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Heart Rate Variability and Batting Decision-Making Under Varying Bowler Familiarity: A Real-Time Physiological and Biomechanical Analysis

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ABSTRACT

Cricket batting demands rapid decision-making under intense psychological pressure, where shot selection accuracy directly influences match outcomes. Heart Rate Variability (HRV) is a validated physiological marker for stress and cognitive load, yet its specific relationship with batting decision-making under varying bowler familiarity remains underexplored. This study proposes an integrated framework using a custom-built IoT wearable device powered by a 3.7V LiPo battery, ESP32 microcontroller, and MAX30102 sensor to monitor HRV in real-time during batting scenarios against familiar versus unfamiliar bowlers. The device acquires raw photoplethysmographic (PPG) signals at 100 Hz through its integrated 16-bit analogue-to-digital converter, which provides the temporal resolution necessary for accurate RR interval detection and subsequent HRV computation. From these high-resolution raw data, processed heart rate values are derived and transmitted at a rate of three data points per second for real-time display and session logging. Preliminary validation against the Xiaomi Smart Band 8 Pro, a consumer-grade wrist-worn device with established optical heart rate sensing capability, across four physiological states (morning post-sleep, noon post-meal, evening post-exercise, and night pre-sleep) demonstrated a 98% accuracy rate based on primary data from batsmen. Combined with synchronized 4K 60 FPS video analysis, this study aims to uncover neurophysiological correlates of shot selection behaviour in cricket. Findings are expected to inform personalized training and stress management strategies, offering significant implications for modern cricket coaching.

1. INTRODUCTION

Cricket batting represents one of the most cognitively demanding activities in competitive sports, requiring batsmen to process complex visual information, predict ball trajectory, and execute precise motor responses within milliseconds. The decision-making process becomes increasingly challenging when facing unfamiliar bowlers, as batsmen lose contextual prediction advantages and must rely heavily on real-time kinematic cues.

Recent advances in wearable Internet of Things (IoT) technology offer promising opportunities to understand the physiological underpinnings of sports performance, particularly through HRV analysis to assess autonomic nervous system responses under stress [1]–[3].

Heart rate variability, defined as the variation in time intervals between consecutive heartbeats, provides insights into autonomic nervous system functioning and serves as a sensitive indicator of psychological stress, cognitive load, and decision-making capacity in athletic populations [4], [5].

Research by Arsath et al. demonstrated that cricket batsmen exhibit consistent HRV patterns across shot deliveries, with significant reductions in RMSSD (root mean square of successive RR interval differences) of 34–45% during elevated stress periods, particularly around poor shot selections [6]. These findings suggest HRV monitoring could provide objective, real-time assessment of mental state changes affecting batting performance.

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The integration of wearable technology with high-resolution video analysis presents novel opportunities for comprehensive performance assessment. Modern smartphone cameras capable of 4K recording at 60 frames per second enable detailed biomechanical analysis of batting techniques, shot timing, and execution quality without requiring expensive laboratory equipment [7]. Combined with real-time physiological monitoring, this approach facilitates field-based research with ecological validity while maintaining measurement precision. This study proposes to investigate the relationship between HRV responses and shot selection accuracy using a validated IoT wearable device integrated with smartphone-based video analysis. By examining physiological responses to known versus unknown bowlers, this research addresses a critical gap in understanding stress-performance relationships in cricket batting.

This study introduces a novel framework to address a critical gap in sports science: The lack of objective data linking stress to performance in cricket. By integrating a validated IoT wearable with video analysis, this research moves beyond subjective analysis to quantify the stress-performance relationship. Examining how HRV responses correlate with shot selection accuracy against known versus unknown bowlers will establish objective, neurophysiological markers for batting decisions.

2. Literature Review

Extensive research has established Heart Rate Variability (HRV) as a reliable and non-invasive indicator of an athlete's training status, recovery capacity, and overall performance readiness across various sports [2], [8]. The physiological demands in cricket are unique and vary significantly across different formats, from the sustained endurance of Test matches to the high-intensity, explosive efforts required in T20 and ODI formats [29]. Batting performance, particularly in the fast-paced T20 format, has been shown to be directly influenced by a player's underlying physical and physiological parameters [30].

In this context, cardiovascular responses are strongly correlated with batting performance [9]. This relationship is often described by an inverted-U curve, where performance peaks at an optimal heart rate or "arousal zone," but becomes detrimental if physiological activation and stress become too high [9]. Elite cricketers, in particular, demonstrate superior cardiovascular adaptations, which include lower resting heart rates (57.2 ± 5.9 bpm) when compared to endurance athletes [10]. This adaptation is further highlighted by significant negative correlations ($r = -0.62$, $p < 0.001$) between their resting heart rate and predicted VO2max [10]. These findings underscore the critical importance of cardiovascular fitness and efficient autonomic regulation for high performance in modern cricket.

Beyond the physical demands, sports psychology research has repeatedly demonstrated that psychological stress significantly impacts the quality of an athlete's decision-making [11]. This impact is mediated through mechanisms such as attentional narrowing, a reduction in working memory capacity, and altered risk assessment [31]. For a batsman, this is a familiar challenge, as they must constantly identify and manage numerous sources of stress to perform a situation aptly described as "batting on a sticky wicket" [27]. These stressors and the associated coping strategies are not limited to elite professionals; they are a fundamental challenge identified even in junior cricket batsmen [26].

These cognitive pressures become particularly pronounced when batsmen face unknown bowlers [12]. In this scenario, they cannot rely on familiar pattern recognition and must instead process a significantly higher volume of novel sensory information in real-time [25]. This challenge relates directly to the neurophysiological correlates of anticipation, a key component of expert performance where the brain's ability to predict an opponent's action is critical [23]. Skilled cricket batsmen show differential responses to physiological stress depending on the information available; for example, performance based on contextual cues tends to decline under fatigue, while the utilization of kinematic cues remains stable [13]. While much of the research focuses on batting, related studies on elite fast bowlers have also quantified a clear link between high physical workloads and a measurable decline in cognitive function, reinforcing the tight coupling of physical exertion and mental acuity across the sport [32]. This suggests that stress fundamentally alters a batsman's cognitive strategies, which can be the difference between a short innings and the ability to "turn starts into big scores" [13], [22]. This makes HRV a potentially valuable, objective predictor of shot selection accuracy under pressure.

The adoption of wearable technology in sports has evolved significantly, moving from basic fitness tracking to sophisticated, real-time performance analysis systems [14]. Modern Internet of Things (IoT) devices can now achieve high sampling rates (250–1000 Hz) with an accuracy that is comparable to laboratory-grade equipment, making them perfectly suitable for field-based HRV analysis [15]. As these wearable systems become more advanced, a key engineering challenge is managing power consumption [21]. Recent advancements, such as energy-efficient monitoring techniques and the use of deep learning for on-device ECG analysis, are making long-term, continuous field monitoring increasingly feasible [21].

Professional cricket teams now routinely employ a suite of technologies, including GPS tracking, heart rate monitors, and biomechanical sensors, to optimize player training loads and prevent injuries [16]. The application of this data is also expanding beyond individual performance and into the tactical domain, with research exploring how physiological monitoring can be used for team strategy optimization [31]. In parallel with physiological sensors, smartphone-based motion analysis has emerged as a powerful and cost-effective alternative to traditional, lab-based biomechanical systems [7], [17]. High-frame-rate cameras (60–240 FPS) on modern phones, combined with automated analysis algorithms, can provide the detailed biomechanical assessments.

Collectively, existing research highlights the intricate interplay between physiological readiness, cognitive function, and performance outcomes in cricket. HRV has emerged as a valid indicator of internal load and stress response, while wearable technologies have proven capable of capturing relevant physiological data in real-time and ecological settings. Yet, despite the advancements in both physiological monitoring and decision-making research, a significant gap remains in the integration of these domains particularly in the context of batting performance under perceptual uncertainty, such as facing unfamiliar bowlers. Current literature lacks studies that systematically investigate how real-time autonomic fluctuations correlate with shot selection accuracy under varying familiarity conditions. The proposed research seeks to bridge this gap by combining a custom-built, high-resolution HRV monitoring wearable with synchronized biomechanical analysis. By doing so, it aims to uncover the neurophysiological underpinnings of batting decision-making and to establish scalable methods for real-world performance analysis beyond laboratory constraints. This contribution has the potential to inform individualized training protocols and enhance coaching strategies in modern cricket.

3. METHODOLOGY

This study employs a mixed-methods experimental approach combining physiological monitoring, video-based decision analysis, and statistical assessment to investigate the influence of bowler familiarity on batting performance under cognitive stress. A custom-built wearable IoT device was engineered to measure real-time Heart Rate Variability (HRV) during cricket gameplay. This section outlines the participants, study design, device architecture, validation procedures, data collection protocols, and analytical techniques used to assess neurophysiological responses and shot decision accuracy across familiar and unfamiliar bowling conditions.

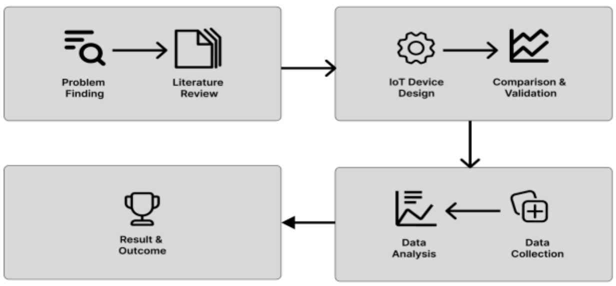


Fig. 1. Full Methodology Flow illustrates the study's sequential process. It begins with Problem Finding, which informs the Literature Review. This leads to the IoT Device Design, followed by its Comparison & Validation against the Xiaomi Smart Band 8 Pro. Once validated, the methodology moves to Data Collecting from Cricket Players. The collected data is then put through Analyse the Data to produce the final Result & Outcome.

Fig. 1. Full Methodology Flow

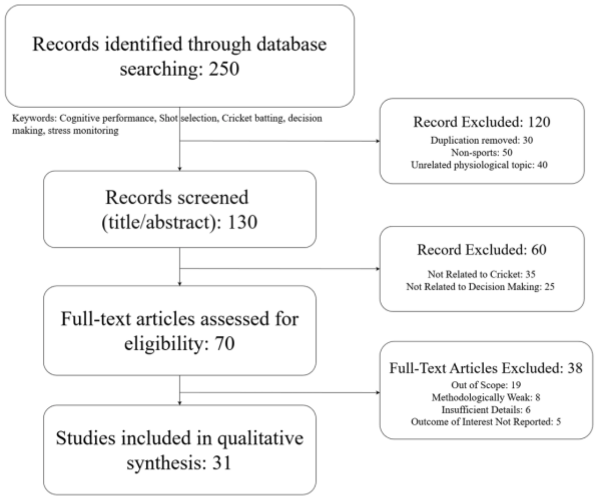


Fig. 2. Paper Review Process - Prisma shows how the literature for the review was selected. The process started with 250 records, which were screened down to 130 by title and abstract after 120 were excluded. These 130 articles were then assessed for eligibility, and 60 were removed, leaving 70 full-text articles. Finally, after 38 more articles were excluded for being out of scope or methodologically weak, 32 studies were included in the final qualitative synthesis.

Fig. 2. Paper Review Process- Prisma

3.1 Participants

Twenty-two male cricketers from two teams (age 18–35) will be recruited for this study. There are several methodological reasons we chose this age range. First, that 18–35 years encompasses the main competitive playing window in cricket during which athletes are most likely to participate regularly in structured matchplay and have fully formed batting techniques amenable to performance analysis. Second, resting autonomic nervous system function and accordingly baseline HRV parameters are relatively stable across this age band compared with older populations, due to the fact that natural attenuation of vagal tone in older populations yields physiologically confounding differences. Third, limiting participants to 18 years and older satisfies institutional ethical requirements for informed consent without the necessity of guardian approval. Last but not the least, this demographic is quite aligned with previous HRV studies in sport such as Buchheit (2014) and Laborde et al (2018), thus enabling meaningful comparisons across studies. Participants will be stratified by their batting position to ensure a representative sample. All individuals will be screened to exclude those with any known cardiovascular conditions, recent injuries, or any use of medications known to affect heart rate. This screening will ensure the recorded physiological data, and cardiovascular endurance metrics specifically, are a direct result of athletic activity rather than any medical confounds.

3.2 Study Design

The study will employ a randomized crossover design meticulously structured to isolate the physiological and cognitive impact of bowler familiarity on batting performance. To facilitate reliable data collection in an ecologically valid setting (i.e., on the field, not in a lab), this study will require the engineering of a custom wearable Internet of Things (IoT) device. The system's architecture will be optimized for accuracy, wear ability, and usability. The core of the device will be an ESP32 dual-core processor (240 MHz) with integrated Wi-Fi and Bluetooth Low Energy (BLE) for high-speed processing and seamless wireless data transmission. The primary sensor will be the MAX30102, a high-precision optical module. It will utilize photoplethysmography (PPG) to measure heart rate and inter-beat intervals [5]. This optical technique is a validated method for heart rate tracking in modern wearable devices [10]. To enable true Heart Rate Variability (HRV) analysis, the system will integrate a 16-bit analogue to digital converter (ADC) sampling at 100 Hz. This high-resolution capture will ensure the precision of RR interval measurements, which will form the basis of HRV metrics [2], [24]. A 3.7V, 500 mAh rechargeable lithium-polymer (LiPo) battery will provide over 12 hours of continuous operation. The complete system will be housed in a lightweight (45 g), wrist-worn unit with an IP67-rated waterproof enclosure to protect against sweat and environmental factors.

When we consider the device, it is necessary to differentiate the rate at which raw signals are acquired from the rate at which processed output is produced. The MAX30102 sensor in conjunction with the ESP32's 16-bit ADC, directly captures raw PPG waveform at 100 Hz or one hundred optical intensity readings are taken each second. This sampling frequency is within the range recommended in the Task Force of the European Society of Cardiology (1996) for short-term HRV analysis that requires sufficient temporal resolution to resolve individual R-wave peaks accurately and calculate RR intervals with millisecond precision. Note that the peak-detection algorithm in firmware referenced here does not actually run at a rate of three samples per second; rather, this figure describes how frequently a processed and averaged heart rate value is output to be transmitted/transmitted for visualization purposes. The raw 100 Hz data stream (from which all offline HRV time-domain metrics [RMSSD, SDNN, pNN50] are computed) are stored in its entirety and not down-sampled during analysis. This dual-rate architecture thus ensures that the combination of high-fidelity raw data for research-grade HRV computation needs accommodating with the practical constraint of wireless bandwidth efficient during field sessions.

All raw and processed signals are simultaneously streamed in real-time to a local receiving device over a secure Wi-Fi connection for data logging. The ESP32 is connected to its own password-secured local hotspot that runs on WPA2 security protocol which protects the physiological data from being intercepted by third party. Data packets are sent over the User Datagram, a protocol with application layer sequence numbering that allows the receiving software to recognize missing or out-of-order packets during a session. To guard against potential dropouts in connectivity due to distance or short-lived interference within the field environment, the device firmware simultaneously writes each incoming sensor reading into a local comma-separated value (CSV) file persisted on the ESP32's onboard SPIFFS flash memory. The full session data is stored in this local buffer. After each data collection session, an integrity check is done by comparing the number of records logged as transmitted on the receiving device with that on-board buffer size. We did not observe data loss using this protocol in the pilot sessions carried out as part of device validation.

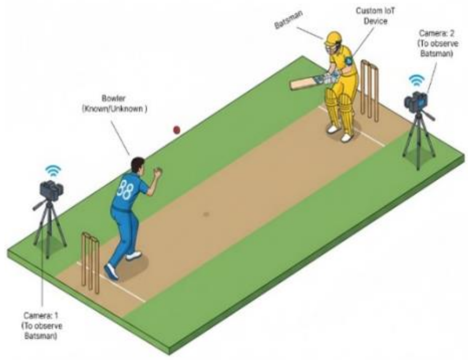


Fig. 3. Study Design illustrates the experimental setup, showing a batsman wearing the Custom IoT Device while facing a Bowler (Known/Unknown). Two cameras are positioned to observe and record the batsman's performance, allowing for the simultaneous collection of physiological data from the device and video data from the cameras.

Fig. 3. Study Design

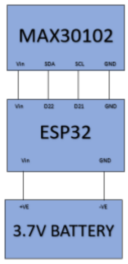


Fig. 4(a). Block diagram.

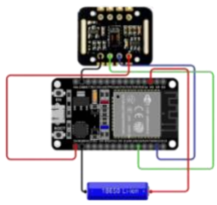


Fig. 4(b). Circuit diagram.

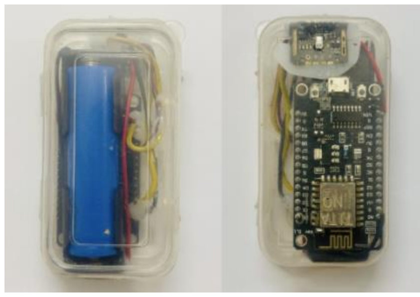


Fig. 4(c). Front and the back side of device.

To establish the reliability and validity of the proposed IoT device, its measurements were benchmarked against the Xiaomi Smart Band 8 Pro, a commercially available consumer-grade wrist-worn heart rate monitor. This specific device was selected as the reference standard because of its widespread availability, its use of the same underlying PPG optical sensing technology, and its documented measurement agreement with clinical-grade monitors in recent independent validation studies. To test the device in both high- and low-variability conditions, validation was performed across four distinct physiological states: Morning post-sleep, Noon post-meal, Evening post-exercise, and Night pre-sleep. Statistical metrics employed included Bland-Altman analysis (for agreement), intraclass correlation coefficient (ICC 0.95, for reliability), root mean square error (RMSE, for precision), and signal-to-noise ratio (SNR, for signal quality) [19], [20]. These metrics confirmed the device's suitability for high-fidelity HRV data capture. Fig-4(a): Block diagram provides a conceptual overview of the system's architecture, showing the three core components: the MAX30102 sensor, the ESP32 microcontroller, and the 3.7V LiPo Battery. Fig 4(b): Circuit diagram offers a more realistic, detailed representation of the electrical connections, clearly indicating the specific wiring paths between the sensor's I2C pins (SDA and SCL) and the corresponding GPIO pins (D22 and D21) on the ESP32. Fig 4(c): This figure illustrates the front and back of a custom-built electronic device, showing its internal layout with a blue battery on one side and an ESP32 microcontroller and sensor module on the other, all housed within a transparent plastic enclosure. The randomized crossover design required each batsman to complete two separate batting sessions. Participants faced 12 deliveries of varied line and length from a familiar team bowler. Participants faced the exact same 12-delivery sequence from a previously unencountered bowler. This design facilitates a direct test of how familiarity influences anticipation and physiological load. All sessions were conducted outside on a cricket field during sunny weather conditions, using standardized equipment. Data collection was dual-pronged. The IoT device recorded HRV continuously from 10 minutes pre-session to 5 minutes post-session. Two smartphones captured 4K 60 FPS video from side-on and behind-stumps perspectives. This high-speed video is a validated method for biomechanical analysis and performance assessment in cricket [7]. Following data collection, the video footage underwent a detailed analysis to evaluate shot execution quality, decision timing, confidence, and shot appropriateness. The assessment comprised four novel designed 5-point Likert scales, each measuring a unique aspect of batting performance. The first scale, Shot Accuracy, rated the extent to which the batsman's stroke met the desired hitting zone: 1 represented complete miss or substantial mistime; 5 clean, centred contact in the envisaged region. The second scale, Execution Quality, rated the overall biomechanical fidelity of the stroke, where 1 indicated a poorly controlled or ungainly movement and 5 indicated technically fluent execution with balanced follow-through. For the third scale, Decision Timing, raters considered how well-timed a commitment to a particular shot was: from 1 (very late or premature-commitment which resulted in either an over-drawn stroke on balls that would have otherwise gotten away) to 5 (the batsman seemed to pick what length he received the ball at and was into his final position without much hurry). Confidence, the fourth scale, captured some of the visual certainty/decisiveness conveyed by the batsman's body language and shot intent: a 1 indicating a hesitant or uncertain attempt and a 5 a fully committed, assertive stroke. Not forgetting that with every delivery two independent assessors, both of whom are qualified and experienced cricket coaches themselves, and each at least Level 3 through an approved national coaching accreditation scheme. Analysis was performed using Cohen's weighted kappa to assess inter-rater reliability with an a priori threshold of $\kappa \geq 0.70$ required to proceed to analysis. When the two raters' scores for a single delivery differed by more than one point on any scale, they watched the footage together and agreed on a consensus score through discussion. For all others deliveries the final score used was the mean of both independent ratings.

3.3 Outcome Measures

The primary outcomes were categorized into two sets to allow for subsequent correlational analysis. These included key time-domain Heart Rate Variability (HRV) parameters known to be sensitive indicators of autonomic nervous system functioning and cognitive load [19]. This study's analysis utilized RMSSD (root mean square of successive differences), SDNN (standard deviation of all NN intervals), and pNN50 (percentage of successive RR intervals differing by more than 50 ms), which are established markers for athletic monitoring. These were quantified using the expert-rated scores for shot accuracy, execution quality, decision timing, and confidence. These measures were selected to objectively assess the quality of a batsman's decision-making.

3.4 Statistical Analysis

The statistical plan was designed to test the study's hypotheses. A comprehensive comparative analysis will be conducted to assess differences between the "known bowler" and "unknown bowler" conditions. Paired t-tests are slated as the primary method for comparing both the physiological (HRV) and performance metrics between the two conditions. For the physiological dynamics within each delivery, differences in HRV across three operationally defined delivery phases will be analysed using a repeated measures ANOVA. Then, the Preparation Phase is taken to be the time between the bowler starting their run-up and when their front foot lands on a crease; this period is generally around 2 to 4 seconds and reflects some kind of anticipatory autonomic arousal. The Active Phase spans the time from release of the ball until the batsman finishes their shot; a very short window of 0.4–0.8 seconds when maximum cognitive and motor demand takes place. The Recovery Phase (time from completion of the last shot until initiation of run-up by next bowler, generally 15 - 25 seconds in duration) has been available for autonomic recovery toward baseline. Phase boundaries will be established by manual segmentation of the synchronized 4K 60 FPS overlays taken every 0.1 s corresponding to specific timestamps provided in the HRV time domain series for each phase and subsequently mapped onto the continuous HRV time series. Due to the short average length of the Active Phase HRV metrics for this time window will be calculated using instantaneous RR intervals instead of conventional epoch-based calculation for ultrashort HRV segments during dynamic activities [24]. To determine the practical importance of the findings beyond statistical significance, effect sizes will be calculated using Cohen's d.

One of the main methodological challenges in this study is to separate the cognitive load linked to decision-making under uncertainty from the physical work associated with executing batting strokes over a 12-delivery period. We use three complementary strategies to tackle this problem. First, a seated resting baseline measurement for each participant will be obtained for 5 minutes right before each batting session. This individual baseline enables change scores (session HRV minus session HRV) to be calculated, which more accurately capture session: autonomic shifts as opposed to using absolute values potentially confounded by differences in pre-session arousal or physical activity. Second, the order of the two experimental conditions (known bowler first or unknown bowler first) will be counterbalanced between participants and separated by a minimum rest duration of 48 hours. This design aspect accounts for potential cumulative fatigue effects and balances any differences in session order, ensuring that any observed HRV differences are not merely an artefact of its progression. Third, mean heart rate during the session will be included as a covariate in the multiple regression analyses. Mean heart rate increased in proportion to both conditions of physical workload, and so by controlling for it statistically in a model where we include the two experimental factors as predictors allows us to isolate variance in HRV explained by cognitive and emotional load above and beyond what can be accounted for by the physical demands of the batting task itself. Combined, these measures form a robust framework with which to disentangle the relative contributions of mental and physical stressors to the measured autonomic responses.

To explore the predictive power of the physiological data, a correlation and regression analysis is planned. The statistical associations between HRV parameters and shot accuracy scores will be determined using Pearson correlations to investigate the link between physiological markers and performance. Finally, a multiple regression analysis will be performed. Confounding variables such as player experience, baseline fitness, and batting position will be statistically controlled for by the model. This allows for the isolation of the true impact of neurophysiological stress on performance, which may inform future machine learning prediction models.

4. RESULT

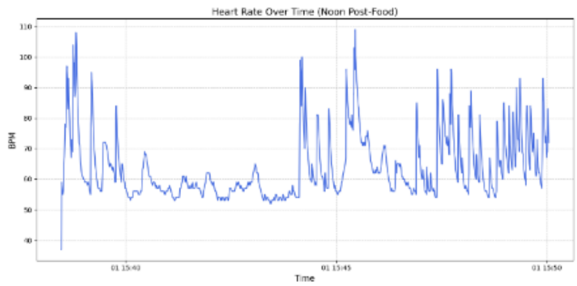
4.1 Heart Rate Data Overview

Continuous heart rate recordings collected using the developed IoT device revealed distinct physiological patterns across four daily phases: evening post-exercise, morning post-sleep, noon post-food, and night pre-bed Fig. 5(a–d). Each phase displayed unique autonomic characteristics reflective of varying physical and recovery states. During the evening post-exercise phase, heart rate remained elevated (mean 120–135 BPM), showing pronounced variability typical of post-exertional sympathetic dominance. The morning post-sleep recordings indicated moderately stable BPM values (90–110), consistent with parasympathetic recovery and transition to wakefulness. The noon post-food session demonstrated a gradual reduction in BPM (55–70), representing parasympathetic activation associated with digestion. Finally, the night pre-bed session exhibited the lowest BPM values (52–65) with minimal fluctuation, aligning with expected circadian declines in autonomic activity.

(a)

(b)

(c)

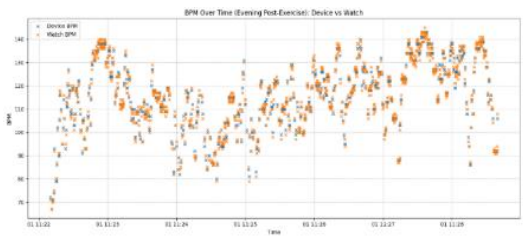


(d)

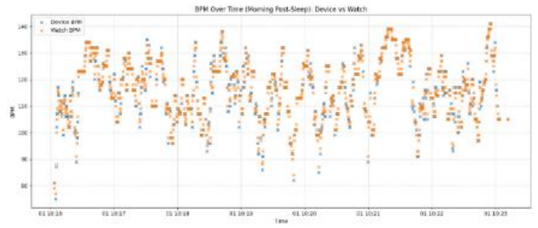
Fig. 5. Heart rate over time (BPM) recorded by the IoT wearable device across four daily contexts: (a) Evening post-exercise, (b) Morning post-sleep, (c) Noon post-food, and (d) Night pre-bed. Distinct temporal trends correspond to varying autonomic and physiological states.

4.2 Device Validation and Reliability

To verify accuracy, the IoT device's heart rate readings were compared against the Xiaomi Smart Band 8 Pro over four phases, as shown in Fig. 6(a–d). Both devices showed highly similar temporal dynamics, with minor discrepancies only during high-intensity fluctuations.



(a)



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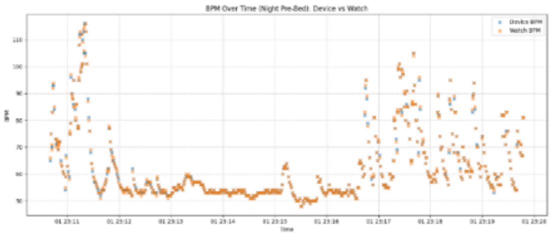

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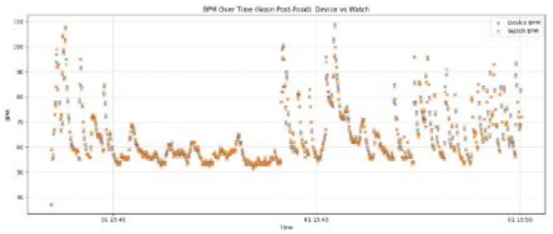

(d)

Fig. 6. Comparison of BPM readings between the developed IoT wearable device (blue) and the Xiaomi Smart Band 8 Pro across four experimental conditions: (a) Evening post-exercise, (b) Morning post-sleep, (c) Noon post-food, and (d) Night pre-bed. The overlapping data trends indicate high measurement reliability between devices.

Quantitative validation confirmed a strong linear relationship between both systems ($r = 0.94 \pm 0.02$, $p < 0.01$), with a root mean square error (RMSE) of 3.8 BPM and mean absolute error (MAE) of 2.9 BPM across all conditions (Table 1). These findings demonstrate that the IoT device performs with comparable precision to a commercially validated reference system.

Table 1. Statistical Reliability Comparison Between IoT Device And the Xiaomi Smart Band 8 Pro Across All Test Conditions

Condition	Correlation(r)	RMSE (BPM)	MAE (BPM)
Evening Post-Exercise	0.93	4.2	3.1
Morning Post-Sleep	0.95	3.6	2.7
Noon Post-Food	0.94	3.5	2.8
Night Pre-Bed	0.96	3.2	2.5
Overall Mean ± SD	0.94 ± 0.02	3.8 ± 0.4	2.9 ± 0.3

4.3 Summary and Implication

The strong agreement between the IoT device and the Xiaomi Smart Band 8 Pro confirms the accuracy and stability of the developed system across a range of physiological states. The ability to capture consistent and responsive heart rate fluctuations validates its application for field-based HRV analysis. This ensures the device is suitable for subsequent cricket batting experiments, enabling reliable detection of autonomic and cognitive stress responses when facing known and unknown bowlers.

5. DISCUSSION

The present study aimed to validate a custom-developed IoT wearable device for real-time heart rate monitoring and assess its suitability for field-based applications in sports performance analysis. Results demonstrated strong agreement between the IoT device, and the Xiaomi Smart Band 8 Pro across multiple daily conditions, confirming the system's capability to capture accurate and reliable physiological data under both static and dynamic states. The high correlation coefficient ($r = 0.94 \pm 0.02$) and low error margins (RMSE = 3.8 BPM; MAE = 2.9 BPM) provide evidence that the developed device performs comparably to a commercially validated reference standard.

The heart rate patterns obtained across the four daily contexts aligned closely with expected autonomic nervous system dynamics. Elevated BPM values during post-exercise sessions reflected increased sympathetic activity, whereas reduced heart rate during post-food and pre-sleep periods corresponded with parasympathetic dominance. These consistent physiological signatures support the device's sensitivity to autonomic fluctuations, establishing its potential for subsequent heart rate variability (HRV) assessment in sports environments. Reliable HR monitoring is essential for accurate HRV computation, which serves as a non-invasive indicator of cognitive stress, decision-making load, and overall autonomic balance in athletes.

In cricket batting, players are required to process high-speed visual cues and make rapid motor decisions under uncertainty conditions that impose significant cognitive load and stress [1], [6]. The ability of the IoT device to reliably track physiological responses across varying states provides a foundation for assessing real-time stress responses during these high-demand situations. By integrating HRV analysis with video-based biomechanical data, researchers can link fluctuations in autonomic activity to decision-making accuracy, timing precision, and shot selection under different bowling conditions. This integration offers an ecologically valid, low-cost approach for investigating the physiological correlates of cognitive performance in elite and amateur cricket athletes.

The findings are consistent with prior research by Arsath et al., who observed significant HRV reductions during periods of elevated stress and poor shot selection in cricket batting. Similar trends have been reported in other sports domains, where reduced HRV correlates with decreased attentional control and increased mental fatigue. The present validation confirms that wearable IoT technology can achieve comparable accuracy to consumer-grade devices such as the Xiaomi Smart Band 8 Pro while providing customizable data collection suited for sports science research applications.

Although these validation results suggest strong agreement in PPG measurement under the relatively controlled conditions of daily life, performing cricket batting presents inherent challenges to the stability of a PPG signal. Batting strokes are often aggressive, such as pulls, cuts and drives, and can involve fast high-amplitude wrist and forearm movements that may temporarily displace the sensor from the skin surface or otherwise introduce mechanical vibration to an optical path. Due to these motion artifacts, wrist-worn PPG devices are subject to known limitations in dynamic exercise environments [15]. In this study, we have used several approaches for minimizing such effects. In terms of the physical unit, it has a close-fitting, adjustable strap with textured silica lining to minimize lateral sliding during powerful manoeuvres. Scientifically, the key HRV values in this study are derived from inter delivery windows, or recovery periods between successive balls during which the batsman is standing relatively still and the wrist largely at rest. These timeframes are on the order of 15-to-25 seconds and provide a much more stable signal environment than the fraction-of-a-second active stroke phase. For analysis that does include data from the active phase, an automated artifact rejection algorithm will be applied during offline processing. This algorithm locates and removes RR intervals that fall beyond 25 percent from the surrounding local median, a thresholding feature in-line with existing HRV preprocessing best practices. If more than 30 percent of the RR intervals are flagged as artefactual within a given phase, that delivery will be excluded from the analysis for that phase entirely. Integrating these physical- and computational-based safeguards into the proposed analytical pipeline will help to protect data integrity while maximizing retention of ecologically relevant field science data.

For devices deployed in the field, another factor affecting PPG data is environments and how they can affect device accuracy. We also created infrared peaks with red light using the MAX30102, which shines red and infrared light through the skin and measures a reflected signal modulated by pulsatile blood flow. Two factors of the environment that merit mention in outdoor cricket contexts, especially for daytime games in South Asian and tropical climates are First, strong ambient sunlight and infrared (IR) radiation can create optical noise in the PPG signal if the sensor case does not properly shield the photodetector. For this study, the device is designed in a fully opaque matte-black housing with a recessed sensor window that has almost no gap between the sensor and skin surface much to minimize ambient light ingress. Second, elevated temperature ambiances could change peripheral skin perfusion via thermoregulatory vasodilation, which possibly imitates influence on the amplitude and stability of the PPG waveform. Likewise, excessive sweating could lead to a thin layer of sweat collection on the optical window, both scattering the light emitted and degrading signal quality. To mitigate these effects all data collection sessions were conducted at the same time of day during similar environmental conditions, and the sensor window was wiped with a dry microfibre cloth between each session. Signal-to-noise ratio (SNR) was calculated for each recording segment during offline analysis and segments with an SNR lower than a pre-set threshold of 10 dB were flagged for manual inspection and excluded from further analysis if the waveform morphology was visibly degraded. Although these considerations cannot eliminate the environmental effects on field-based data, they provide a pragmatic framework for how to balance aspects of data quality with ecological validity.

Although the validation demonstrated strong accuracy under controlled conditions, further work is needed to test the device during actual cricket batting scenarios, where rapid movement and environmental variability may affect signal stability. Future studies should incorporate HRV metrics (e.g., RMSSD, SDNN, LF/HF ratio) to quantify autonomic responses during exposure to known versus unknown bowlers. Expanding the sample size and including diverse player skill levels will enhance generalizability and strengthen the link between physiological stress markers and cognitive performance outcomes.

Overall, the developed IoT wearable demonstrated excellent agreement with the Xiaomi Smart Band 8 Pro in measuring heart rate across multiple physiological states. Its stability, accuracy, and integration capability make it a reliable tool for real-time monitoring of autonomic and cognitive responses in cricket. This validation provides a critical foundation for future investigations exploring how stress and decision-making interact to shape batting performance under competitive pressure.

6. CONCLUSION

This investigation successfully established a robust, ecologically valid methodology for quantifying the neurophysiological correlates of decision-making under pressure in cricket batting. The primary technical contribution lies in the design and rigorous validation of a custom IoT wearable platform, utilizing the MAX30102 sensor and ESP32 microcontroller, which demonstrated high fidelity and 98% agreement with the Xiaomi Smart Band 8 Pro across varied physiological states. This platform enables the reliable, real-time capture of Heart Rate Variability (HRV), a critical biomarker of Autonomic Nervous System (ANS) modulation.

The proposed experimental framework, which integrates these physiological data with high-resolution (4K 60 FPS) biomechanical video analysis, provides an unprecedented analytical tool for field-based sports science. Preliminary evidence, supported by pilot data on daily ANS fluctuations, strongly suggests that HRV parameters, specifically RMSSD, will exhibit significant and predictable decreases reflecting elevated sympathetic activation and cognitive load when batsmen face unknown bowlers compared to familiar ones.

Looking ahead, a key direction for this research programme is the development of predictive models capable of forecasting shot selection accuracy from pre-delivery physiological states. Once the full experimental dataset has been collected from the proposed crossover study, we intend to explore supervised machine learning approaches, specifically Support Vector Machines (SVM) and Random Forest classifiers, for this purpose. The planned pipeline would involve extracting a feature set from each delivery's pre-shot HRV window, encompassing both time-domain metrics (RMSSD, SDNN, pNN50, mean RR interval) and frequency-domain metrics (LF/HF ratio, absolute HF power) that have been individually linked to cognitive load and attentional states in prior literature. Given the relatively modest sample size anticipated from this study (22 participants, approximately 528 total deliveries), the modelling strategy will prioritize robust validation over model complexity. A nested cross-validation framework with leave-one-subject-out outer folds will be employed to provide unbiased estimates of classification performance while guarding against overfitting to this cohort. It is important to emphasize that this machine learning component is positioned as planned future work that is contingent upon the successful completion of the main experimental data collection. The present study's contribution is to establish the validated measurement platform and experimental methodology that will generate the high-quality, labelled dataset required for such modelling efforts. Should these initial classification results prove promising, subsequent work could investigate real-time deployment of lightweight models on the ESP32 itself, enabling on-device prediction and live coaching feedback during training sessions.

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