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# Mechanical Deviations in Stride Characteristics During Running in the Severe Intensity Domain Are Associated With a Decline in Muscle Oxygenation

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## ABSTRACT

We explored the impact of running in the severe intensity domain on running mechanics and muscle oxygenation in competitive runners by investigating the relationship between mechanical deviations from typical stride characteristics and muscle oxygen saturation ($SmO_2$) in the quadriceps muscle. Sixteen youth competitive runners performed an 8-min exhaustive running test on an outdoor track. Running mechanics were continuously monitored using inertial measurement units. Rectus femoris $SmO_2$ and total hemoglobin (a measure of blood volume) were continuously monitored by near-infrared spectroscopy. One-class support vector machine (OCSVM) modeling was employed for subject-specific analysis of the kinematic data. Statistical analysis included principal component analysis, ANOVA, and correlation analysis. Mechanical deviations from typical stride characteristics increased as the running test progressed. Specifically, the percentage of outliers in the OCSVM model rose gradually from $2.2 \pm 0.8\%$ at the start to $43.6 \pm 28.2\%$ at the end ($p < 0.001$, mean ± SD throughout). $SmO_2$ dropped from $74.3 \pm 8.4\%$ at baseline to $10.1 \pm 6.8\%$ at the end ($p < 0.001$). A moderate negative correlation ($r = -0.61$, $p = 0.013$) was found between the average $SmO_2$ and the percentage of outlier strides during the last 15% of the run. During high-intensity running, alterations in running biomechanics may occur, linked to decreased quadriceps muscle oxygenation. These parameters highlight the potential of using running kinematics and muscle oxygenation in training to optimize performance and reduce injury risks. Our research contributes to understanding biomechanical and physiological responses to endurance running and emphasizes the importance of individualized monitoring.

## 1 | Introduction

Endurance running requires the ability to withstand fatigue, which typically entails a decrease in performance attributes over a specific time. Fatigue has been defined by Enoka and Duchateau [1] as a disabling symptom in which physical and cognitive function is limited by interactions between performance fatigability and perceived fatigability. Running while fatigued can lead to changes in technique and increase the risk of musculoskeletal injuries [2]. Recognizing fatigue and understanding the performance indices that affect endurance running are crucial for effective training planning.

Research has shown that individuals modify their movement patterns to maintain task performance when fatigue accumulates by increasing motor variability [3]. The development of fatigue from repetitive movements significantly influences both the spatial and temporal characteristics of posture and movement, as observed in the literature [4]. When individuals engage in continuous physical tasks, the motor system exhibits a certain degree of adaptability by subtly adjusting both movement strategies and coordination patterns to offset the diminishing capabilities of fatigued muscles [5]. Moreover, temporal adjustments become apparent in the synchronization of movement timings, such as the closer occurrence of peak velocities between different joints, indicating a shift toward more unified movement patterns to conserve energy and maintain performance [6]. Despite these adjustments, the fundamental characteristics of the tasks are preserved, underscoring the human motor system's ability to dynamically reorganize itself [7]. This capacity for adaptation ensures that, even when fatigue impacts muscle function, the efficiency and effectiveness of movements are sustained, showcasing the resilience and flexibility of motor control in response to physical challenges.

Bates and coworkers [8] identified unique performance characteristics among five elite runners that were not evident when a group-based analysis approach was adopted. Nevertheless, running biomechanics have mostly been investigated using group-based analyses. While group analysis is valuable for understanding differences between groups and identifying universal features of human movement [9], it often masks the unique characteristics of individual performers [10, 11]. In contrast, single-subject analysis can effectively identify emerging patterns and track changes within an individual, regardless of level of expertise. With the substantial improvement in wearable inertial measurement unit (IMU) sensors in terms of quality, cost, and ease of recording very large time series data, such systems are increasingly used to quantify fatigue, training load, and running mechanics, as well as to explore movement patterns [12]. IMUs are often chosen by researchers to track changes in stride characteristics because of their capacity to continuously monitor stride characteristics of running biomechanics. Thus, they provide a comprehensive view of how an individual's running form evolves under stress, offering a link between biomechanical changes and performance outcomes. The ability to capture this information continuously and noninvasively makes IMUs an ideal tool for this purpose.

Advanced data analysis techniques, such as supervised machine learning models, have been proposed to model the complex relationships between biomechanical parameters and outcomes of interest, like fatigue and health status. [13]. The one-class support vector machine (OCSVM) is a method for identifying deviations from normative patterns [14]. When considering movement-based disciplines, such as endurance running, it is crucial to detect biomechanical alterations in relation to the dominant movement pattern, early enough to minimize injury risk and optimize performance. The power of the OCSVM lies in its ability to train on a single "norm group," representative of typical performance patterns, and then discern deviations or outliers from this established norm. Kobsar and Ferber's work [15] exemplifies the application of OCSVM in the context of gait patterns after clinical intervention. Their approach, which was also adopted by Hawley et al. [16] in identifying fatigue-related changes in whole-body kinematics over the course of a 60-min repetitive lifting protocol, opens the possibility of applying OCSVM to track deviations in endurance running movement patterns.

Biomechanical studies relating to running are rarely accompanied by physiological measures of effort. Yet, such an interdisciplinary approach can shed light on whether (and which) changes in muscle physiology during exercise, especially hard and fatiguing exercise, can explain changes in movement patterns. One such physiological parameter is muscle oxygenation, expressed as muscle oxygen saturation ($SmO_2$) and defined as the percentage of total heme molecules (as part of hemoglobin, myoglobin, and cytochrome structure) in muscle tissue that carry bound oxygen at the time of measurement. $SmO_2$ is assessed with wearable devices that use near-infrared spectroscopy to distinguish between oxygenated and deoxygenated heme and then calculate oxygenated heme as a percentage of total heme. $SmO_2$ has been shown to drop substantially during exhaustive endurance exercise [17].

Thus, the aims of the present study were to (a) quantify the deviation path of stride characteristics during running in the severe intensity domain using multiple time series of lower extremity kinematics and (b) associate such deviations with $SmO_2$ as a physiological index of muscle function. We hypothesized that deviations (outliers) from a fundamental running pattern, marked by acute changes in running biomechanics, would increase rapidly as a function of running time. We also hypothesized that, at that stage, changes in $SmO_2$ would account for a considerable part of the variance in the running pattern.

## 2 | Materials and Methods

### 2.1 | Participants

Eighteen youth competitive runners (10 male and 8 female) participated voluntarily in the study initially after providing written informed consent. All runners were healthy and free of any neuromuscular or musculoskeletal problems. They were required to have at least 3 years of regular training and at least 2 years of competing in national championships at distances between 1500 and 3000 m. The research was approved by the Ethics Committee of the School of Physical Education and Sport Science at Thessaloniki (EC-12/18-5-2020).

### 2.2 | Protocol and Instrumentation

Biomechanical and physiological data were collected simultaneously during an 8-min running test near exhaustion on a 300-m looping outdoor track. To minimize variation in ambient conditions, testing of all participants was completed within four consecutive days between 17:00 and 20:00. Air temperature and humidity were 27.3–29.1°C and 47.8%–49.2%, respectively. Participants were familiarized with the equipment 1 day before, when they came to the field for an easy 5-min run while wearing all the measuring equipment.

On the testing day, the participants were asked not to eat anything during the 3 h preceding testing. They began with a light running warm-up at a self-paced speed for 10 min, followed by 5 min of dynamic stretching. The main task was an 8-min run at a steady speed as fast as possible. Runners were instructed to keep a constant velocity throughout the test, and the researchers checked that with an electronic chronometer every 100 m. The pace was individually calculated, based on Riegel's formula and each participant's most recent competition pace [18]. If a deviation larger than ±10% was observed, verbal notification was given to increase or reduce the pace accordingly. Participants were not included in the analysis if they deviated from the instructed pace more than 3 times.

During the test, subjects received verbal encouragement to continue until the 8 min was reached. To ensure that they approached exhaustion in the end, the following criteria were used: a heart rate (HR, monitored continuously through a Polar H10 monitor, Kempele, Finland) of ±10 bpm from the age-predicted maximum (220—age) and a rating of perceived exertion >17 (reported upon completion of the test) on the 6-to-20-point Borg scale. Participants wore their preferred running spikes during the test.

$SmO_2$ was continuously measured using a portable, wireless NIRS sensor (Moxy Monitor, Fortiori Design LLC, Hutchinson, MN) fixed on the right rectus femoris and held in place with adhesive tape and by the participants' elastic shorts. The sensor was covered with a light shield supplied by the manufacturer to minimize interference from ambient light. $SmO_2$ data were recorded wirelessly at a frequency of 2 Hz through the VO2 Master Manager mobile application (VO2 Master Health Sensors, Vernon, BC) and were averaged over every 10 s, starting from the moment each runner acquired a steady speed (8–10 m after the onset of running). The so-called total hemoglobin (tHb) was also recorded and analyzed in the same way. This dimensionless quantity reflects the local total (i.e., both oxygenated and deoxygenated) heme concentration. Because the amount of heme in a muscle fiber does not change during exercise, a change in total heme concentration will reflect a change in the amount of hemoglobin inside the blood vessels. Hence, tHb is used to follow changes in local muscle blood volume. HR was averaged over every 10 s too.

Lower extremity kinematics were quantified using a pair of wireless Bluetooth, 9-degree-of-freedom IMUs (k-Sens [now K-Move]), Kinvent, Biomechanique, Montpellier, France with 120-Hz sampling frequency. This sensor has been successfully used in other studies [19, 20]. Linear acceleration and angular velocity were used for further analysis. The minimum detectable step of the IMU sensors was 4 mg/L SB (least significant bit) for the accelerometer and 0.06°/s for the gyroscope. The maximum detectable value for the accelerometer was 16 *g* and for the gyroscope 2000°/s. The IMU sensors were fixed on the middle of the tibial bone and at the lower foot (metatarsals). Both sensors were synchronized through an android OS mobile application.

One month after the aforementioned test, we subjected 10 of the participants to a run at 75% of the speed of the main run for 8 min and measured only lower extremity kinematics, as described above. This run served as a control test.

## 2.3 | Preprocessing

Raw kinematic signals were low-pass filtered at 20 Hz. All extracted features represented discrete values from every stride. These features were sourced from the two aforementioned sensors (tibia and foot), each providing data across six channels: three linear accelerations and three angular velocities, 12 channels in total. All data extraction processes were performed using R v4.3.1 (R Foundation for Statistical Computing, Vienna, Austria). A peak-to-peak algorithm on the largest component of the acceleration signal was used to determine stride time intervals (Figure 1A). To achieve temporal normalization and ensure consistency in stride segmentation, all linear accelerometric and angular velocity data were interpolated to a 100-point representation per stride (Figure 1B).

Following this, the triaxial accelerations and angular velocities (comprising the anteroposterior, mediolateral, and vertical axes) from each sensor were transformed and concatenated, resulting in a $1 \times 600$ data vector per sensor. Measurements from the two sensors were further concatenated horizontally, creating a $1 \times 1200$ vector, which provided a holistic representation of the movement pattern exhibited within each stride. For each test comprising $m$ strides, the derived linear accelerometric vectors were collated into an $m \times 1200$ matrix.

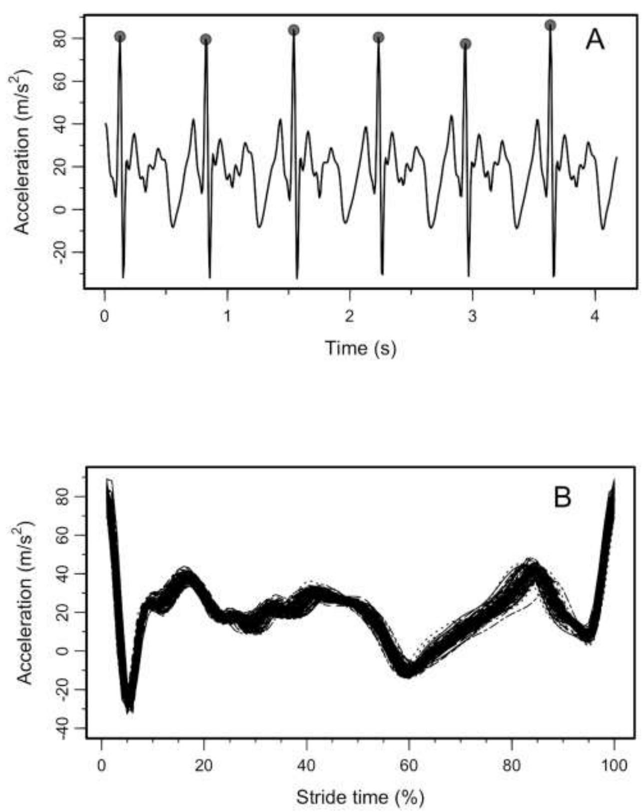


**FIGURE 1** | Temporal normalization of vertical acceleration data. (A) Typical vertical acceleration recording from a participant's tibia sensor during seven strides (delimited by the dots). (B) Superimposition of the first 100 strides from an individual, normalized to a 0%–100% temporal scale.

## 2.4 | Subject-Specific Modeling

To reduce the high dimensionality ($m \times 1200$) of the kinematic data matrix, which can make subsequent analyses computationally intensive and might risk overfitting when building predictive models, we utilized principal component analysis (PCA). This approach aimed to extract the most salient features, ensuring that the motion profile of each stride was captured in a manner consistent with the proposal by Daffertshofer et al. [21]. This was achieved using covariance matrix decomposition and implemented with the scikit-learn (1.4.2) Python library. The data were separated into a training set, which encompassed the initial 40% of the test (i.e., 3.2 min), and four testing sets, each containing 15% of the remaining data (1.2 min each). Then, PCA was implemented on these five datasets of each participant separately. To maintain uniformity and avoid any data leakage, the PCA extraction was initially performed in the training set. Subsequently, that PCA fit was implemented in each of the testing sets, using the coefficients obtained from the training set (i.e., mean and SD) to ensure that the principal component (PC) scores of the testing sets were appropriately aligned with their corresponding training set data [13, 15].

For every participant, an individualized one-class model was established based on his/her stride characteristics obtained from the PC scores by use of OCSVM to detect deviations from established movement patterns. Model fitting was employed using the OCSVM object with a radial basis function (RBF) kernel from Python's scikit-learn library (1.3.0), which is based on the algorithm described by Schölkopf et al. [14, 22]. The classifier's boundary was trained based on the PC scores that represented 95% of the variance. The RBF kernel was paired with a "nu" and a "gamma" parameter for fine-tuning. Nu was set to 1%, thus directing the model to identify and classify the most distinct 1% of the strides as outliers, while treating the remaining 99% as typical strides [16]. This approach ensures that only the most extreme variations in stride patterns are flagged, thus maintaining a high threshold for outlier detection. By configuring "nu" in this manner, we achieved a controlled sensitivity to deviations, which is critical given the model's purpose to detect abnormal stride behaviors in a practical context.

This fine-tuning was carried out individually to maintain the subject-specific nature of the model. The gamma parameter controls how strict or flexible the decision boundary is between normal data and outliers and was set based on the grid search approach [22]. The value that produced the best F1 score was chosen as input to the model.

## 2.5 | Statistical Analysis

Descriptive statistics are presented as the mean and SD. A one-way repeated-measures ANOVA was performed on the results of the OCSVM models for the near-maximal test to examine whether the percentages of outliers differed between the selected data segments (i.e., the training and the four testing sets), after verifying that the distribution of the parameters did not differ significantly from normal according to the Shapiro–Wilk test. The Mauchly's test was used to assess the sphericity assumption, and the Greenhouse–Geisser sphericity correction was applied, since violation of the assumption was detected. Partial eta squared ($\eta_p^2$) was used to assess the effect size. Post hoc analysis to examine pairwise differences was performed using Student's $t$ test with Bonferroni correction for multiple comparisons. For the control test run, the Friedman repeated-measures test was used due to violation of the normality assumption. Baseline and final values of $SmO_2$ and tHb were compared through the Wilcoxon signed-rank test. Pearson correlation analysis was used to examine the relationship between the average $SmO_2$ and the percentage of outliers in each dataset. Statistical significance was declared at $p < 0.05$. All statistical analyses were performed with R v4.3.1 (R Foundation for Statistical Computing, Vienna, Austria).

## 3 | Results

Two of the 18 participants (both females) were excluded from the analysis for failure to meet the criterion of not deviating from the instructed pace more than 3 times. The characteristics of the remaining 16 participants and their performance during the test are shown in Table 1.

The average number of PCs explaining 95% of the total variance in the running pattern within the training set of each participant was 57. Figure 2 is a simplified visualization of the model's decision boundary for a representative individual, employing only two PCs. The actual boundary, as defined by the OCSVM and subsequent analyses, was set in a multidimensional PC space for each individual.

The percentages of outliers in the training set and the four testing sets were, in sequence, $2.2 \pm 0.8$, $3.2 \pm 1.6$, $7.3 \pm 4.8$, $17.5 \pm 11.9$, and $43.6 \pm 28.2\%$ ($F_{1.25,18.73} = 30.25$, $p < 0.0001$, $\eta_p^2 = 0.67$, Figure 3). The percentage of outliers in the 85%–100% set differed significantly from those in all preceding ones, and the percentage of outliers in the 70%–85% set differed significantly from those in the 0%–40% and 40%–55% sets (all $p < 0.001$). The corresponding percentages of outliers in the submaximal (control) test were $2.47 \pm 0.98$, $4.43 \pm 2.36$, $5.19 \pm 2.93$, $6.77 \pm 4.21$, and $6.62 \pm 4.85$, with no statistically significant differences between sets.

Figure 4 presents the kinetics of rectus femoris $SmO_2$, rectus femoris tHb, and HR during the run. Regarding $SmO_2$, there was a significant drop from $74.3 \pm 8.4\%$ at baseline to $10.1 \pm 6.8\%$ in the end ($p < 0.001$). One can discern two

**TABLE 1** | Characteristics and performance of the participants during the test (mean ± SD).

| Characteristic | Males ($n = 10$) | Females ($n = 6$) |
|---|---|---|
| Age (years) | 16.3 ± 0.9 | 15.8 ± 0.7 |
| Weight (kg) | 69.4 ± 5.3 | 61.2 ± 3.3 |
| Height (m) | 1.78 ± 0.06 | 1.63 ± 0.05 |
| Total strides | 679 ± 28 | 700 ± 25 |
| Speed (m/s) | 4.49 ± 0.32 | 3.91 ± 0.21 |

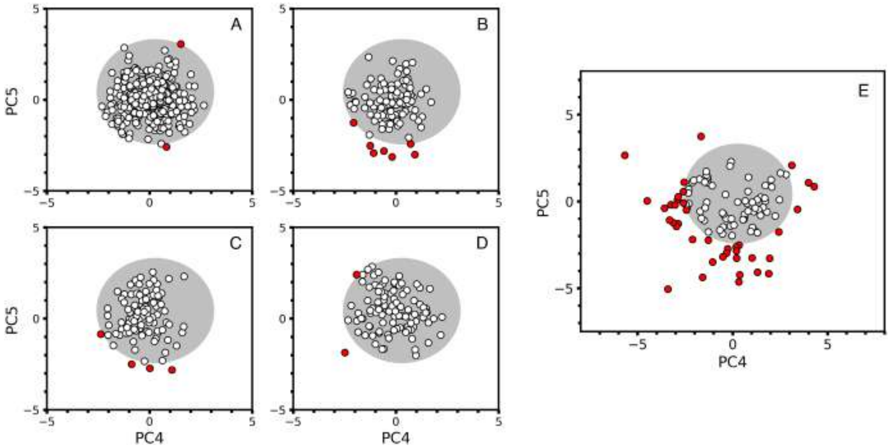


**FIGURE 2** | Two-dimensional principal component analysis score plots of the stride characteristics of a participant during 0%–40% (A), 40%–55% (B), 55%–70% (C), 70%–85% (D), and 85%–100% (E) of the run. The decision boundary of the one-class support vector machine is the outline of the shaded area; this area is considered "normal." White circles represent inlier strides, and red circles represent outlier strides.

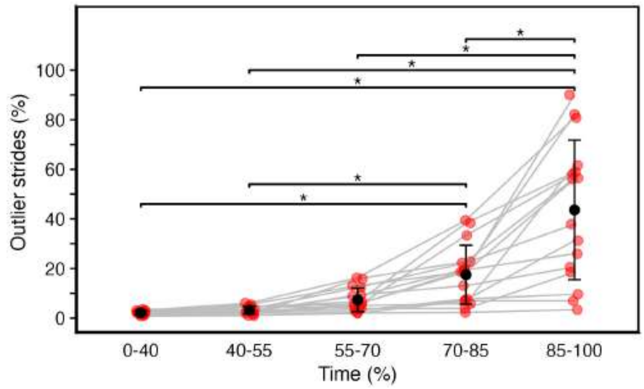


**FIGURE 3** | Individual (colored dots), mean (black dots), and SD (whiskers) percentages of outlier strides in each of the five datasets. *$p < 0.001$.

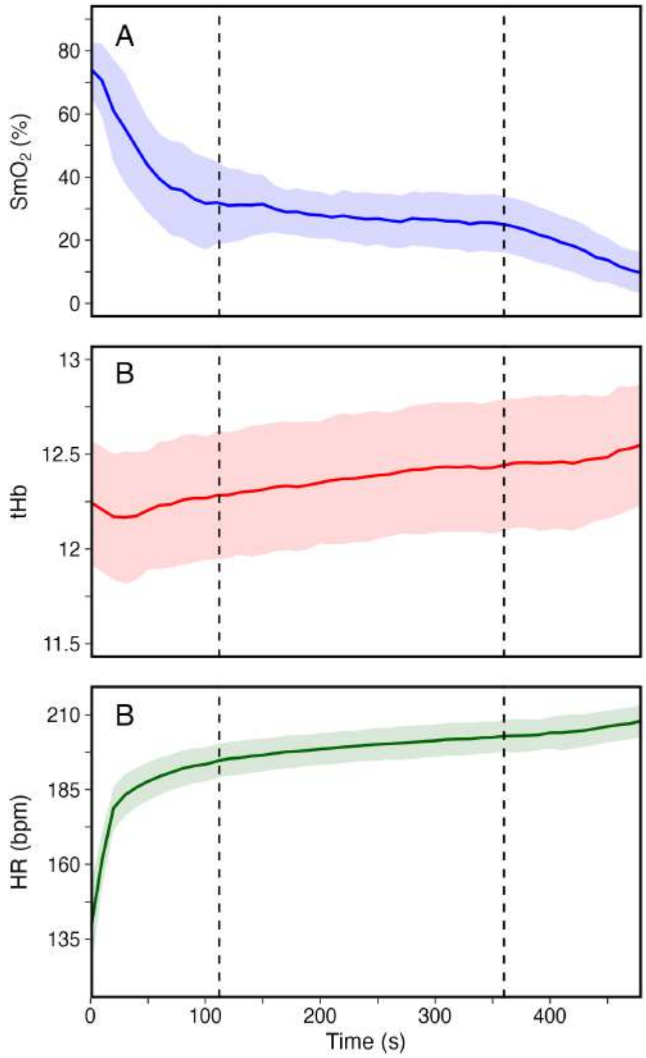


**FIGURE 4** | Mean and SD of rectus femoris oxygen saturation (A), rectus femoris total hemoglobin (B), and heart rate (C) during the run. The vertical broken lines represent potential breakpoints in $SmO_2$.

breakpoints (visually estimated by two independent researchers), marking the transitions from a rapid initial drop to a slow decrease during most of the run to a more rapid (though not as rapid as the initial one) drop toward the end. The tHb curve displayed a biphasic response, decreasing during the initial half minute and increasing almost linearly afterward. This resulted in a final value of tHb that was significantly higher than baseline ($12.51 \pm 0.34$ vs $12.25 \pm 0.35$, $p < 0.001$). Finally, HR exhibited a rapid increase during the first half minute, followed by a slower rise throughout the rest of the test, which ended at $205 \pm 6$ bpm.

Based on the substantial drop in $SmO_2$ during the end of the run, we examined whether there was any correlation with the substantial increase in outlier strides over the same period. We found a moderate negative correlation ($r = -0.61$, $p = 0.013$) between the average $SmO_2$ during 85%–100% of the run and the percentage of stride outliers during the same interval (Figure 5). No such correlation was found between $SmO_2$ and stride outliers during the preceding intervals.

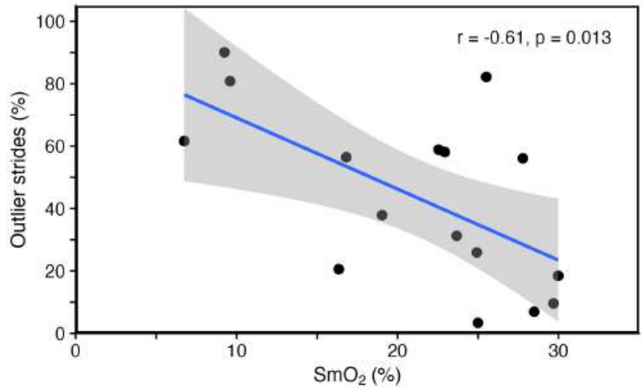


**FIGURE 5** | Scatter plot of the relationship between rectus femoris $SmO_2$ and the percentage of outlier strides during 85%–100% of the run. The linear regression line fitted to the data points and the 95% confidence band are also displayed.

## 4 | Discussion

The primary aim of this study was to explore mechanical deviations in stride characteristics during high-intensity running, specifically within the severe-intensity domain, as indicated by a continuous drop in $SmO_2$ during the test [17]. The subject-specific application of OCSVM models effectively pinpointed instances where participants departed from baseline running patterns. This approach enabled us to confirm the first hypothesis of the study (i.e., deviations from the fundamental running pattern would increase rapidly as runners approached the end of the test). Indeed, the mean percentage of outliers more than doubled (rising from 17.5% to 43.6%) between the fourth (70%–85%) and fifth (85%–100%) segments of the run (Figure 3). No such change was seen in the control test at 75% of the maximal speed, thus showing that the changes measured in the main test were not artifact.

The number of deviations in the last segment of the main run (and only that) correlated moderately and negatively with muscle oxygenation, lending support to our second hypothesis (i.e., changes in $SmO_2$ would account for a considerable part of the variance in the running pattern). As the run progresses, especially in the final segment, several factors whose influence on movement during the most fatigued states increases could drive the correlation between deviations and decreased muscle oxygenation. These include gradual energy depletion leading to neuromuscular fatigue and impaired movement control [23]; an oxygen supply–demand mismatch under increasing physiological stress [24]; accumulation of acidity affecting muscle efficiency [24]; adaptive changes as individuals seek more efficient movement strategies due to fatigue [25, 26]; and mental fatigue impacting focus and motor control [27]. Together, these factors increase biomechanical variability considerably, thus emphasizing the complex interplay between physiological strain and biomechanical response.

Coaches can easily spot changes in running kinematics during prolonged high-intensity running by the stiff movements of middle-distance runners near the finish or of marathoners after the halfway point. These subtle changes become evident as runners strive to maintain a constant pace. Research has documented significant fatigue-induced kinematic changes during constant-speed runs of varying durations and intensities, ranging from 10 min at a speed exceeding the 5-km race pace [28] to a marathon [29]. In a continuous protocol similar to ours, Derrick et al. [30] induced fatigue in 10 recreational runners at speeds matching their best 3200-m effort for about 15 min. Data collected during the first, middle, and last minutes of the run revealed progressive kinematic changes, including increased knee flexion at initial ground contact and midstance. Similarly, Van Gheluwe & Madsen [31] found increased peak pronation angle and rear-foot eversion angle in runners as they approached exhaustion. Our study advances such previous work by employing continuous monitoring of runners' movement patterns alongside physiological markers. By utilizing a multivariate analysis, we offer a different perspective of the dynamics at play. Most relevant studies in the literature employed analysis of discrete features and measured their deviation in various phases of a trial. By contrast, our features are series of PC components that imprint the kinematic behavior based on all the available information for every stride. Furthermore, we measured the deviation from phase to phase using a metric that quantifies the number of outliers. Despite the fact that direct comparison with other studies cannot be made, the idea that fatigue affects the mechanical behavior of the system is also reflected in our study.

Fatigue influences lower extremity mechanics during running. With fatigue imposing adverse effects on neuromuscular function, a reduction in the transfer of mechanical energy during the stretch-shortening cycle can be expected [23, 32], along with an increase in muscle reaction times [33]. As the body experiences physiological stress, the muscles become less efficient, leading to altered biomechanics. However, it is worth considering that these alterations may not be necessarily detrimental. Banks & Aghazadeh [25] and Srinivasan & Mathiassen [26] suggest that such variations could represent mechanical adaptations toward a more energy-efficient or comfortable movement pattern under fatigue. Apart from the energy efficiency hypothesis, fatigue in this case could be the control variable, the scaling of which may be responsible for moving to a different attractor [34], according to the dynamic systems theory perspective. This theory posits that the behavioral state (attractor) of an order parameter (running mechanics in this case) is dependent on the scaling of a control parameter. Such transition phases are characterized by highly variable patterns [35] of the order parameter. This hypothesis is particularly relevant to the three participants who exhibited an exceedingly high percentage of outlier strides in the latter part of the test (see Figure 3). By observing the $SmO_2$ kinetics during the same time interval, one is tempted to count this variable as the control parameter governing the behavior state of the order parameter, that is, the mechanics of movement. However, without further detailed analysis, it is premature to definitively state that $SmO_2$ kinetics govern these biomechanical changes. Acknowledging this, our speculation opens up new hypotheses for research and is a logical next question in our exploration of the intricate relationship between physiological responses and biomechanical adjustments during intense exercise.

The negative association between the percentage of outlier strides and rectus femoris $SmO_2$ in the last segment of the test showed that the variation in $SmO_2$ explained 37% (i.e., $r^2$) of the variation in stride outliers. From a physiological standpoint, $SmO_2$ is a measure of the balance between oxygen delivery and consumption in muscle tissue, thus providing insight into the muscle's metabolic state [36]. Low $SmO_2$ levels, particularly during high-intensity activities, are indicative of inadequate oxygen supply to the muscles. This inadequacy may be critical, as oxygen is essential for aerobic metabolism, which predominantly supports muscle activity during endurance sports [37]. As athletes approach maximal exercise intensity, insufficient oxygen supply may lead to suboptimal muscle contractions [38]. This could manifest as inconsistent stride patterns, detectable as deviations (outliers) from the normal pattern that the OCSVM algorithm established in the data set. The fact that, of the three participants who exhibited an exceedingly high percentage of outlier strides in the latter part of the test, one did not display low $SmO_2$ (see Figure 5) is probably due to factors that explain the remaining 63% of the variation. These factors may include individual fitness levels, biomechanical efficiency, or differential responses to stress among individuals. This underscores the importance of conducting analyses that are tailored to each individual. Alternatively, our findings may be interpreted as showing that inconsistencies in stride patterns could precipitate a reduction in $SmO_2$ toward the end of a run by increasing the muscular effort required, thereby elevating oxygen consumption beyond what the circulatory system can replenish. Such biomechanical inefficiencies could, therefore, lead to a drop in $SmO_2$ levels, signifying a metabolic stress response within the muscles. This perspective introduces a bidirectional relationship whereby stride pattern irregularities could both result from and contribute to the observed decrease in muscle oxygenation, thus pointing to a complex feedback loop between biomechanical actions and physiological responses under severe exertion.

The triphasic response of rectus femoris oxygenation to exhaustive running observed in the present study has also been described by Kirby et al. [17]. The first, rapidly descending, phase can be explained by the abrupt rise in energy demand upon the commencement of running, a rise that could not be matched by the oxygen supply from the blood. Indeed, during the same period, tHb was below baseline. This initial drop in tHb can be explained by an increase in muscle tension, which squeezes blood out of the muscle upon the onset of exercise [39]. The subsequent near-linear rise of tHb up to the end of exercise may be due to sustained vasodilation [40], which balanced the effect of muscle tension (i.e., tHb returned to baseline) at a time coinciding with the end of the rapid drop in $SmO_2$. It is then possible that this vasodilation and the high HR increased the oxygen delivery to the muscle substantially, thus curbing the decrease in muscle oxygenation throughout the remainder of the exercise test. Finally, the more rapid drop in muscle oxygenation near the end of exercise, despite a sustained rise in blood supply and a constant exercise intensity, suggests a deterioration of running economy (resulting in depletion of muscle oxygen) due to deviation from the normal running pattern, as also mentioned in the previous paragraph.

Although our correlation analysis showed that a considerable portion (37%) of the variation in the percentage of outlier strides during the last segment of the test could be explained by the variation in rectus femoris oxygenation, it nevertheless leaves plenty of room for other potential factors influencing stride deviations. Psychological stress and mental fatigue can indirectly impact intermittent running performance by increasing the perception of effort, suggesting that these factors influence running biomechanics [27]. Additionally, biomechanical constraints, such as the athlete's running speed and motor skill level, affect movement variability, including stride length and joint kinematics [41]. It is also vital to distinguish between correlation and causation. The observed relationship between $SmO_2$ and percentage of outlier strides does not necessarily show that low muscle oxygenation causes stride inconsistencies (as also discussed above). Controlled experiments are needed to establish causality.

Our findings on muscle oxygenation and running kinematics during fatigue can be further contextualized by considering the concept of physiological resilience, as explored in recent reports [42, 43]. Physiological resilience, that is, the capacity to sustain performance amidst accumulating physiological stress, might influence how athletes maintain muscle oxygenation levels and efficient running mechanics under fatigue. This perspective suggests that individuals with higher physiological resilience can better counteract the adverse effects of fatigue, thereby preserving optimal muscle oxygenation and movement patterns [43]. This can be conceptualized visually in Figure 3, where the two last segments exhibit large data dispersion, implying highly individualized responses and, indirectly, different resilience levels.

The strength of our findings is limited by the fact that, although homogeneous, the sample was relatively small and consisted of well-trained track athletes. This could limit the generalizability of the findings to a broader population, including recreational runners or athletes from other sports. Secondly, the protocol employed may not fully replicate the complexity of fatigue development in different running contexts, such as varying terrains or longer endurance events. Additionally, the reliance on wearable devices for measuring muscle oxygenation may not capture the full spectrum of physiological changes during intense exercise. Finally, although we took all necessary precautions (stable fixing and appropriate data collection and processing) to minimize sweat and movement artifacts, we cannot rule out the possibility that they may have had some impact on the recorded data, although this is not expected to affect the quality and validity of the results. Future research should aim to address these limitations by incorporating a more diverse participant pool, varied fatigue-inducing conditions, and additional physiological measures to deepen our understanding of how severe exertion affects running biomechanics.

## 5 | Conclusion

In conclusion, the present study elucidates the interplay between deviations in high-intensity running mechanics and quadriceps muscle oxygenation, employing a subject-specific approach with OCSVM models. Our findings reveal increases in mechanical deviations, which correlate with decreased muscle oxygenation, supporting the hypothesis that alterations in running biomechanics are likely linked to physiological resilience.

These insights underscore the importance of individualized monitoring in training, aiming to optimize performance and minimize injury risks. There is evidence [2] that deviations from normal kinematics can stress the musculoskeletal system, and compensatory movements may increase the risk of injury by creating imbalances and impairing shock absorption. Given the repetitive nature of running, minor kinematic changes can accumulate, potentially resulting in considerable repetitive stress injuries [2]. This research contributes novel perspectives on the biomechanical and physiological responses to endurance running, emphasizing the usefulness of continuous monitoring for enhancing athletic performance.

## 6 | Perspective

Understanding the correlation between deviations in normal running pattern and muscle oxygen depletion has some practical implications. Real-time monitoring of $SmO_2$ or stride outliers, both of which are feasible with current technology and mathematical modeling, could serve as an early warning system, allowing athletes and/or coaches to take measures and make adjustments before running technique deteriorates. For example, one could either apply technique adjustments to sustain mechanical efficiency and shift the occurrence of this phenomenon further to the right on the timeline of the trial or appropriately manipulate rest time during interval training protocols to recover and perform with the typical movement pattern. Beyond immediate practical applications, our research could open new paths for further scientific inquiry. Subsequent studies could explore how individual differences in responses to fatigue and mechanical efficiency could correlate with long-term outcomes like performance improvements and injury rates, potentially leading to new insights into athletic training and health maintenance.

### Conflicts of Interest

The authors declare no conflicts of interest.

### Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

### References

1. R. M. Enoka and J. Duchateau, "Translating Fatigue to Human Performance," *Medicine and Science in Sports and Exercise* 48, no. 11 (2016): 2228–2238.

2. A. C. Clansey, M. Hanlon, E. S. Wallace, and M. J. Lake, "Effects of Fatigue on Running Mechanics Associated With Tibial Stress Fracture Risk," *Medicine and Science in Sports and Exercise* 44, no. 10 (2012): 1917–1923.

3. J. R. Fuller, J. Fung, and J. N. Côté, "Time-Dependent Adaptations to Posture and Movement Characteristics During the Development of Repetitive Reaching Induced Fatigue," *Experimental Brain Research* 211, no. 1 (2011): 133–143.

4. F. Cignetti, F. Schena, and A. Rouard, "Effects of Fatigue on Inter-Cycle Variability in Cross-Country Skiing," *Journal of Biomechanics* 42, no. 10 (2009): 1452–1459.

5. P. Madeleine and D. Farina, "Time to Task Failure in Shoulder Elevation Is Associated to Increase in Amplitude and to Spatial Heterogeneity of Upper Trapezius Mechanomyographic Signals," *European Journal of Applied Physiology* 102, no. 3 (2008): 325–333.

6. N. Forestier and V. Nougier, "The Effects of Muscular Fatigue on the Coordination of a Multijoint Movement in Human," *Neuroscience Letters* 252, no. 3 (1998): 187–190.

7. A. Holtermann, C. Grönlund, J. Stefan Karlsson, and K. Roeleveld, "Spatial Distribution of Active Muscle Fibre Characteristics in the Upper Trapezius Muscle and Its Dependency on Contraction Level and Duration," *Journal of Electromyography and Kinesiology* 18, no. 3 (2008): 372–381.

8. B. T. Bates, L. R. Osternig, B. R. Mason, and S. L. James, "Functional Variability of the Lower Extremity During the Support Phase of Running," *Medicine and Science in Sports* 11, no. 4 (1979): 328–331.

9. C. Chalitsios, T. Nikodelis, V. Konstantakos, and I. Kollias, "Sensitivity of Movement Features to Fatigue During an Exhaustive Treadmill Run," *European Journal of Sport Science* 22, no. 9 (2022): 1374–1382.

10. C. Chalitsios, T. Nikodelis, G. Mavrommatis, and I. Kollias, "Subject-Specific Sensitivity of Several Biomechanical Features to Fatigue During an Exhaustive Treadmill Run," *Scientific Reports* 14, no. 1 (2024): 1004.

11. F. Horst, F. Hoitz, D. Slijepcevic, et al., "Identification of Subject-Specific Responses to Footwear During Running," *Scientific Reports* 13, no. 1 (2023): 11284.

12. C. A. Clermont, L. C. Benson, S. T. Osis, D. Kobsar, and R. Ferber, "Running Patterns for Male and Female Competitive and Recreational Runners Based on Accelerometer Data," *Journal of Sports Sciences* 37, no. 2 (2019): 204–211.

13. E. Halilaj, A. Rajagopal, M. Fiterau, J. L. Hicks, T. J. Hastie, and S. L. Delp, "Machine Learning in Human Movement Biomechanics: Best Practices, Common Pitfalls, and New Opportunities," *Journal of Biomechanics* 81 (2018): 1–11.

14. B. Schölkopf, J. C. Platt, J. Shawe-Taylor, A. J. Smola, and R. C. Williamson, "Estimating the Support of a High-Dimensional Distribution," *Neural Computation* 13, no. 7 (2001): 1443–1471.

15. D. Kobsar and R. Ferber, "Wearable Sensor Data to Track Subject-Specific Movement Patterns Related to Clinical Outcomes Using a Machine Learning Approach," *Sensors* 18, no. 9 (2018): 2828.

16. S. J. Hawley, A. Hamilton-Wright, and S. L. Fischer, "Detecting Subject-Specific Fatigue-Related Changes in Lifting Kinematics Using a Machine Learning Approach," *Ergonomics* 66, no. 1 (2023): 113–124.

17. B. S. Kirby, D. A. Clark, E. M. Bradley, and B. W. Wilkins, "The Balance of Muscle Oxygen Supply and Demand Reveals Critical Metabolic Rate and Predicts Time to Exhaustion," *Journal of Applied Physiology* 130, no. 6 (2021): 1915–1927.

18. P. S. Riegel, "Athletic Records and Human Endurance," *American Scientist* 69, no. 3 (1981): 285–290.

19. R. Grigoriou, T. Nikodelis, D. Kugiumtzis, and I. Kollias, "Classification Methods can Identify External Constrains in Swimming," *Journal of Biomechanics* 82 (2019): 381–386.

20. F. Tekin, T. Can-Akman, and A. Kitiş, "Evaluation of the Validity and Reliability of the KFORCE Sens® Electrogoniometer in Evaluation of Wrist Proprioception," *Hand Surgery and Rehabilitation* 41, no. 2 (2022): 183–188.

21. A. Daffertshofer, C. J. C. Lamoth, O. G. Meijer, and P. J. Beek, "PCA in Studying Coordination and Variability: A Tutorial," *Clinical Biomechanics* 19, no. 4 (2004): 415–428.

22. B. Schölkopf, R. C. Williamson, A. Smola, J. Shawe-Taylor, and J. Platt, "Support Vector Method for Novelty Detection," in *Advances in*

*Neural Information Processing Systems*, eds. M. I. Jordan, Y. LeCun, and S. A. Solla (London: MIT Press, 1999).

23. J. Mizrahi, O. Verbitsky, and E. Isakov, “Fatigue-Related Loading Imbalance on the Shank in Running: A Possible Factor in Stress Fractures,” *Annals of Biomedical Engineering* 28, no. 4 (2000): 463–469.

24. K. Wasserman, B. J. Whipp, S. N. Koyl, and W. L. Beaver, “Anaerobic Threshold and Respiratory Gas Exchange During Exercise,” *Journal of Applied Physiology* 35, no. 2 (1973): 236–243.

25. A. D. Banks and F. Aghazadeh, “Progressive Fatigue Effects on Manual Lifting Factors,” *Human Factors and Ergonomics in Manufacturing & Service Industries* 19, no. 5 (2009): 361–377.

26. D. Srinivasan and S. E. Mathiassen, “Motor Variability in Occupational Health and Performance,” *Clinical Biomechanics* 27, no. 10 (2012): 979–993.

27. M. R. Smith, S. M. Marcora, and A. J. Coutts, “Mental Fatigue Impairs Intermittent Running Performance,” *Medicine and Science in Sports and Exercise* 47, no. 8 (2015): 1682–1690.

28. S. Willwacher, M. Sanno, and G. P. Brüggemann, “Fatigue Matters: An Intense 10 km Run Alters Frontal and Transverse Plane Joint Kinematics in Competitive and Recreational Adult Runners,” *Gait & Posture* 76 (2020): 277–283.

29. C. Nicol, P. V. Komi, and P. Marconnet, “Effects of Marathon Fatigue on Running Kinematics and Economy,” *Scandinavian Journal of Medicine & Science in Sports* 1, no. 4 (1991): 195–204.

30. T. R. Derrick, D. Dereu, and S. P. McLean, “Impacts and Kinematic Adjustments During an Exhaustive Run,” *Medicine and Science in Sports and Exercise* 34, no. 6 (2002): 998–1002.

31. B. V. Gheluwe and C. Madsen, “Frontal Rearfoot Kinematics in Running Prior to Volitional Exhaustion,” *Journal of Applied Biomechanics* 13, no. 1 (1997): 66–75.

32. J. Mizrahi, O. Verbitsky, and E. Isakov, “Shock Accelerations and Attenuation in Downhill and Level Running,” *Clinical Biomechanics* 15, no. 1 (2000): 15–20.

33. J. Mizrahi, O. Verbitsky, and E. Isakov, “Fatigue-Induced Changes in Decline Running,” *Clinical Biomechanics* 16, no. 3 (2001): 207–212.

34. J. A. S. Kelso, *Dynamic Patterns: The Self-Organization of Brain and Behavior* (Cambridge, MA: The MIT Press, 1995), 334.

35. M. C. Granatosky, C. M. Bryce, J. Hanna, et al., “Inter-Stride Variability Triggers Gait Transitions in Mammals and Birds,” *Proceedings of the Biological Sciences* 285, no. 1893 (2018): 20181766.

36. R. Boushel, H. Langberg, J. Olesen, J. Gonzales-Alonzo, J. Bülow, and M. Kjaer, “Monitoring Tissue Oxygen Availability With Near Infrared Spectroscopy (NIRS) in Health and Disease,” *Scandinavian Journal of Medicine & Science in Sports* 11, no. 4 (2001): 213–222.

37. M. Ihsan, C. R. Abbiss, M. Lipski, M. Buchheit, and G. Watson, “Muscle Oxygenation and Blood Volume Reliability During Continuous and Intermittent Running,” *International Journal of Sports Medicine* 34, no. 7 (2013): 637–645.

38. M. Amann and J. A. L. Calbet, “Convective Oxygen Transport and Fatigue,” *Journal of Applied Physiology* 104, no. 3 (2008): 861–870.

39. R. Kime, J. Im, D. Moser, S. Nioka, T. Katsumura, and B. Chance, “Noninvasive Determination of Exercise-Induced Vasodilation During Bicycle Exercise Using Near Infrared Spectroscopy,” *Medical Science Monitor* 15, no. 3 (2009): CR89–CR94.

40. V. Mougios, *Exercise Biochemistry* (Champaign, IL: Human Kinetics, 2019), 362.

41. W. Wang, F. Qu, S. Li, and L. Wang, “Effects of Motor Skill Level and Speed on Movement Variability During Running,” *Journal of Biomechanics* 127 (2021): 110680.

42. I. E. Clark, A. Vanhatalo, C. Thompson, et al., “Changes in the Power-Duration Relationship Following Prolonged Exercise: Estimation Using Conventional and All-Out Protocols and Relationship With Muscle Glycogen,” *American Journal of Physiology Regulatory, Integrative and Comparative Physiology* 317, no. 1 (2019): R59–R67.

43. A. M. Jones, “The Fourth Dimension: Physiological Resilience as an Independent Determinant of Endurance Exercise Performance,” *Journal of Physiology* (2023), https://doi.org/10.1113/JP284205.