical Considerations

This study was approved by the Ethics Committee of the Graduate School of Engineering, Mie University (Approval No. 135; approved on 12 October 2025). All participants received a detailed explanation of the study procedures and provided written informed consent prior to participation. The study was conducted in accordance with the principles of the Declaration of Helsinki.

2.6. Statistical Analysis

All statistical analyses were performed using Python (NumPy libraries). Continuous variables are presented as mean ± standard deviation (SD). Prior to group comparisons, data normality was assessed using the Shapiro–Wilk test. Homogeneity of variance between groups was evaluated using Levene's test. For comparisons between the two age groups (Group A and Group B), Welch's *t*-test was applied when the data followed a normal distribution. When the assumption of normality was violated, the non-parametric Mann–Whitney U test was used instead. To investigate position-related differences among midfielders (MF), forwards (FW), defenders (DF), and goalkeepers (GK), one-way analysis of variance (ANOVA) was performed for normally distributed variables. For variables that did not satisfy normality assumptions, the Kruskal–Wallis test was employed.

Statistical significance was defined as a two-tailed *p*-value of less than 0.05. Given the exploratory nature of this pilot study and the small sample (n = 14), primary analyses were conducted without a priori multiple comparison correction; all unadjusted results should be interpreted as preliminary and hypothesis-generating. To assess robustness, a post hoc Benjamini–Hochberg (BH) false discovery rate (FDR) correction was applied across the ten primary age-group comparisons ($\alpha = 0.05$). Under BH correction, only maximum heart rate ($p = 0.0017$; BH threshold = 0.005) remained statistically significant, while RMSSD ($p = 0.031$) and Beat Count ($p = 0.015$) did not survive correction and should be regarded as exploratory findings. In addition to hypothesis testing, standardized effect sizes were computed for all between-group comparisons: Hedges' g (with small-sample correction factor J) was calculated as g = J × (μ_A − μ_B)/s_pooled, where s_pooled is the pooled standard deviation and J = 1 − 3/(4df − 1) corrects for positive bias with small df. For ANOVA results, partial eta-squared (η^2) was calculated as η^2 = (F × df_between)/(F ×

df_between + df_within). All effect sizes are accompanied by 95% confidence intervals. Descriptive statistics and graphical inspections were used to evaluate physiological trends across age groups and playing positions.

3. Results

3.1. Age-Related Differences in Physical Activity and Physiological Parameters

The comparison between younger players (Group A, ≤23 years, n = 7) and older players (Group B, ≥24 years, n = 7) revealed no significant differences in accelerometry-derived physical activity metrics. Mean step counts were 70.73 ± 16.81 and 74.26 ± 11.97 for Groups A and B, respectively ($p = 0.660$). Similarly, energy expenditure did not differ significantly between groups (9.69 ± 2.76 vs. 10.71 ± 1.63, $p = 0.420$). Skin temperature tended to be higher in Group A than in Group B (27.46 ± 1.70 °C vs. 26.01 ± 1.11 °C), although the difference did not reach statistical significance ($p = 0.087$). Mean heart rate was comparable between groups (74.59 ± 3.38 bpm vs. 73.12 ± 5.09 bpm, $p = 0.539$). Conversation time ratio also showed no significant difference (29.31 ± 14.04% vs. 38.33 ± 13.61%, $p = 0.246$).

3.2. Synthetic Acceleration Analysis

The synthetic acceleration analysis demonstrated comparable overall mechanical load between age groups. The younger group exhibited a mean synthetic acceleration of 1038.38 ± 110.15, whereas the older group showed a mean value of 1042.02 ± 148.81. Welch's *t*-test revealed no statistically significant difference between groups (t = −1.641, $p = 0.101$); Hedges' g = −0.03 [95% CI: −0.96, 0.96], indicating a negligible effect size.

Although no significant age-related difference was detected, the older group displayed greater variability in acceleration data, largely attributable to one highly active participant whose acceleration profile indicated substantially greater movement intensity than the rest of the cohort.

3.3. Heart Rate Variability Indices

Significant age-related differences were observed in autonomic nervous system markers. RMSSD was significantly higher in Group A than in Group B (169.57 ± 56.63 ms vs. 159.20 ± 49.52 ms, $p = 0.031$), indicating enhanced parasympathetic modulation in younger athletes. In contrast, pNN50 did not differ significantly between groups (40.59 ± 19.34% vs. 40.43 ± 18.06%, $p = 0.918$). Beat Count was significantly lower in Group A than in Group B (114.77 ± 38.30 vs. 122.84 ± 37.00, $p = 0.015$), suggesting lower overall cardiac workload in younger players. Across all participants, the overall mean values were 164.71 ± 53.68 ms for RMSSD, 40.52 ± 18.73% for pNN50, and 118.52 ± 37.89 for Beat Count (Figure 2).

Standardized effect sizes for the primary HRV comparisons were as follows. For RMSSD, Hedges' g = 0.18 [95% CI: −0.80, 1.17], indicating a small effect. For pNN50, Hedges' g = 0.01 [95% CI: −0.97, 0.99], a negligible effect. For Beat Count, Hedges' g = −0.20 [95% CI: −1.18, 0.78], a small effect. Following BH–FDR correction across the ten primary comparisons, the uncorrected *p*-values for RMSSD ($p = 0.031$; BH threshold = 0.015) and Beat Count ($p = 0.015$; BH threshold = 0.010) did not meet the adjusted significance threshold; accordingly, these findings should be interpreted as exploratory. The wide confidence intervals reflect the limited sample size (n = 7 per group) and underline the need for replication in larger cohorts.

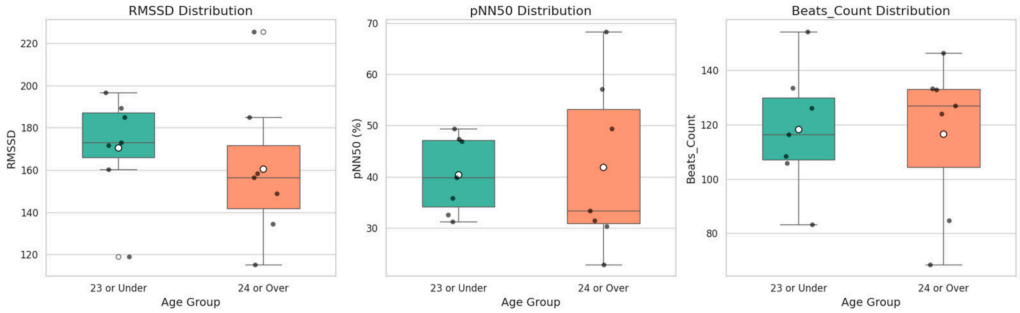


Figure 2. Comparison of heart rate variability time series indicators. Black dots represent individual participant measurements. White circles indicate group mean values. The central line within each box denotes the median, while the lower and upper edges correspond to the first and third quartiles, respectively. The box therefore contains the interquartile range (IQR), representing the central 50% of the data. Whiskers extend to the range of non-outlier values, and points located outside the whiskers are treated as outliers.

3.4. Position-Based Comparisons

Position-based differences in physiological and HRV parameters were evaluated using the metrics summarized in Figure 3. One-way ANOVA demonstrated no significant positional effects for step count ($F = 0.877$, $p = 0.446$, $\eta^2 = 0.149$), energy expenditure ($F = 1.336$, $p = 0.306$, $\eta^2 = 0.211$), skin temperature ($F = 0.024$, $p = 0.977$, $\eta^2 = 0.005$), heart rate ($F = 0.580$, $p = 0.578$, $\eta^2 = 0.104$), or conversation time ratio ($F = 1.769$, $p = 0.220$, $\eta^2 = 0.261$).

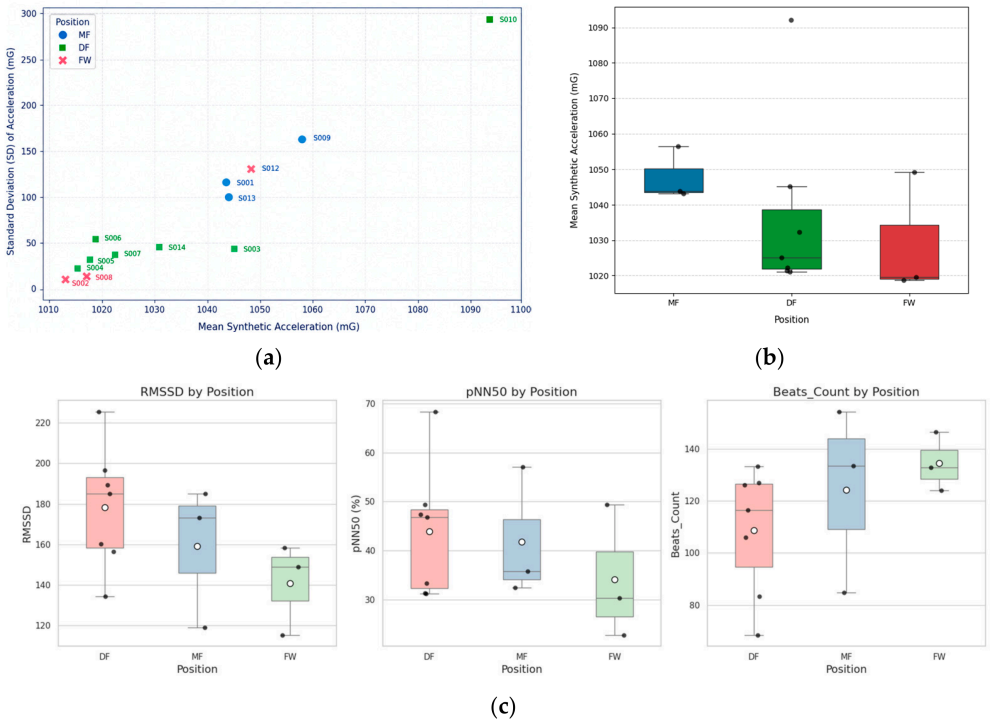


Figure 3. Data comparison by position. (**a**) shows scatter plot of bio acceleration (by position). Blue represents midfielders, green represents defenders, and red represents forwards (the numbers in the diagram refer to the subject numbers). (**b**) shows the mean and variance of the composite acceleration. (**c**) shows position-based comparison of HRV parameters (RMSSD, pNN50, Beat Count) among defenders (DF), midfielders (MF), and forwards (FW). This figure uses the same plotting conventions as Figure 2. Black dots represent individual participant measurements, while white circles indicate group mean values. The central line within each box denotes the median, and the lower and upper edges correspond to the first and third quartiles, respectively. Boxes represent the interquartile range (IQR), whiskers indicate the range of non-outlier values, and points outside the whiskers are treated as outliers.

For RMSSD, ANOVA yielded F = 1.717 (p = 0.229, η^2 = 0.256, medium effect); for pNN50, F = 0.566 (p = 0.585, η^2 = 0.102, small effect); and for Beat Count, F = 1.207 (p = 0.339, η^2 = 0.194, small-to-medium effect). Tukey's post hoc comparisons confirmed the absence of significant pairwise differences between positions. The absence of significant positional differences is likely attributable to tactical rotation during training sessions, which reduces systematic positional load differentiation, combined with the small per-position subgroup sizes (DF: n = 4, MF: n = 5, FW: n = 4) that limit statistical power for detecting moderate effects.

However, descriptive statistics suggested a tendency toward higher RMSSD values in defenders (177.30 ± 50.84 ms) compared to midfielders (154.67 ± 60.10 ms) and forwards (141.52 ± 35.31 ms), whereas Beat Count tended to be lower in defenders than in the other positions.

3.5. Heart Rate Recovery Analysis

To evaluate recovery dynamics near the end of the monitoring period, HRV parameters were analyzed within two predefined time windows, as summarized in Figure 4. (1) 20–10 min before the end of recording and (2) the final 10 min before recording termination. During the first time window, Group A exhibited significantly higher RMSSD values than Group B (166.42 ± 47.93 ms vs. 146.40 ± 42.10 ms, p = 0.041). Beat Count was significantly lower in Group A (118.44 ± 35.10 vs. 128.52 ± 32.40, p = 0.046). No significant difference was observed for pNN50 (p = 0.385). In the final 10 min period, none of the HRV indices differed significantly between groups. RMSSD (154.20 ± 52.14 ms vs. 142.11 ± 39.88 ms, p = 0.231), pNN50 (35.84 ± 18.12% vs. 34.55 ± 16.10%, p = 0.742), and Beat Count (129.15 ± 33.42 vs. 132.84 ± 29.54, p = 0.584) all demonstrated convergence between the age groups.

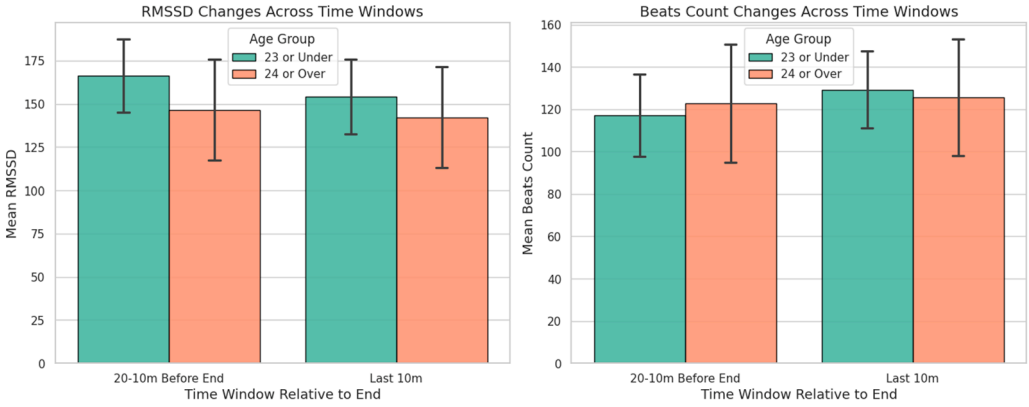


Figure 4. Comparison of Heart Rate Recovery between Group A and B. Green bars represent players aged 23 years or under (Group A), and orange bars represent players aged 24 years or older (Group B). Bars indicate group mean values, and error bars denote the standard deviation (SD).

Effect sizes for the 20–10 min recovery window: RMSSD, Hedges' g = 0.42 [95% CI: −0.58, 1.41], small-to-medium effect; Beat Count, Hedges' g = −0.28 [95% CI: −1.27, 0.71], small effect. For the final 10 min window, RMSSD Hedges' g = 0.24 [95% CI: −0.74, 1.23], a small and non-significant effect, consistent with the convergence of recovery indices between groups.

3.6. Maximum Heart Rate

Maximum heart rate differed significantly between age groups. Group A exhibited a significantly higher maximum heart rate than Group B (189.43 ± 7.30 bpm vs. 172.14 ± 8.65 bpm; t = 4.041, p = 0.0017, Figure 5). The observed reduction in maximum

heart rate among older athletes is consistent with the well-established age-related decline in cardiac chronotropic responsiveness. In contrast, age-related differences in heart rate recovery were less pronounced, suggesting preserved autonomic recovery capacity among trained professional soccer players despite increasing age.; Hedges' g = 2.02 [95% CI: 0.78, 3.26], large effect.

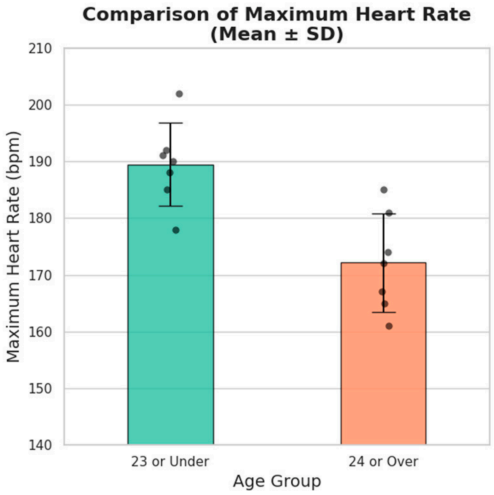


Figure 5. Comparison of maximum heart rates. Bars represent the mean maximum heart rate, error bars indicate ± SD, and individual dots represent the maximum heart rate of each participant.

Importantly, HRmax was the only variable to remain statistically significant after BH–FDR correction across ten primary comparisons (BH threshold = 0.005), and its very large effect size (Hedges' g = 2.02) provides robust evidence of an age-related decline in maximal cardiac chronotropic capacity even within this homogeneous cohort of professional athletes.

Comparison of Group A and B: A shows a significantly higher maximum heart rate than B.

4. Discussion

The primary finding of the present study was that younger professional soccer players (≤23 years) exhibited significantly greater parasympathetic activity, as reflected by higher RMSSD values, than older players (≥24 years), despite comparable levels of physical activity and mechanical workload. Furthermore, maximum heart rate was significantly higher in younger athletes, whereas accelerometry-derived workload metrics did not differ between age groups. These findings suggest that age-related physiological differences may be more readily detected through autonomic nervous system markers than through conventional activity-based measurements.

4.1. Age-Related Differences in Autonomic Regulation

Heart rate variability (HRV) is widely recognized as a noninvasive indicator of autonomic nervous system function and recovery status in athletes [14–17]. Among HRV indices, RMSSD is considered one of the most reliable markers of cardiac parasympathetic modulation and has been extensively used for monitoring training adaptation and recovery [15,16].

In the present study, RMSSD was significantly higher in younger players than in older players. This finding is consistent with previous investigations demonstrating that cardiac autonomic regulation correlates with age, even in healthy and physically active populations [41,45,54]. Although all participants in the present study were professional athletes

exposed to similar training loads, younger players maintained greater vagal modulation, consistent with greater autonomic flexibility and recovery capacity in younger athletes.

Interestingly, pNN50 did not differ significantly between groups. Previous studies have reported that RMSSD is less sensitive to recording artifacts and provides greater day-to-day stability than pNN50 in athletic populations [15,16]. Therefore, RMSSD may be a more practical marker for routine field monitoring of professional soccer players.

4.2. External Workload Versus Internal Physiological Load

A notable observation was that step count, energy expenditure, synthetic acceleration, and heart rate showed no significant age-related differences. These findings indicate that both age groups experienced comparable external workloads during the monitored training session.

Previous football monitoring studies have emphasized external load variables such as running distance, sprint frequency, accelerometry, and energy expenditure as indicators of training stress [31,36]. However, several researchers have argued that external load alone cannot fully explain individual physiological responses to training [17,18].

The present findings support this concept. Despite similar movement patterns and mechanical load, significant differences were observed in autonomic function. Therefore, wearable HRV monitoring may provide important complementary information regarding internal physiological load that cannot be captured by accelerometry alone.

4.3. Heart Rate Recovery Characteristics

The recovery analysis revealed that younger players demonstrated significantly higher RMSSD and significantly lower Beat Count during the period 20–10 min before the end of monitoring. However, these differences disappeared during the final 10 min.

This pattern suggests that younger athletes may initiate parasympathetic reactivation earlier during recovery. Nevertheless, older professional players eventually reached a comparable recovery state by the end of the monitoring period.

A plausible mechanistic explanation for the convergence of HRV metrics in late recovery relates to chronic training-induced autonomic adaptation. Sustained professional training is known to up-regulate cardiac vagal tone through structural and functional cardiac remodeling, including increased stroke volume, enhanced sinus node responsiveness, and elevated parasympathetic outflow at rest [14,15,24]. In older professional athletes, although resting vagal tone may be attenuated relative to their younger peers, years of high-volume training likely preserve sufficient parasympathetic reserve to support complete autonomic recovery within the 3 h monitoring window. This interpretation aligns with evidence from Dupuy et al. [24] and Suzic Lazic et al. [28], who reported that long-term endurance training substantially attenuates age-related declines in post-exercise parasympathetic reactivation in elite athletes. The initial lag in older players' parasympathetic rebound (detectable in the 20–10 min window) may reflect slower sympathetic withdrawal kinetics rather than a fundamental deficit in vagal capacity.

These observations are consistent with previous reports indicating that exercise capacity and training status may have a stronger influence on heart rate recovery (HRR) than chronological age among trained athletes [28]. Dupuy et al. reported that post-exercise parasympathetic reactivation was comparable between highly trained adult endurance athletes and younger subjects [24]. Similarly, studies of elite athletes have shown that regular endurance training can attenuate age-related declines in autonomic recovery [11,28].

Therefore, although younger players appeared to recover more rapidly during the early recovery phase, long-term professional training may help preserve recovery capacity among older elite athletes.

4.4. Maximum Heart Rate and Physiological Aging

Maximum heart rate was significantly higher in younger players than in older players. This finding is consistent with established physiological evidence demonstrating a progressive decline in maximum heart rate with aging [45,59,64].

Unlike HRV-derived recovery indices, maximum heart rate is strongly influenced by intrinsic cardiac mechanisms, including sinoatrial node function and β-adrenergic responsiveness, both of which decline with age [45]. Importantly, previous research has shown that even highly trained athletes cannot completely prevent this age-related reduction in maximal heart rate [59].

Therefore, the present findings support the established concept that maximum heart rate reflects biological aging even in elite athletic populations.

4.5. Comparison with Previous Soccer Studies

Several recent studies have investigated HRV monitoring in soccer players, primarily focusing on fatigue detection, overtraining, recovery assessment, and training-load management [29,31]. Lipka et al. concluded that HRV monitoring is a useful tool for identifying recovery status and training adaptation in soccer players [29].

However, relatively few studies have specifically examined age-related differences in autonomic regulation among professional soccer players under real-world training conditions. Most previous studies have relied on short-term ECG recordings, laboratory-based protocols, or chest-strap devices [14,15,29].

The present study differs from previous investigations by continuously monitoring athletes throughout routine morning activities using a compact wrist-worn biosensor. This approach enabled simultaneous assessment of locomotor activity, behavioral patterns, and autonomic function under ecologically valid field conditions.

Accuracy of Wrist-PPG-Derived HRV During Dynamic Exercise

HRV indices in this study were derived from pulse-to-pulse intervals (PPI) recorded by the wrist-worn Silmee™ W22, which employs photoplethysmography (PPG). While PPG-based PPI is widely accepted as an approximation of ECG-derived RR intervals under resting or low-movement conditions, accuracy may be reduced during dynamic exercise due to motion artifacts at the wrist. Several studies have validated wrist-PPG HRV metrics against chest-ECG references: Leti et al. reported strong correlations ($r > 0.90$) for RMSSD between PPG and ECG during low-intensity exercise in trained athletes, while accuracy deteriorated at higher intensities. Similarly, Georgiou et al. demonstrated that wrist-PPG RMSSD agrees with ECG-RMSSD within acceptable limits (bias < 5 ms) at moderate intensity but underestimates HRV during high-intensity bouts. The Silmee™ W22 incorporates proprietary motion artifact suppression algorithms; however, device-specific validation data against ECG during professional soccer training are not currently available in the published literature. To mitigate this limitation, we applied a rigorous multi-stage PPI artifact correction pipeline (physiological filtering, ±30% adjacent-difference filter, local median filter, and Kubios-modeled interpolation) that removes physiologically implausible intervals and corrects transient artifacts prior to HRV computation. Nonetheless, residual motion-related noise cannot be entirely excluded, and the time-domain HRV estimates presented here should be interpreted with this caveat in mind. Future studies should include simultaneous ECG reference recording to quantify device-specific accuracy in the elite soccer context.

4.6. Novelty of the Present Study

The present study makes several distinct contributions relative to existing soccer wearable research. Most critically, it is—to the authors' knowledge—the first study to combine continuous 3 h wrist-PPG HRV monitoring with simultaneous tri-axial accelerometry during routine professional soccer training, enabling direct within-session comparison of external mechanical load and internal autonomic load in the same participants without requiring any interruption to normal training. This real-world continuous monitoring design contrasts with the predominant approach of short-duration (5–10 min) supine ECG recordings conducted in a laboratory or in standardized pre-training windows [14,15,29]. Second, this study targets a narrow, homogeneous cohort (elite male professional soccer players from a single J-League club), enabling age-related physiological differences to be detected against a controlled backdrop of identical tactical training demands—a design advantage that broad heterogeneous cohorts cannot offer. Third, the finding that HRmax shows robust age-related differentiation (large effect, FDR-corrected) even within this homogeneous group, while RMSSD differences require larger samples for definitive confirmation, has direct practical implications for how sports scientists should prioritize wearable metrics for age-sensitive athlete monitoring. Collectively, the study demonstrates that a single compact wrist-worn biosensor can replace multiple monitoring modalities in field conditions, a finding with significant translational value for routine team practice.

4.7. Practical Applications in Coaching

Despite the exploratory nature of the present findings, several practical observations may be informative for sports science practitioners working with professional soccer clubs.

Wearable RMSSD monitoring for age-differentiated recovery management. The observed trend toward lower RMSSD in older players (Group B, $\geq$24 years), if confirmed in larger cohorts, would suggest that older professional athletes may require extended recovery windows after high-load sessions. Coaching staff can use daily morning RMSSD measurements—readily obtained via the same wrist-worn biosensor used in this study—to track individual athletes' autonomic recovery trajectories. Practically, if an older player's RMSSD on a training morning falls below their rolling 7-day baseline by >20%, a reduction in session intensity or volume that day may be warranted to prevent accumulated autonomic fatigue. Younger players with characteristically higher RMSSD variance may tolerate more aggressive loading.

HRmax as a reliable age biomarker. In contrast to RMSSD, maximum heart rate showed a robust, large-effect age-related difference (Hedges' g = 2.02, FDR-corrected). Coaching staff should be aware that maximum HR-based training zone prescriptions (e.g., percentage of HRmax) must be adjusted for age; applying younger players' HRmax targets to older athletes will systematically underestimate the relative intensity and may lead to unintended overload.

Session monitoring without laboratory infrastructure. The present protocol—a single wrist-worn device recording continuously during normal training—required no specialized laboratory setup, no interruption to training, and no additional burden on athletes. This demonstrates the feasibility of integrating physiological profiling directly into routine practice, making autonomic monitoring accessible to clubs that lack high-performance laboratory facilities.

Several important limitations must be considered when interpreting the present findings.

Sample size and generalizability. The sample comprised only 14 male professional players (n = 7 per group) from a single Japanese J-League club, recruited during a single training session. This small, single-club, single-sex, single-nationality sample severely limits statistical power for all comparisons beyond HRmax. Replication in larger, multi-

club, mixed-nationality cohorts is essential. The present study is best characterized as a preliminary or feasibility study rather than one providing definitive physiological profiles.

Age grouping rationale. Participants were divided at the threshold of 23/24 years, which corresponds to the FIFA convention distinguishing senior from under-23 competition eligibility and reflects the developmental milestone at which professional soccer players typically transition from academy contracts to full senior terms in the Japanese professional league system. While this division has administrative and sporting relevance, it does not correspond to a sharply defined biological inflection point in autonomic aging, and the optimal age threshold for detecting clinically meaningful HRV divergence in elite athletes remains to be established by longitudinal data.

PPG accuracy during dynamic exercise. The Silmee™ W22 derives cardiac intervals via wrist-worn PPG, which is more susceptible to motion artifacts during high-intensity exercise than chest-ECG or chest-strap optical HR monitors. Although rigorous multi-stage artifact correction was applied, residual noise from wrist motion during soccer training cannot be entirely excluded. Device-specific validation of the Silmee™ W22 against simultaneous ECG during professional soccer has not yet been published, and HRV estimates should be interpreted accordingly.

Restriction to time-domain HRV. Analysis was limited to time-domain HRV indices (RMSSD, pNN50, Beat Count). Frequency-domain analysis (LF, HF power, LF/HF ratio) and nonlinear metrics (approximate entropy, sample entropy, DFA $\alpha 1$) were not computed. Frequency-domain analysis during dynamic soccer training is technically challenging because it requires artifact-free stationary segments of sufficient duration (typically $\geq$5 min), which cannot be guaranteed during active training with frequent acceleration and deceleration bouts. Nonlinear HRV analysis would require re-processing of the full raw PPI series. Future studies with dedicated analysis windows (e.g., warm-up rest, post-session recovery) should include frequency-domain and nonlinear domains to provide a more complete characterization of autonomic regulation.

Confounding factors not fully controlled. Key confounders including prior training load in the 48 h preceding measurement, preceding night's sleep quality and duration (beyond self-report VAS), seasonal competitive context, and session-internal intensity variation were not quantitatively characterized. While team scheduling standardized the preceding 24 h load, inter-individual variation in accumulated fatigue, nutritional state, and hydration may have influenced HRV. Future studies should incorporate objective sleep monitoring (e.g., actigraphy) and session RPE to better characterize and statistically control these confounders.

Multiple comparisons and statistical power. Ten primary age-group comparisons and six recovery window comparisons were performed. After BH–FDR correction, only HRmax remained statistically significant. The RMSSD and Beat Count findings (p = 0.031 and p = 0.015 uncorrected) carry elevated Type I error risk and should be treated as hypothesis-generating until replicated with adequate sample sizes. Bootstrap internal validation, Bayesian analysis, and minimum detectable effect (MDE) reporting are recommended for future studies with larger samples.

Cross-sectional design. The cross-sectional setup cannot distinguish whether lower RMSSD in older players reflects chronological aging, differential training history, accumulated micro-injury, or other age-correlated factors. Longitudinal tracking across competitive seasons is required to establish causal or directional relationships between aging and autonomic adaptation in elite soccer.

5. Conclusions

This study investigated age-related differences in autonomic nervous system activity and physical workload among professional soccer players during routine morning training sessions using a compact wrist-worn wearable biosensor. The objective was to determine whether physiological responses assessed by heart rate variability (HRV) indices provide additional information beyond conventional accelerometry-based measures of external workload in elite athletes.

The results demonstrated that younger professional soccer players exhibited significantly greater parasympathetic modulation, as reflected by higher RMSSD values, and achieved significantly higher maximum heart rates than older players, despite experiencing comparable accelerometry-derived physical workloads during training. In contrast, no significant differences were observed in physical activity indices, pNN50, heart rate recovery, or positional comparisons. These findings indicate that age-related physiological adaptations may be more readily detected through autonomic nervous system markers than through conventional activity-based metrics alone.

The present findings are consistent with previous reports showing an age-associated decline in parasympathetic activity and cardiovascular responsiveness. Importantly, however, this study extends existing knowledge by demonstrating these differences under real-world training conditions in professional soccer players using continuous wearable monitoring rather than laboratory-based assessments. This ecological approach provides practical evidence that subtle physiological differences associated with aging can be identified during routine team activities without disrupting normal training.

Overall, the findings suggest that wearable HRV monitoring represents a valuable tool for individualized athlete management, enabling coaches and sports scientists to assess recovery status, autonomic adaptation, and long-term physiological changes associated with aging. Incorporating continuous HRV monitoring into daily training practice may facilitate more personalized training prescription, optimize recovery strategies, and contribute to injury prevention and performance maintenance in elite soccer environments. Future studies involving larger cohorts and longitudinal follow-up are warranted to further clarify age-related autonomic adaptations and establish wearable-derived HRV metrics as reliable biomarkers for athlete monitoring.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Due to ethical and privacy restrictions, the raw data cannot be made publicly available. However, de-identified data can be provided by the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ANOVA	Analysis of Variance
BPM	Beats Per Minute
ECG	Electrocardiography
HR	Heart Rate
HRR	Heart Rate Recovery
HRV	Heart Rate Variability
PPG	Photoplethysmography
RMSSD	Root Mean Square of Successive Differences
SD	Standard Deviation
SDNN	Standard Deviation of Normal-to-Normal Intervals
LF	Low Frequency
HF	High Frequency
LF/HF	Ratio of Low Frequency to High Frequency Power
pNN50	Percentage of Successive NN Intervals Differing by More Than 50 ms

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