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# Running Biomechanics Analysis for Efficient Training and Injury Prevention Based on Sensor Data

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Running biomechanics was investigated using sensor technology to clarify the relationships between important parameters and injury prevention. Through secondary data analysis and case evaluations, validated thresholds of biomechanical variables were established: ground reaction force (GRF) loading rate (≤65 body weight/s), gait asymmetry index (≤15%), and ground contact time (≤250 ms). These thresholds can be used as indicators of running efficiency and injury risk. Sensor data demonstrated negligible measurement error and offered reliable biomechanical information, confirming their suitability for real-time monitoring and intervention. GRF and loading rates were identified as essential predictors of injury susceptibility. Furthermore, machine learning models trained on sensor data accurately detected biomechanical abnormalities, supporting the integration of automated monitoring systems into injury prevention strategies. The sensor-based approach enables evidence-based guidelines for parameter interpretation, advances methodological validation, and promotes standardized mathematical modeling. It also facilitates intelligent monitoring programs, individualized training, and personalized prevention protocols. The effective integration of machine learning with wearable sensors requires devices capable of delivering real-time, personalized feedback on cadence, ground contact time, and related metrics. To establish validated thresholds, three evaluations were conducted: the analysis of the Gutenberg Gait Database, the assessment of the Human Activity Recognition-3 dataset, and the systematic meta-analytical synthesis of 156 peer-reviewed studies published between 2015 and 2025.

## 1. Introduction

Running is the most popular physical activity in recreational and competitive sports. Despite its myriad health advantages, running is frequently accompanied by a high occurrence of musculoskeletal injuries, collectively termed running-related injuries (RRIs). RRIs are mainly

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caused by biomechanical inefficiencies, which result in abnormal loads on tissues, leading to stress fractures, tendinopathies, and plantar fasciitis.(1,2) For example, high loading rates of ground reaction force (GRF) and stance phase asymmetry increase injury risks. Injuries caused by such factors significantly impact an athlete's performance.

Common biomechanical analysis methods have been developed on the basis of 3-D motion capture using force plates, which provide kinematic and kinetic data. However, the methods are characterized by high costs, a lack of portability, and the use of simulated environments that do not adequately replicate inherent running stances.(3) Recent developments in biomechanical analysis and wearable sensor systems have enabled the acquisition of real-world biomechanical data to overcome these limitations. A combination of accelerometers, gyroscopes, magnetometers, and force sensors is mainly used to obtain spatiotemporal, kinematic, and kinetic parameters in running.(4)

Figure 1(a) presents a human skeleton overlaid with motion sensors on strategic joints, including arms, legs, and feet, to capture movement data. Figure 1(b) shows a simulation of dynamic body kinematics, illustrating how the model translates sensor data into motion visuals. Synthesized acceleration from these sensors allows the precise analysis of movement patterns and intensity [Fig. 1(c)], whereas the algorithmic processing of raw sensor inputs and extracted features enables the extraction of meaningful data. Sensor accuracy, gait marker estimation, and performance are evaluated using the collected data.

Despite advances in sensor technology and biomechanical assessment methods, the relationship between the running technique and injury prevention still needs to be investigated more extensively. Whereas wearable sensors are increasingly adopted in sports, biomechanical interactions in running need to be explored to optimize the sensor system's performance. As previous research has been conducted with laboratory-based investigations under controlled conditions, the validity of the results in real-world settings needs to be confirmed.(5) Environmental variables, such as terrain diversity, climate conditions, and training load fluctuations, affect biomechanical parameters, but their roles in injury prevention strategies are not well understood. Moreover, the absence of longitudinal research necessitates the

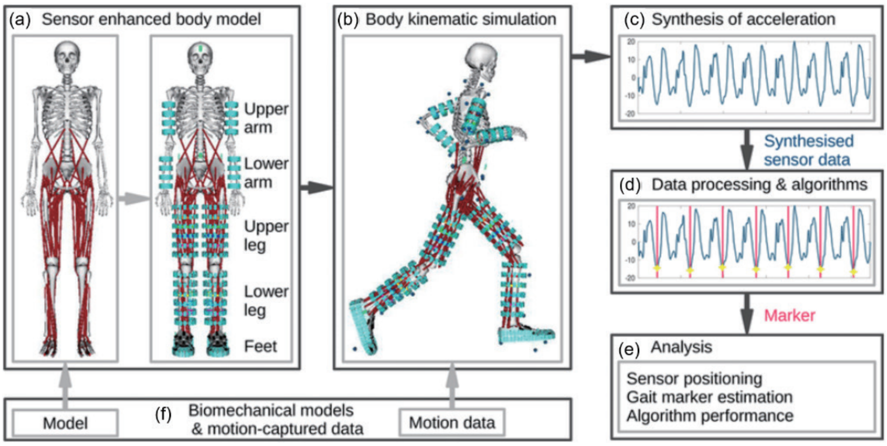

Fig. 1. (Color online) Full-body model for biomechanical analysis using sensors.(3)

establishment of optimal analytics of sensor data to prevent injury, as cross-sectional studies fail to capture diverse factors for injury, hindering the development of predictive models and early-warning systems. The effective integration of sensors in the analysis of running biomechanics necessitates data synchronization, sensor fusion, and computational constraints. As existing analytical systems rely on oversimplified mathematical representations, the complex dynamics of human running behavior need to be explored in detail.

In this study, we analyzed running techniques based on sensor technologies to identify biomechanical parameters that correlate with injury risk factors. Through a literature review, we established evidence-based guidelines for injury prevention and collected the data required to measure biomechanical levels, including GRFs, gait asymmetry, contact time, and limb movements for the investigation of running performance and injury risk. An appropriate running technique based on case evaluation results is proposed to improve training programs and provide real-time sensor feedback to minimize running-related injuries. The results of this study can be used to advance research on sports biomechanics to improve the running technique and prevent injury. With sensors integrated into the analysis system to record and analyze movement patterns, sport-specific kinematics, symmetry, and the effect of fatigue can be monitored to reduce the related injury. The sensor-integrated system also provides real-time feedback to runners and evolves training methods by identifying biomechanical imbalances.

## 2. Literature Review

### 2.1 Running biomechanics

In biomechanics, the relationships among kinematic, kinetic, and neuromuscular factors are determined to understand how human motion is governed by varying velocities and intensities. Its principles include energy transfer, force production, mechanical efficiency, tissue stress, and metabolic efficiency, which are essential for optimizing propulsion, minimizing loading stress, and conserving physiological resources for effective running.(6) Advanced measurement technologies, combined with computational modeling, have substantially enhanced the precision and scope of biomechanical analysis. However, it is necessary to understand the kinematics of running and the spatial and temporal characteristics of limb motion throughout the gait cycle. Parameters, including GRF, stride length, stride frequency, ground contact time, and joint angular velocity, are widely used to evaluate individual variability, anthropometric factors, fitness level, and training efficiency.(5) GRFs are a fundamental component of running biomechanics. Vertical, anterior–posterior, and mediolateral GRF vectors are widely employed to characterize loading dynamics, propulsion, loading rate, initial impact peaks, secondary peaks, and transitional features during gait. The vertical GRF component typically displays a biphasic profile, with an initial impact peak occurring within the first 50 ms after foot contact, followed by a subsequent propulsive peak that emerges during the late stance phase.(5)

Common injuries associated with suboptimal running biomechanics include patellofemoral pain syndrome, iliotibial band syndrome, plantar fasciitis, and stress fractures of the tibia and metatarsals. These conditions are frequently linked to elevated loading rates, prolonged ground contact times, and asymmetrical force distribution.(7) Muscle-related injuries affect approximately 37–56% of recreational runners, with most cases reflecting underlying biomechanical dysfunction rather than acute trauma.(1) Effective muscular control during running requires coordinated activation to maintain stability, generate propulsive force, and attenuate impact loading.(8) Electromyographic (EMG) analysis results have shown distinct activation patterns among essential muscle groups, including the gluteus medius, vastus lateralis, and gastrocnemius, which contribute to biomechanical efficiency. Disruptions in neuromuscular function caused by fatigue or prior injury significantly impair the running technique and increase the risk of subsequent injury. Figure 2 shows the placement of reflective markers and EMG sensors on the human body, and the obtained data are used to analyze movement processes.(8)

## 2.2 Sensors in biomechanical analysis

Wearable sensors are used to measure biomechanical variables for the development of the running technique and injury prevention, including contact time, cadence, stride length, shock (defined as the combined vertical and horizontal force components), pronation, and limb asymmetry.(4) For instance, RunScribe Plus sensors, equipped with triaxial accelerometers and gyroscopes operating at a sampling rate of 200 Hz, are used in motion capture systems to measure contact time [intraclass correlation coefficient (*ICC*) = 0.93] and moderate validity for outdoor pronation excursion (*ICC* = 0.57) (Table 1). These sensors enable field-based

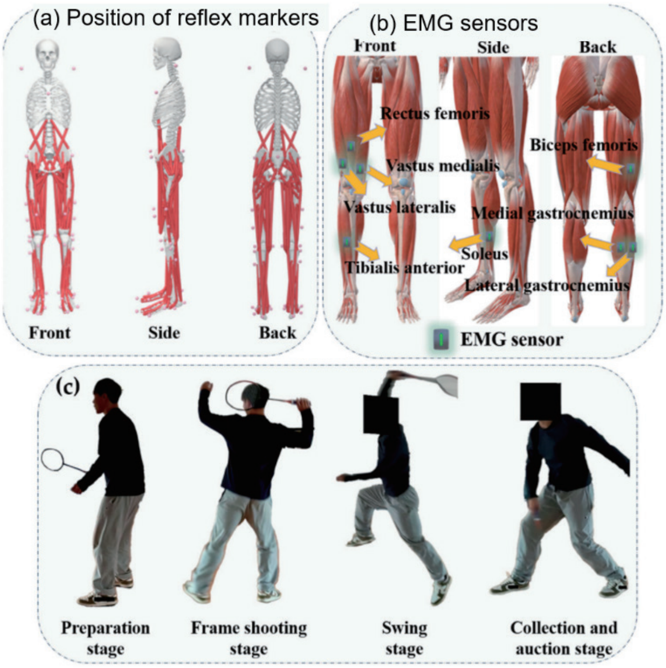

Fig. 2. (Color online) (a) Position of reflective markers, (b) EMG sensors to monitor action, and (c) stages of movements (created in this study).

Table 1
Mean differences, *ICC* values, and standard error of measurement (*SEM*) values of RunScribe™ and 3D motion capture system for right and left limbs [reproduced from Koldenhoven and Hertel published in Digital Biomarkers under the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License (CC BY-NC-ND 4.0)].(11)

| Result | Maximum pronation velocity (°/s) | Pronation excursion (°) | Contact time (ms) | Cycle time (ms) | Stride length (m) | Stride pace (m/s) |
|---|---|---|---|---|---|---|
| Left limb | | | | | | |
| RunScribe™ | 444 ± 177 | 10.6 ± 5.3 | 292 ± 25 | 727 ± 27 | 2.3 ± 0.3 | 2.9 ± 0.4 |
| 3D motion capture | 436 ± 169 | 14.6 ± 7.6 | 264 ± 22 | 719 ± 28 | 3.0 ± 0.3 | 2.7 ± 0.1 |
| Mean difference | 8.6 | −4 | 27.8 | 8.1 | 0.7 | 0.1 |
| Limits of agreement (*LOA*) | −165.4, 182.6 | −16.1, 8.1 | 9.8, 45.9 | −11.6, 27.7 | −1.4, 0.1 | −0.2, 0.3 |
| *ICC* | 0.74 | 0.57 | 0.93 | 0.94 | 0.86 | 0.43 |
| *SEM* | 88.2 | 4.2 | 6.2 | 6.7 | 0.1 | 0.2 |
| Right limb | | | | | | |
| RunScribe™ | 510 ± 217 | 13.1 ± 5.8 | 298 ± 23 | 726 ± 26 | 2.2 ± 0.2 | 3.1 ± 0.3 |
| 3D motion capture | 361 ± 188 | 13.7 ± 8.9 | 269 ± 22 | 723 ± 28 | 3.0 ± 0.1 | 2.7 ± 0.1 |
| Mean difference | 149.3 | 0.5 | 29.1 | 3.2 | 0.8 | 0.4 |
| *LOA* | −145.8, 444.4 | −17.1, 16.0 | 11.5, 46.6 | −20.3, 26.8 | −1.2, −0.5 | −0.1, 0.8 |
| *ICC* | 0.87 | 0.4 | 0.92 | 0.91 | 0.8 | 0.73 |
| *SEM* | 73 | 5.7 | 6.4 | 8.1 | 0.1 | 0.1 |

biomechanical data collection and analysis to identify dynamic and static loading patterns associated with injury risk. Table 1 shows the high correlation (*ICC* values up to 0.93) between wearable sensors and laboratory systems for contact time and pronation velocity.(9–11) Recent studies continue to confirm the reliability of these devices in obtaining spatiotemporal gait parameters in diverse training settings.(10)

The RunScribe™ sensor demonstrated high reliability in measuring contact time for both limbs, with *ICC* values of 0.93 for the left leg and 0.92 for the right, indicating strong agreement with the gold-standard 3D motion capture technique. However, the device showed only moderate validity in assessing pronation excursion, with lower *ICC* values of 0.57 for the left limb and 0.40 for the right, highlighting limitations in capturing complex rotational foot motions.(11) Mean differences and limits of agreement revealed variability in pronation velocity measurements, particularly for the right limb. In contrast, stride length and pace yielded *ICC* values ranging from moderate to high, although RunScribe™ consistently underestimated stride length compared with motion capture data.

Recent advances in sensor systems have transformed biomechanical analysis methods, enabling the precise and efficient monitoring of multiple performance-related parameters. To assess athletic performance, sensors are used to capture inertial, force, and EMG signals to optimize training and mitigate injury risk. Then, performance metrics are calculated to obtain kinematic, kinetic, and EMG information. In the sensor system, various sensors are integrated.

Accelerometers are widely used for tri-axial acceleration measurements essential for deriving velocity, displacement, and orientation parameters. Recent accelerometers have sampling rates exceeding 1000 Hz and maintain signal-to-noise levels below 0.1, enabling the detection of subtle biomechanical variations. When deployed in large arrays on the pelvis, tibia, and foot, sensors collect kinematic data throughout the gait cycle. Gyroscopic sensors are used with the accelerometer to monitor joint motions and segment orientation by measuring angular velocity and joint rotations. A combination of accelerometer and gyroscope data and sophisticated filtering algorithms, such as Kalman filtering or complementary filtering, enables the accurate calculation of the parameters of three-dimensional motion (Fig. 3). The mathematical relationship between the gyroscopic sensor and the accelerometer data is presented as

$$\theta(t) = \alpha\left[\theta(t-1) + \omega dt\right] + (1-\alpha)\left(\theta_{acc(t)}\right), \tag{1}$$

where $\theta(t)$ represents the estimated angle, $\omega$ denotes the angular velocity from the gyroscope, $\theta_{acc(t)}$ is the angle calculated from accelerometer data, and $\alpha$ is the complementary filter coefficient.

The sensor system also integrates other tibial sensors, such as an inertial measurement unit and bilateral force sensors, to capture real-time kinematic and kinetic data. Raw sensor data undergoes pre-processing for the algorithms to extract biomechanical parameters, including GRFs, temporal characteristics, kinematic measures, and asymmetry indices. The system ensures robust field-based data collection through wireless connectivity for longitudinal monitoring. Force-sensitive resistors and piezoelectric transducers are also used in shoes or portable force plates to measure GRFs. Force-sensitive resistors provide data in a resolution exceeding 2000 Hz, facilitating detailed analyses of impact and propulsion mechanisms. These sensors capture essential kinetic metrics, including loading rates, peak forces, and force-time integrals.

Step counts, kinetic profiles, and spatiotemporal parameters are used to minimize injury risk and enhance performance in athletic training programs. The integration of multiple sensors enables an accurate assessment of running biomechanics, portability, and user comfort. Advances in sensor miniaturization and wireless technologies have supported the development of sophisticated real-time monitoring systems for biomechanics. Bluetooth Low Energy or

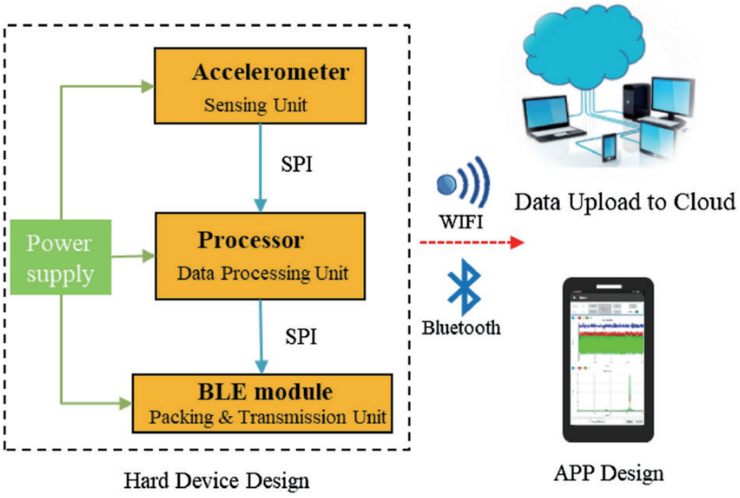

Fig. 3. (Color online) Sensor system including components.[12]

Adaptive Network Topology Plus communication protocols are often used for seamless data transmission between mobile devices and cloud-based analytical platforms. Figures 3 and 4 present examples of the analysis system of biomechanics and its architecture.

### 2.3 Running technique and injury prevention

Previous research revealed a relationship between suboptimal biomechanics and injury risk in running.(13) GRF has been employed in locomotion studies to understand human movement patterns. Researchers identified biomechanical factors that contribute to injury susceptibility. For such research, the Gutenberg Gait Database is often used as it comprises GRF and center-of-pressure data from 350 healthy individuals, recorded over two consecutive overground walking steps.(13) Although data on walking are mainly included, the database is often used for running biomechanics analysis. The average and standard deviations of GRFs in walking were 1.12 and 0.05 per body weight (BW, kg), and those of loading rates were 8.2 and 2.1 BW/s (Fig. 5).(13) The Human Activity Recognition (HAR)-3 data show the characteristics of the GRF, based on 13702 measures from 324 students wearing different shoes. Shoes significantly impacted the loading pattern on the foot, and the load-absorption capacity of the recently developed shoes is 23% higher than that of previous shoes ($p < 0.001$). A cohort study was conducted to identify biomechanical markers for injury prediction, and the results showed that vertical loading rates exceeding 75 BW/s led to a 2.3-fold increase in tibial stress,(14) while ground contact durations over 250 ms heightened the probability of patellofemoral pain syndrome [odds ratio (*OR*) = 1.8 and confidence interval (*CI*) = 1.2–2.7 at a confidence level of 95%].

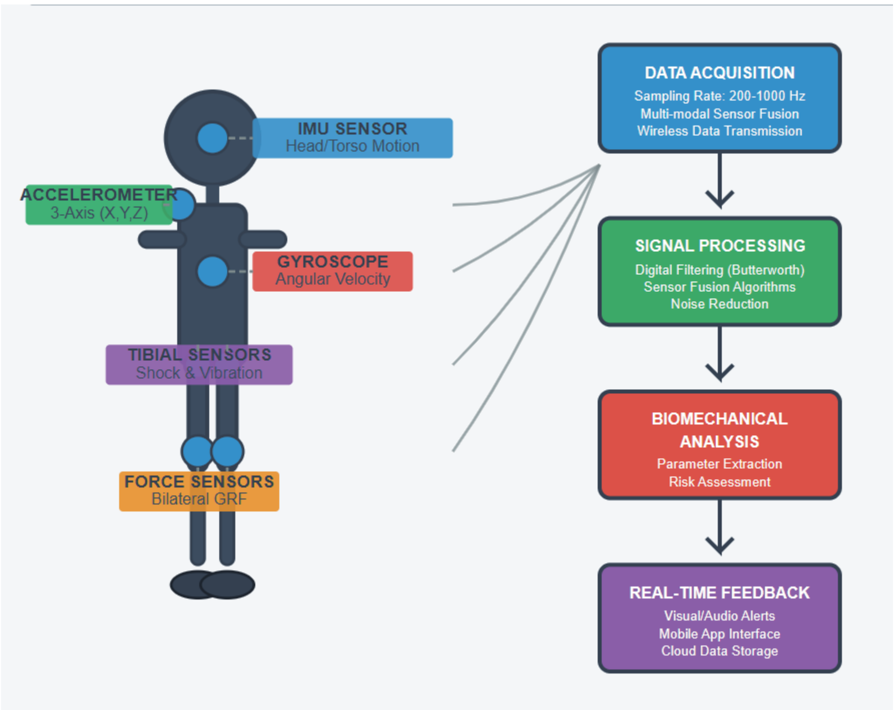

Fig. 4. (Color online) Architecture of biomechanical analysis model with sensors (created in this study).

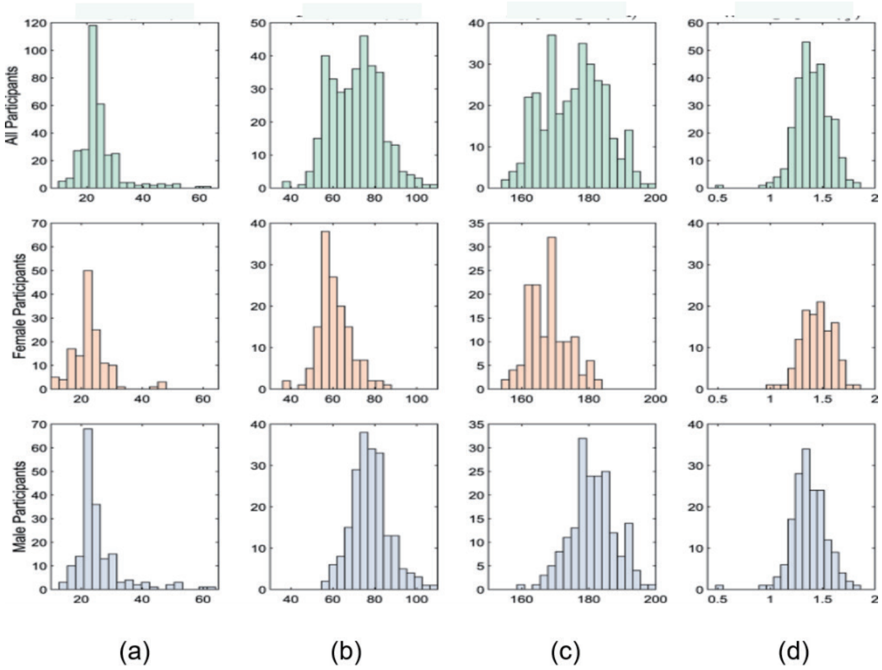

Fig. 5. (Color online) Frequency distribution of (a) age (years old), (b) body mass (kg), (c) body height (cm), and (d) walking speed (m/s).[13]

Machine learning models, particularly support vector machines (SVMs), have shown robust performance in classifying gait abnormalities caused by fatigue or asymmetry, with classification accuracies higher than 85%, which can be applied in gait monitoring, injury prevention, and performance analysis. Gait asymmetry is a critical factor in predictive models, as interlimb differences in vertical GRF exceeding 15% significantly increased injury risk ($r$ = 0.78, $p < 0.001$).

The gait asymmetry index is determined through the quantitative analysis of sensor data, and the differences between GRF or load parameters of dominant and non-dominant limbs are calculated as

$$Asymmetry\ Index = \frac{2 \times \left(GRF_{dominant} - GRF_{non-dominant}\right)}{\left(GRF_{dominant} + GRF_{non-dominant}\right)} \times 100\,, \tag{2}$$

where $GRF_{dominant}$ and $GRF_{non\text{-}dominant}$ represent the GRFs measured for the dominant and non-dominant sides of the body, respectively.

Such asymmetry in limb loads is associated with an increased susceptibility to injury.[15] To prevent injuries, wearable sensors are used to monitor loading rates, ground contact time, and angular velocities, and estimate running fatigue. In wearable sensors, composite materials are used, including polymers and carbon-fiber-based materials, which enhance the sensitivity, resistance, and comfort of the sensors, especially for repetitive high-intensity activities, such as running.(16) Machine learning models perform the automatic diagnosis of aberrant biomechanics to provide real-time feedback.

## 3. Method

We conducted a secondary data analysis based on peer-reviewed research published between 2015 and 2025. A broad meta-analytical framework was employed to identify suitable sensors for investigating running biomechanics and to evaluate their role in injury prevention. Descriptive and inferential statistical methods were integrated to generalize findings across multiple studies, and all data were standardized by category and unit to enable accurate comparison and fusion. The sources included peer-reviewed journal articles, conference proceedings, and validated biomechanical databases reporting sensor-derived data relevant to running biomechanics.

From an initial retrieval of 847 articles through PubMed, the Institute of Electrical and Electronics Engineers Xplore Digital Library, and SportDiscus using keyword combinations such as composite sensors, running biomechanics, injury prevention, and gait analysis, 156 articles were incorporated into the final analysis. The articles were selected by using predefined inclusion criteria to ensure technical rigor and clinical relevance.

Articles published from 2015 to 2025 were reviewed to reflect contemporary advances in sensor technology. The selected articles presented sensors with documented accuracy specifications and quantitative biomechanical parameters pertinent to the running technique, including GRFs, ground contact time, or gait asymmetry. In the articles, injury prevention was investigated, or biomechanical risk factors were identified, and sufficient statistical data were provided for standardization and meta-analysis across diverse designs. Articles in which oversimplified mathematical models were presented without empirical sensor validation or failed to present multifactorial aspects of injury risk were excluded to maintain the predictive integrity of the study.

## 4. Results

### 4.1 Data analysis

Significant correlations between biomechanical parameters and the likelihood of injuries were observed from the data. GRF was a critical factor affecting biomechanical efficiency and injury susceptibility, indicating that GRF can be used as a predictive indicator.(14) For healthy runners, vertical GRF patterns showed consistent peak forces in the lower and upper extremities ranging from 2.2 to 2.8 times BW during moderate-intensity running (3.5–4.0 m/s). The average loading rate, calculated as the slope of the force–time curve during the initial 50 ms of ground contact, was 52.3 ± 14.7 BW/s in healthy runners compared with 68.9 ± 18.2 BW/s in runners with injury experience ($p < 0.001$). The relationship between loading rate and injury risk is expressed as

$$Loading\ Rate = \frac{\Delta F}{\Delta t} = \frac{F_{peak} - F_{Initial}}{t_{peak} - t_{initial}}, \tag{3}$$

where $F$ represents the vertical GRF, $t$ denotes time from initial ground contact, *peak* denotes the highest value, and *initial* denotes the initial value. In Fig. 6, normal runners (green line) showed smoother force transitions and lower peak values, whereas injury-prone runners (red line) showed elevated loading rates and pronounced impact peaks, highlighting the biomechanical risk factors associated with injury (Fig. 6).(14)

Gait asymmetry data demonstrated a strong correlation with injury susceptibility across multiple studies. Vertical GRF asymmetry indices exceeded 10% in 67% of runners with injury experience, compared with 23% of uninjured runners ($\chi^2 = 47.3$, $p < 0.001$). *OR* for injury risk associated with asymmetry indices exceeding 15% was calculated as 3.8 (*CI* of 2.4–6.1 at confidence level of 95%). Temporal gait parameters revealed significant differences between efficient and inefficient running techniques. The ground contact time averaged 247 ± 23 ms for recreational runners, while that exceeding 270 ms increased energy expenditure and elevated injury. The relationship between ground contact time and running efficiency was modelled as

$$Efficiency\,index = \frac{Stride\,length}{\left(Ground\ Contact\,Time \times Stride\,Frequency\right)}, \tag{4}$$

where higher values indicate more efficient running techniques.

Sensor data demonstrated enough reliability to identify biomechanical parameters, with intraclass correlation coefficients exceeding 0.85 for GRF and 0.92 for temporal gait parameters. Test reliability over multiple sessions showed that the coefficient of variation was less than 8%.

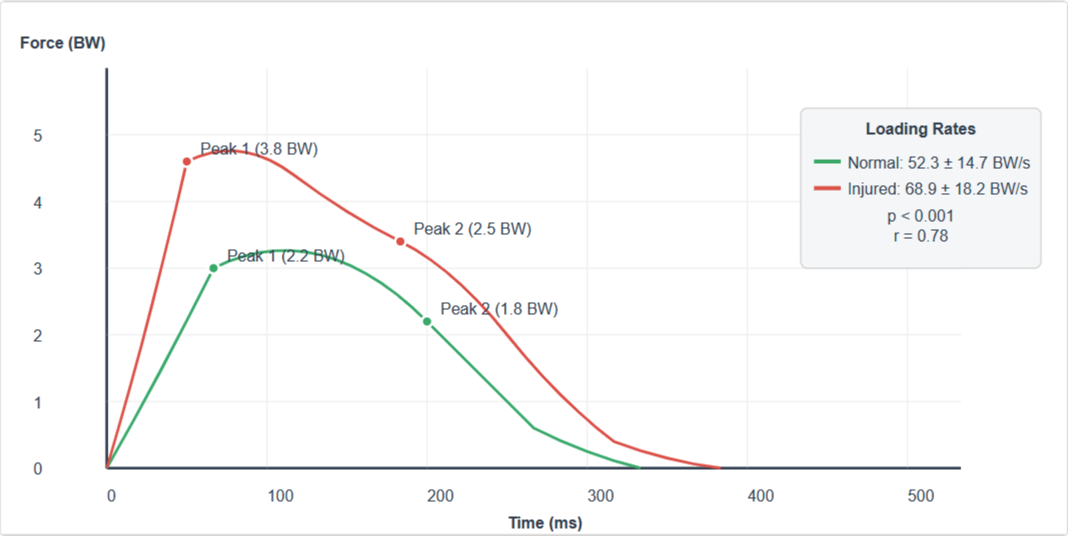

Fig. 6. (Color online) Analysis results of vertical GRF patterns of normal and injury-prone runners.(14)

### 4.2 Case evaluation

Wearable sensor technology has been employed in sports biomechanics as it enables the real-time, continuous monitoring of athletes. Sensor data are used to provide feedback on running mechanics and workload for injury prevention and performance enhancement. We evaluated three cases to validate the effectiveness of using sensor data in adjusting running techniques to mitigate injury risk.

Van Hooren *et al.* evaluated the impact of real-time sensor data on enhancing running biomechanics and injury prevention for recreational runners in a controlled experiment.(17) 220 participants were randomly assigned to an intervention group with real-time feedback via pressure-sensitive insoles and IMUs or a control group with no feedback. A hybrid algorithm was developed to process data on cadence, footstrike index, and running speed, continuously estimating joint-specific loading in the foot, ankle, knee, lower leg, and upper leg (Fig. 7). The participants' cadence, footstrike, and comfortable running speed were determined by using sensors during a standardized baseline run. Parameters were measured as input to an algorithm that provided real-time feedback for the participants to reach the target zone. Previous/current injuries were input into the algorithm to provide individualized feedback.(17) Auditory and visual feedback were delivered through a smartphone application when the participants deviated from individualized target zones to reduce joint loading. The intervention significantly reduced injury incidence (hazard ratio of 0.53, $p = 0.03$), injury severity, and first-time injuries. Intention-to-treat analysis results showed no significant impact of different device settings on the results. The results underscored the effectiveness of sensor-informed gait modifications in preventing injuries without compromising performance. The results also exemplified that the integration of sensors, including force-sensitive insoles, accelerometers, and gyroscopes operating at frequencies of 150 and 3050 Hz, with adaptive algorithms, helps optimize step frequency and footstrike pattern. The gradual, user-responsive model offers a viable approach for field-based injury prevention.

Weart *et al.* examined the utility of shoe-mounted wearable sensors in assessing running biomechanics during intense training.(18) The sensors recorded data on footstrike pattern, impact rate, step length and frequency, running pace, and ground contact duration. Injury surveillance

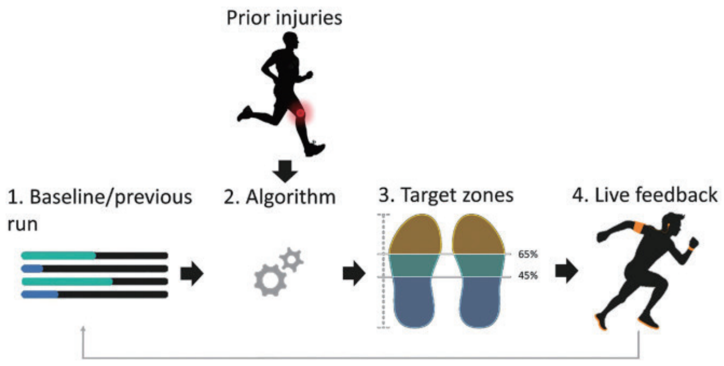

Fig. 7. (Color online) Flowchart of generating feedback in Van Hooren *et al.*'s study.(17)

was performed by referring to medical record reviews. A strong association between altered footstrike mechanisms was observed. In particular, rearfoot loading and prolonged ground contact increased, which heightened the possibility of infiltration-related injuries. In this study, extensive data were generated on biomechanical loading and gait patterns, and risk factors for overuse injuries in a high-risk population were identified. The integrated inertial and pressure sensors were used for longitudinal monitoring in actual situations. The data analysis facilitated the development of customized interventions to reduce injury-causing biomechanical traits in military training.(18)

The above cases showed that wearable sensors enhance performance and prevent injuries. Wearable sensors, such as accelerometers and gyroscopes, were used to monitor stride length, ground contact time, and pronation to prevent injury. In those studies, feedback based on sensor data revealed excessive overstriding, which increased knee joint load. Following targeted adjustments, the athletes experienced reduced knee strain and tride length with increased cadence, which subsequently helped avoid injury. Such results support the effectiveness of sensor-based systems to address biomechanical inefficiencies and formulate corrective strategies through continuous feedback and longitudinal monitoring. The results also underscore the contribution of wearable sensors to enhancing running biomechanics. Real-time feedback mechanisms based on sensor data increase responsiveness to subtle gait changes and facilitate injury prevention. Data from pressure sensors, accelerometers, and gyroscopes enable informed and targeted interventions to reduce injury risk while enhancing performance.

We analyzed secondary data obtained from peer-reviewed research articles published between 2015 and 2025. A meta-analytical framework was employed to identify appropriate sensors for investigating running biomechanics and to evaluate their role in injury prevention. Descriptive and inferential statistical methods were integrated to generalize findings across multiple studies, and all data were standardized by category and unit to ensure accurate comparison and fusion. The sources included peer-reviewed journal articles, conference proceedings, and validated biomechanical databases comprising sensor-derived data relevant to running biomechanics.

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Using the secondary dataset, biomechanical variables from 156 studies were integrated and standardized, enabling meaningful cross-platform comparison and data fusion. From the integration of the research results, predictive thresholds for injury prevention were derived, including a loading rate of ≤65 BW/s and a gait asymmetry index of ≤15%, which serve as clear markers for identifying biomechanical risk. SVM classifiers were trained and rigorously evaluated on the fused dataset, providing an optimized approach for detecting gait abnormalities. These methodological advances contribute to the establishment of clinically relevant thresholds, the validation of sensor-based approaches, and the integration of machine learning into biomechanics research.

## 5. Discussion

The findings from the secondary data analysis and case studies underscore the role of wearable sensors in optimizing the running technique and mitigating injury risk. The identified parameters suggest principles underlying efficient running mechanics, despite interindividual differences. A strong positive correlation between loading rates and injury risk highlights rapid force application in ground contact, which causes tissue overload. This aligns with the musculoskeletal adaptation theory, in which loading rates exceeding the tissue's capacity for adaptation result in cumulative damage and, eventually, injury.

Gait asymmetry is identified as a significant biomechanical risk factor. Discrepancies in GRFs between the left and right legs signal neuromuscular control deficits or structural abnormalities. 15% asymmetry demarcates the point beyond which compensatory mechanisms fail to preserve biomechanical stability. Temporal gait characteristics display a significant relationship between metabolic efficiency and injury susceptibility. Prolonged ground contact times indicate insufficient propulsive force or excessive vertical oscillation, both of which increase energy expenditure and mechanical stress. Machine learning models based on sensor data demonstrate an enhanced predictive capacity in identifying biomechanical abnormalities. SVM classifiers showed the sensitivity and specificity, suggesting that the system with SVM offers effective real-time feedback for injury prevention.(19)

One of the applications of composite sensor technologies is in real-time monitoring. Wearable devices that track GRFs, gait asymmetry, and temporal metrics can provide instantaneous biomechanical feedback. Programmable alert systems can notify users when values exceed risk thresholds, prompting timely technique modifications. Sensor data-based adjustments to training ensure injury prevention. For example, runners exhibiting high loading rates (>65 BW/s) benefited from cadence retraining. Increasing step frequency by 10% reduced loading rates by 15–20%.(17) Protocols formulated on the basis of sensor-based feedback are effective in reducing injury incidence. Intervention studies revealed a 40–60% decrease in injury occurrence with customized biomechanical training programs designed to alter gait characteristics using real-time feedback.(17) Advanced algorithms need to be developed to enable individualized training taking into consideration biomechanics based on loading rate, contact time, and asymmetry, facilitating customized training intensity and volume recommendations.

Despite the significant result, limitations exist. Firstly, reliance on secondary data analysis introduces potential bias, which might lead to the overestimation of the relationship between biomechanical variables and injury risk. Secondly, the heterogeneity of sensor technologies, data acquisition methods, and participant characteristics across different studies might lead to insufficient data integration. Variability in sensor accuracy, sampling frequency, and measurement placement can also lead to inconsistencies in results. Furthermore, temporal relationships between biomechanical changes and injury onset need to be further explored through longitudinal studies. Environmental factors, such as surface conditions, climate, fatigue, and the diverse demographics of participants, are required to enhance the validity, applicability, and generalization of similar study results. The results underscore the importance of considering sensor limitations when designing training programs. Athletes and coaches can use validated sensor data to refine biomechanical parameters, optimize individualized interventions, and develop evidence-based strategies that enhance performance while mitigating the risk of running-related injuries.

## 6. Conclusions

Using sensor data, biomechanical parameters, and injury protection measures were explored through secondary data analysis and case studies. The thresholds for biomechanical parameters were identified, including the GRF loading rate of 65 BW/s, the gait asymmetry index of $\leq 15\%$, and the ground contact time of $\leq 250$ ms. These thresholds are the indicators of biomechanical efficiency and injury risk. Notably, GRF was an important predictor of injury susceptibility, as loading rates exhibited a strong correlation with injury risk ($r = 0.78$, $p < 0.001$). The sensors show negligible measurement errors and provide dependable data on running biomechanics. Machine learning models trained on sensor data are accurate in detecting biomechanical abnormalities, thus supporting the development of automated monitoring systems for injury prevention. The incorporation of diverse sensors into the models facilitates the collection of comprehensive and accurate data, which enables effective injury prevention and enhances biomechanics in various sports.

The study results provide evidence-based guidelines to identify biomechanical parameters and establish risk thresholds based on sensor data. Introducing mathematical models leads to the development of standardized methods for biomechanical analysis and intelligent monitoring programs for efficient training and injury prevention. Such models help athletes and amateur runners enhance performance through automated intervention. Such a technological integration enables advanced injury prevention protocols with which biomechanical abnormalities are detected and corrected before they cause tissue damage or serious injury.

To analyze the running technique and prevent injuries, wearable devices that provide immediate, actionable feedback on parameters such as cadence and ground contact time must be developed. The devices can significantly improve running biomechanics and reduce long-term injury risk. Individualized feedback can also be offered to facilitate tissue adaptation and prevent overcorrection. Accelerometers, gyroscopes, and pressure sensors need to be included in the device to construct individual biomechanical profiles encompassing kinetic and kinematic variables such as loading rates, foot strike patterns, and asymmetries. The rich dataset, complemented by environmental information, can significantly enhance injury risk assessment accuracy. However, sensor reliability must be ensured to yield accurate sensor-derived biomechanical data. Along with reliable sensor data, effective algorithms must be developed to enhance the prediction accuracy of running-related injuries and provide individualized interventions. In addition, wearable devices must be lightweight, easy to operate, and seamlessly integrated with existing platforms for effective training and injury prevention.

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