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Wearable Biometrics and Shooting Performance: A Pilot Study of Readiness for Advanced Military Training

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Abstract: This study evaluates the relationship between biometric indicators and competitive shooting performance in a military training context. Using wearable data from Oura Rings and Polar H-10 heart-rate sensors, we implemented a dual-framework approach: (1) weekly lifestyle and recovery metrics analyzed through within-person statistical models to identify associations with shooting performance, and (2) a live heart-rate monitoring dashboard synchronized with shot events to provide real-time physiological feedback for shooters and coaches. Sleep latency emerged as the strongest weekly predictor ($r = -0.43$, $p = .02$), with five mean-centered biometric features collectively explaining 53% of within-person variance in shooting scores ($R^2 = 0.53$). Although constrained by sample size, this pilot study establishes a scalable framework for integrating wearable biometrics into precision performance training environments relevant to military operational readiness and lethality.

Keywords: Performance optimization, biometric monitoring, human performance analytics, pilot study

1. Introduction and Background

Within the United States Army, wearable biometrics have evolved from tools primarily supporting identity verification into tools that enhance training cycles and lethality (Fischer Connectors, 2024). Advances in sensor capabilities and data accuracy now enable data-driven human performance optimization, reinforcing the Army's emphasis on treating Soldiers as a weapons system. Using biometric data from Oura Rings and Polar H-10 heart-rate sensors, this study examines shooting performance through both long-term and short-term biometric indicators to generate actionable insights for the military community. The United States Military Academy (USMA) Skeet and Trap Team serves as the data collection case study, as skeet and trap shooting's transversal target movement patterns correspond to techniques anticipated in future battlefield engagements.

Biometric data were analyzed through two complementary lines of effort whose names derive from the concrete slabs skeet shooters compete on, colloquially known as "the pad." "On-the-pad" analysis focuses on the period when a participant is actively shooting, while "off-the-pad" analysis focuses on lifestyle data leading up to a session. The first, "off-the-pad" lifestyle analysis (LOE 1), used Oura Rings to evaluate whether deviations from an individual shooter's physiological baseline correspond with changes in shooting performance. The second, an "on-the-pad" dashboard (LOE 2), provides a live heart-rate feedback loop integrated with the shooting environment, enabling analysis of heart rate in the lead-up to, during, and after each shot. Together, these lines of effort address the central question: how do deviations from a shooter's biometric baseline — at both the weekly (LOE 1) and shot-level (LOE 2) timescales — associate with changes in shooting performance? This study combines both LOEs to determine whether biometric baseline deviations provide actionable information for a data-centric coaching platform, and whether targeted adjustments — physiological regulation in the moment or broader lifestyle modifications — are associated with improved shooting performance and, ultimately, warfighter lethality. Although participants are cadets competing in skeet and trap, the analytical methods may generalize to other military units and sports analytics contexts.

2. Literature Review

Across sports, academic, and tactical domains, wearable biometric monitoring has become a critical tool for understanding how an athlete's physiological state influences performance under stress. Advances in sensor accuracy now enable continuous measurement of heart rate, heart-rate variability (HRV), sleep, movement, and workload — detecting fatigue and readiness changes not apparent through subjective assessment. Research has demonstrated that sleep quality, autonomic balance, and stress regulation are linked to cognitive functioning, emotional stability, and decision-making, all especially critical in precision tasks, where small internal fluctuations can degrade timing and fine motor control (Nemec, Thomas, Gile, Tong, & Mattison, 2019; Pointer, Gesun, & Watson, 2025).

A wealth of research has established HRV as a critical indicator of sleep quality and recovery (Chalmers et al., 2022), with both linked to chronic stress (da Estrela, McGrath, Booij, & Gouin, 2021) and shown to have longitudinal effects on athletic and cognitive performance (Mah, Mah, Kezirian, & Dement, 2011). Within shooting sports specifically, sleep duration, quality, timing, and latency have been shown to directly affect mood state and performance in elite shooters (Lu, An, & Qiu, 2022). While links between HRV, sleep quality, and shooting performance are well established, the precise mechanisms by which sleep affects individual shooters require discipline-specific investigation. Athletic and military studies further demonstrate that mental fatigue and heightened anxiety impair decision quality and emotional regulation even when aggregate accuracy is preserved, and higher-performing shooters tend to exhibit lower state anxiety and more stable HRV profiles (Stephenson, Thompson, Merrigan, Stone, & Hagen, 2021; Head et al., 2017). HRV and sleep-derived indicators have similarly been used to assess readiness, resilience, and training capacity in military contexts, underscoring the relevance of biometric monitoring in high-stakes environments where marginal gains can have outsized effects (Migliaccio, Padulo, & Russo, 2024).

Despite this growing body of work, research characterizing shot-level variation while accounting for individual biometric baselines and controlling for team-level effects remains limited. Previous shooting studies have primarily relied on post hoc analysis of performance outcomes rather than prospective, shot-synchronous measurement frameworks (Leonelli, 2025; de Amorim, Meira Jr., & Vickers, 2024). Although adaptive Bayesian methods have begun emerging in team sports, no comparable framework exists for shooting performance or integrated biometric data (Macrì Demartino, Egidi, & Torelli, 2025). Further, discipline-specific validation for skeet and trap remains sparse, with minimal integration of multiple biometric streams and little application of modern machine-learning approaches linking longitudinal wellness patterns to event-level performance. This study addresses these gaps by integrating sleep and cardiovascular metrics with shot- and week-level performance data in a competitive skeet and trap environment, extending established biometric frameworks into a precision-shooting context directly relevant to military operations.

3. LOE 1: Oura Ring Analysis

3.1. Methods and Materials

3.1.1. Procedure

For LOE 1, the participant pool consisted of second- through fourth-year cadets on the USMA Skeet and Trap Team who elected to participate in this optional study. Analysis was restricted to six non-consecutive weeks in which participants both wore their Oura Rings and completed a scored shooting round, resulting in a final sample of $n = 28$ person-weeks from 8 unique participants, each observed across 1–4 weeks (median: 4). Throughout the academic year, participants wore their Oura Rings continuously to collect longitudinal lifestyle data. Biometric data from weeks in which a scored round occurred were then extracted and processed through a structured pipeline. Each row in the final dataset represents one shooter over one week, including biometric variables temporally aligned with the shooting score recorded at that week's end.

3.1.2. Measures

Biometric data were extracted from the Oura Enterprise Platform, an organizational monitoring tool providing aggregated weekly measures of cardiovascular activity, recovery status, and sleep quality. These measures were selected based on established literature emphasizing stress regulation, autonomic balance, and sleep quality as key contributors to precision performance. Average heart rate served as an indicator of physiological activation, while heart rate variability reflected overall recovery and stress resilience. Sleep metrics were selected for their relationship with fatigue, cognitive control, and performance consistency under pressure. Temperature deviation served as a general marker of systemic strain or recovery status. Shooting scores were defined on a 0–100 scale; most scored rounds comprised 100 total shots, while 150-shot rounds were rescaled proportionally rather than excluded, as they represented valid performance observations. Shooting scores had a mean of $\mu = 76.9$ ($\sigma = 10.0$), a median of 79.5, and a range of 53–90. Shooting performance was measured using official competition scores aligned with the preceding biometric week.

3.1.3. Analysis Approach

To evaluate the relationship between long-term biometric indicators and shooting performance, several complementary analytical approaches were used. After processing and aggregating the Oura data, the final dataset comprised person-week observations with both temporal and identifying variables. Exploratory analysis included person-mean centering of biometric features, correlation between centered predictors and centered shooting scores, and OLS regression with mean-centered features. Person-mean centering separates within-shooter variation from between-shooter differences; without it, associations may be dominated by who is the better shooter overall rather than by week-to-week changes within each individual. The intraclass correlation coefficient (ICC) was used to quantify this variability. Pearson and Spearman correlations between centered predictors and shooting scores informed feature selection for OLS regression. Predictors were then selected using variance inflation factor (VIF) analysis, retaining the five features with meaningful associations with shooting score while minimizing multicollinearity. An OLS model with standard errors clustered by shooter accounted for within-person correlation, as conventional standard errors were undersized given repeated observations per individual. Coefficients from this model provide directional estimates of how deviations in biometric indicators correspond with deviations in shooting score.

3.2. Results

Within-person correlations between mean-centered biometric features and shooting score are presented in Figure 1. These correlations quantify how deviations from a shooter's typical physiological state correspond with deviations from that shooter's typical performance. Among the biometric variables examined, sleep latency demonstrated the strongest association with shooting performance based on the Pearson correlation ($r = -0.43$, $p = .02$), indicating that weeks in which shooters took longer to fall asleep corresponded with lower scores relative to their individual baseline. An ICC of approximately 0.36 indicated that a substantial portion of score variance was attributable to between-shooter differences, reinforcing the importance of modeling within-shooter deviations from individual baselines.

To assess relative importance, we estimated an OLS regression model using five mean-centered biometric predictors selected to mitigate collinearity, with the highest Pearson-correlated features retained from each domain (Table 1). Coefficients, clustered standard errors, t-statistics, and p-values are reported in Table 1. Together, these five predictors explained approximately 53% of the variance in centered shooting scores ($R^2 = 0.53$).

Table 1: OLS regression on five mean-centered biometric predictors of centered shooting score by shooter.

Feature	Coefficient	Std. Error	t	p
HRV Balance	-0.14	0.02	-9.34	$< .001$
High Stress Time	-0.00	0.00	-4.09	$< .001$
Average Heart Rate	-0.53	0.13	-3.99	$< .001$
Vascular Age	-1.22	0.35	-3.50	$< .01$
Sleep Latency	-0.01	0.01	-2.48	$= .013$

3.3. Discussion

The long-term analysis of Oura data enabled exploratory assessment of biometric variables associated with shooting outcomes relative to each shooter's own baseline. The strongest signals emerged from sleep-related metrics and average heart rate, consistent with the hypothesis that these would be the dominant predictors of shooting score. Sleep-related variables may affect shooting performance by influencing cognitive processing, motor coordination, and sustained attention, while elevated heart rate may indicate physiological strain or incomplete recovery — both impairing the stability and focus required for precision shooting. Person-mean centering isolated within-shooter physiological variation, allowing the study to evaluate whether deviations from an individual's typical biometric state correspond with changes in performance. These results should be interpreted as exploratory signals identifying candidate physiological factors that may influence shooting performance; nevertheless, the findings support the potential value of wearable biometric monitoring in precision tasks where subtle physiological fluctuations may influence outcomes.

This study faced several limitations, the most significant being the constraint to six non-consecutive weeks of data collection, selected based on the highest Oura Ring compliance among participants who also completed scored shooting rounds. This substantially limited the LOE 1 analytic sample, as many weeks included participants who completed scored rounds but did not wear their Oura Ring, or vice versa. Consequently, only a subset of participants wore their rings consistently, limiting

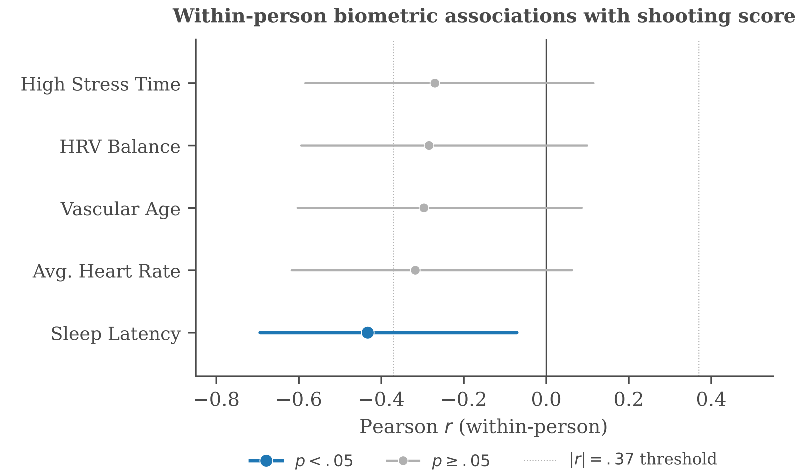

Figure 1: Within-person Pearson correlations between mean-centered biometric features and shooting score.

the ability to track biometric variation across a full training cycle. Future work should prioritize expanding data collection to determine whether these associations hold or evolve over a complete season.

4. LOE 2: Live Heart Rate Dashboard

LOE 2 was developed to contextualize the findings of the longitudinal analysis by examining shot-level physiological variation in real time. This web-based monitoring dashboard[1] links a participant's live heart rate to real-time shot events, as shown in Figure 2. By synchronizing beat-level heart rate with labeled shot outcomes, the dashboard enables examination of cardiovascular state immediately before, during, and after each shot — capturing transient physiological deviations that may degrade performance even when weekly biometric indicators appear favorable. However, Institutional Review Board (IRB) constraints prevented on-the-pad data storage and offline analysis using the Polar sensors, limiting quantitative evaluation of dashboard outputs. As a result, Figures 2 and 3 display simulated data, though the system is capable of collecting live training data.

The dashboard integrates two synchronized hardware streams: a Polar H-10 chest strap capturing beat-by-beat heart rate via Bluetooth, and a continuous microphone feed detecting shot timing through a configurable decibel threshold. Both streams are synchronized via a shared system clock on the end-user device, ensuring precise alignment between heart rate and shot events — critical given the rapid succession of shots in skeet and trap. As events are plotted in real time, an observer manually labels each detected shot as a hit or miss, with the label appended to the synchronized record.

Within LOE 2, three metrics were derived from the synchronized Polar H-10 and microphone streams: (1) *Instantaneous Heart Rate* was computed from RR intervals recorded via Bluetooth, converted to beat-by-beat heart rate as $HR_{inst} = 60{,}000/RR_{ms}$; (2) *Potential Shot Events* were identified from continuous audio decibel readings computed from the RMS amplitude of each microphone frame as $dB = 20\log_{10}(RMS) + 100$, with frames exceeding a user-configurable threshold (default 70 dB) flagged as potential shots; (3) *Shot Labels* were assigned by an observer selecting "hit" or "miss" to confirm each flagged event, with non-shot detections dismissed and excluded from the dataset. Labels were recorded alongside the instantaneous heart rate and audio peak at that moment, and CSV export has been validated with external users to support downstream offline analysis.

This system visualizes physiological fluctuations immediately before, during, and after shot execution, enabling identification of stress responses that may contribute to performance deviations. For example, unexpected heart-rate spikes in shooters who typically demonstrate stable physiological profiles may help explain isolated performance errors. A fundamental element of performance development is each shooter's individual "shot routine" — the repeated sequence from stance through target acquisition and shot execution (Orbach & Blumenstein, 2022; Laaksonen, Ainegren, & Lisspers, 2011) — which preserves shot integrity by transitioning arousal from the sympathetic to the parasympathetic nervous system (Park, Park, Lim, & Lee, 2020). A characteristic heart-rate spike immediately before the shot breaks, followed by a return to baseline, reflects the physiological

[1]Source code available at `https://github.com/connordurand/hr-shot-monitor`

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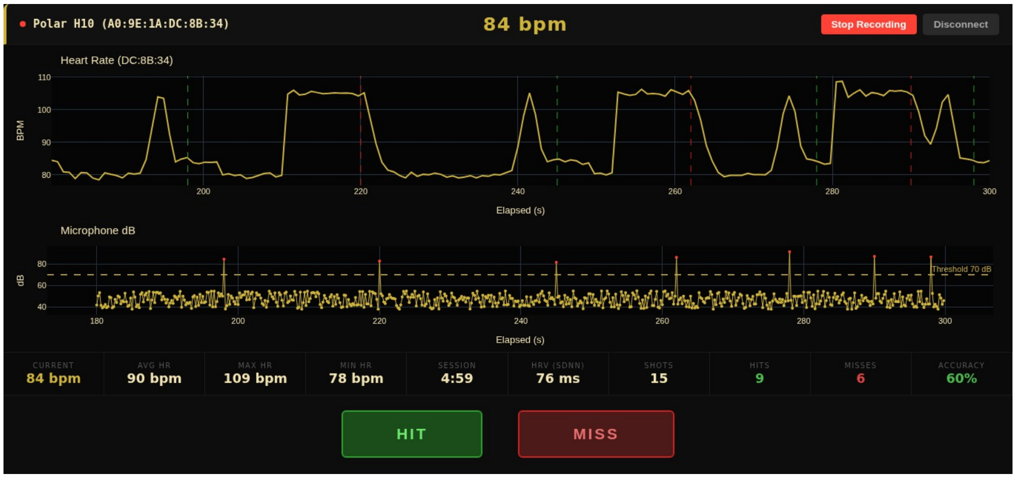

Figure 2: Live Monitor Dashboard (Simulated Data)

Figure 3: Shot Analytics Dashboard (Simulated Data)

underpinnings of a well-executed routine, often attributed to muscle memory (Zhao & Zhang, 2025). By visualizing shot-level physiological data in real time, the dashboard serves as a coaching tool — enabling shooter-specific feedback, displaying deviations from an established shot routine, and tracking scores and heart rate across a training cycle.

5. Conclusion

Although limited by sample size and study duration, this study establishes a replicable framework for integrating wearable biometrics into military training environments — exporting longitudinal biometric data, integrating shooting scores through a structured pipeline, and applying person-mean centering, correlation analysis, VIF-based feature selection, and clustered OLS regression to isolate within-person physiological signals associated with performance.

Wearable sensors are increasingly used in human performance monitoring, yet little research connects biometrics to precision shooting. This pilot study explored these relationships both "off-the-pad" and "on-the-pad," emphasizing the importance of controlling for each individual's biometric baseline rather than attempting to predict performance in aggregate. Results indicate that sleep metrics have the strongest associations with week-to-week changes in individual shooting performance, with moderate associations observed for heart rate. Future work will apply this methodology to additional observations, using estimated OLS coefficients and individual biometric baselines to drive predictive analytics. With a larger and more continuous dataset, integrating LOE 1 longitudinal data and LOE 2 live heart-rate monitoring into a unified dashboard would enable adaptive, real-time, personalized feedback for both coaches and shooters.

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