Improving Performance with OpenPose: Analyzing Post-Run Feedback through a Prescriptive Dashboard

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Running biomechanics play a crucial role in performance and injury prevention. This study aimed to evaluate the influence of post-run feedback on key running metrics – cadence, overstriding, and vertical oscillation. We utilized OpenPose, a state-of-the-art pose estimation tool, to capture participants' running patterns, which were subsequently presented through a prescriptive dashboard. Participants ran for 10 minutes, received feedback, and then ran for another 10 minutes. Our findings suggest that post-run feedback can lead to adjustments in running metrics, with varying degrees of change observed among participants. Notably, vertical oscillation showed significant changes across all participants, while cadence and overstriding exhibited individual variances. Although some participants' metrics aligned more closely with ideal biomechanics benchmarks post-feedback, others did not show uniform improvements. The study underscores the potential of tools like OpenPose and analytical dashboards in providing insights that may influence running behaviors, setting the stage for further research in this domain.

Additional Key Words and Phrases: OpenPose, Computer Vision, Running, Cadence, Overstriding, Vertical Oscillation, Prescriptive Dashboard

1 INTRODUCTION

In recent years, OpenPose, a real-time multi-person keypoint detection library, has emerged as a valuable tool for sports analysis, particularly in the domain of running[9] and various other athletic activities[14, 20]. This advanced framework offers an innovative approach for precisely estimating critical points on body parts such as the body, face, hands, and feet[3].

Running analysis typically involves three crucial parameters: Vertical Oscillation (the degree of "bounce" in a runner's step), Overstriding (taking strides that are too long), and Cadence (the number of steps a runner takes in a minute). These parameters significantly influence running efficiency and injury risk[18, 21].

The innovative real-time detection provided by OpenPose has been recognized in different sporting environments, ranging from football[20] to tennis[14], where estimation of body key points can significantly influence strategic planning and performance assessment. Meanwhile, the contribution of OpenPose has been equally profound in healthcare settings such as gait analysis, as seen in the diagnosis and monitoring of diseases like Parkinson's[4].

The efficacy of video-based biomechanical analysis in sports has been well established[21], and OpenPose's marker-less motion capture capabilities further extend its potential for usage in such analyses[9]. This approach eliminates the need for physical markers, simplifying data acquisition and potentially increasing the applicability of biomechanical analysis in real-world settings.

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In this study, it is leveraged OpenPose's capabilities to feed real-time data into a prescriptive dashboard. This dashboard visualizes key running metrics and offers actionable insights to guide runners toward optimal performance [23]. The choice of visualization, including bar graphs, is grounded in research highlighting the importance of graph literacy and numeracy in data interpretation[5].

Additionally, mindful of the potential for cognitive overload with excessive or improper color use, our dashboard design prioritizes clarity and intuitiveness. This ensures that runners receive feedback in an understandable and actionable manner, without overwhelming them[2].

This paper will delve deeper into the application of OpenPose in three running parameters analysis: Vertical Oscillation, Cadence, and Overstriding. Moreover, this data will be fed into a prescriptive dashboard. This dashboard visualizes key running metrics and offers actionable insights to guide runners toward optimal performance [23]. The choice of visualization, including bar graphs, is grounded in research highlighting the importance of graph literacy and numeracy in data interpretation[5].

Additionally, mindful of the potential for cognitive overload with excessive or improper color use, our dashboard design prioritizes clarity and intuitiveness. This ensures that runners receive feedback in an understandable and actionable manner without overwhelming them[2].

2 RESEARCH QUESTION

Primary Research Question:

How does using OpenPose's real-time keypoint detection, in conjunction with a prescriptive dashboard offering feedback, influence key running metrics (Cadence, overstriding, and vertical oscillation) in participants?

Sub-Questions:

(1) To what extent does Cadence change in participants after receiving feedback from the dashboard?
(2) How does feedback influence the degree of overstriding in participants?
(3) What changes are observed in vertical oscillation post-feedback?
(4) Are the observed changes in running metrics consistent across all participants, or are there individual variances?
(5) How do the changes in metrics align with ideal running biomechanics benchmarks?

3 RELATED WORK

OpenPose has demonstrated its efficacy in various sporting environments, including football and tennis, where accurate estimation of body key points is crucial for performance assessment and strategic planning [14, 20]. Its markerless motion capture capabilities make it a valuable tool for video-based biomechanical analysis in sports [9].

Previous studies have explored different methods for gait analysis and running parameter extraction. Souza [21] employed tape-based markers to identify anatomical landmarks on runners, allowing for visual examination of running form. Castelli et al. [15] developed a machine-learning approach for clinical gait analysis, utilizing segmental markers on clothing for tracking movements. Feng B. et al. [9] evaluated a low-cost, single-camera system for running gait analysis using OpenPose but highlighted some limitations. Moro M. et al. [16] introduced a markerless approach for gait analysis using RGB video data, demonstrating accuracy comparable to marker-based systems.

The significance of vertical oscillation, cadence, and overstriding in running biomechanics and injury risk has been well-documented. Understanding these parameters can help optimize running performance and reduce the potential for injuries [1, 8, 11, 17, 21].

Clinical dashboards have become an instrumental tool in healthcare to convey performance feedback compared to quality benchmarks. These dashboards utilize data visualization techniques to enhance comprehension and guide actionable insights. However, the true efficacy of these dashboards hinges upon the user's proficiency in interpreting the visualized data.

A recent study delved into the comprehension of quality targets presented in clinical dashboards among home care nurses. It revealed a marked correlation between graph literacy, numeracy, and understanding of the data. Specifically, nurses with heightened graph literacy and numeracy exhibited a more nuanced grasp of the quality targets presented in the dashboard format [6]. This finding accentuates the necessity of tailoring dashboard designs to cater to diverse levels of numeracy and graph literacy among its users.

A comprehensive exploration into the design and applicability of clinical dashboards was presented in a study focused on home care nurses. The research leveraged Feedback Intervention Theory (FIT) to guide the development and evaluation of a prototype clinical dashboard tailored for this demographic. The study emphasized the pivotal role of timely and actionable feedback in influencing clinician behavior, particularly when juxtaposed against established quality standards. Furthermore, the research highlighted the diverse challenges in identifying the optimal components of a feedback intervention, given the variations in content, delivery mode, and frequency [5].

In the educational domain, an experimental study was conducted among fourth-grade students in Ningxia, China. This study investigated the efficacy of two different types of dashboards (descriptive and prescriptive) in the subject of mathematics. These dashboards were based on the "Big Data for Learning" platform developed by the research group. The goal was to assess if personalized learning supported by the two dashboards could significantly improve student learning outcomes and if there were noticeable changes in students' learning strategies and attitudes towards learning. The findings suggest that both dashboards were effective in promoting students' cognitive development, with the prescriptive dashboard showing a slightly greater facilitative effect. This research underscores the potential of dashboard analytics to influence self-directed learning processes, especially when students' prior knowledge and self-directed learning skills are deficient [23].

Fig. 1. Subject running on the treadmill (green rectangle). Tripod with the smart phone on it (orange rectangle). Blue arrow depicts distance from tripod to treadmill .

Similar principles apply to our study on running biomechanics. Using OpenPose for pose estimation combined with a prescriptive dashboard to delineate key metrics necessitates that runners, much like healthcare professionals or students, are adept at parsing the feedback presented. Such comprehension is pivotal, bridging the gap between mere feedback and actionable, performance-enhancing insights.

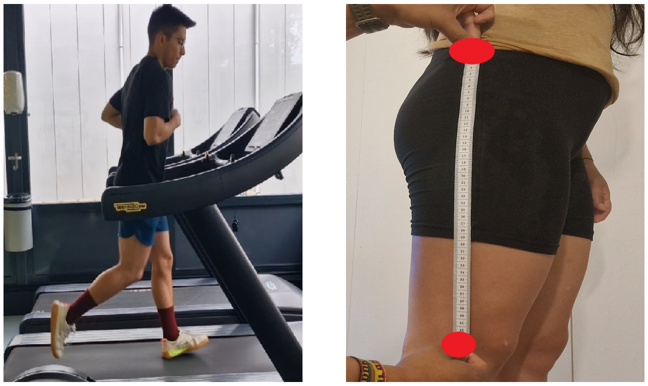
4 METHODOLOGY

In this section, we describe the approach taken for overstriding, cadence, and vertical oscillation computation by using the OpenPose library and the implementation of a prescriptive dashboard to give feedback to the user.

4.1 Data Collection and Video Processing

Eight subjects were recruited to participate in a research project involving running on a treadmill (see Figure 2a). Prior to beginning the activity, the participants were given an inform of consent; next the participants were instructed to warm up by running for two to two minutes. All of them were told to engage in autonomous pace-running for one minute at 9km per hour.

The entire procedure was carefully recorded using a Samsung Galaxy S22 Ultra camera, capturing footage at a rate of 30 frames per second (FPS). To maintain stability and avoid any unintentional movements that could potentially impact the reliability of the data, the camera was securely mounted on a tripod with a height set to 128 cm and placed at 195cm distance from the treadmill (see Figure 1). To accurately track the participants' cadence, manual step counting was employed. Additionally, it must be said that the videos were captured from a unilateral perspective (see Figure 2a), with the camera positioned fixedly and pointing towards the right side of the runner.



(a) (b)

Fig. 2. (a) A subject runs on a treadmill at a consistent speed. Additionally, the camera records the right side of the individual (sagittal plane perspective). After finishing their exercise, (b) their thigh is measured from the side (from the right hip to the right knee) using a measuring tape.

In terms of participant demographics, the study was comprised of individuals aged between 22 to 24 years. Notably, none of the participants have a history of any injuries pertinent to athletic activity or running, primarily because they did not engage in regular running activity. Additionally, an imperative aspect of the data collection involved the measurement of each subject's right thigh using a tape measure (see Figure 2b). The range among the participants' thighs is between 39 to 47 cm. The rationale behind this process is tied to the scaling considerations crucial to the objectives and interpretations of this research.

Furthermore, to ensure the accuracy and authenticity of the data for comparison with the system's cadence measurements, a meticulous examination of each video was conducted to accurately determine the number of steps taken by each participant. This rigorous process involved closely scrutinizing the recorded videos to identify and count the exact number of steps performed by each individual. By obtaining this real and reliable step count data, a comprehensive and meaningful comparison with the cadence readings provided by the system could be established, facilitating a robust evaluation of its performance and accuracy in estimating the participants' step rates.

4.2 Parameters Extraction

Table 1 provides a comprehensive description of the parameters extracted from OpenPose, their implications in running biomechanics, and the corresponding visual perception used to measure them by using OpenPose.

4.2.1 Cadence extraction: The determination of step rate relies on analyzing the variation in knee angle [19] across consecutive frames. To obtain these angles, three keypoint coordinates associated with the middle hip, right knee, and right ankle are extracted from the dataset keypoints. Represented as $\upsilon = \{x_f^i, y_f^i\}$, $\nu = \{x_f^j, y_f^j\}$ and $\omega = \{x_f^k, y_f^k\}$ represent the coordinates of the middle hip (i), knee (j), and ankle (k) respectively in frame f. Being j the central point and i and k as its adjacent nodes, we can form vectors and the Euclidean distance D between point a and point b, a and b being to adjacent can be calculated by:

$$D_E(a,b) = \sqrt{\left(x_t^a - x_t^b\right)^2 + \left(y_t^a - y_t^b\right)^2} \tag{1}$$

To get the range of motion at j:

$$\theta\,(j) = \arccos\left(\frac{ji \cdot jk}{|ji||jk|}\right)$$

As depicted in Figure 3, the estimation of the subject's step count involves counting the peaks of the knee angle relative to the middle hip and ankle. It is important to note that the knee flexion/extension is exclusively computed for a single leg. However, due to the processing of frames by OpenPose, which may occasionally mix up the legs, some noise is introduced into the data.

In this context, it could be argued that the number of high or lower peaks observed in the knee angle represents the count of steps taken by the selected leg, considering the knee angle alteration during the leg's flexion when executing a step. To accurately determine the total number of peaks, it became necessary to employ specific techniques for peak smoothing, such as the Savitzky-Golay filter. This technique effectively eliminates noisy data while preserving important data features, such as width, as highlighted in previous studies [10]. Utilizing these filtering and smoothing methods ensures a more precise calculation of the step count by mitigating the influence of noise and enhancing the accuracy of the analysis.

4.2.2 Vertical Oscillation extraction: To compute the vertical oscillation, first, the displacement of the middle hip is been tracked in every frame of the video. Figure 4 shows the vertical displacement over frames, where the number of oscillations or high peaks may equal the number of steps, the subject total step number is 28. However, due to noise in the peaks, the total number of high peaks is 33. To address this problem, smoothing has been done on the peaks only to get the average width distance in order to reduce noise in the data. Figure 6 represents both the original vertical oscillation from raw data and the smoothed curve of that data. Even though the smoothed curve has lower vertical oscillation, it could be said that it still conserves the width of the raw data [10]. By separating

Table 1. Description of parameters extracted from OpenPose

Parameters	**Implications**	**Visual Perception**
Cadence	Low speed, overstriding [11]	angle between ankle and center of mass with knee position point as center point
Overstriding	Meniscal injury, Patellofemoral pain syndrome[7, 11, 17]	angle between middle hip and ankle with knee position point as center point
Vertical Oscillation	Higher ground impact[1, 8]	vertical movement of middle hip

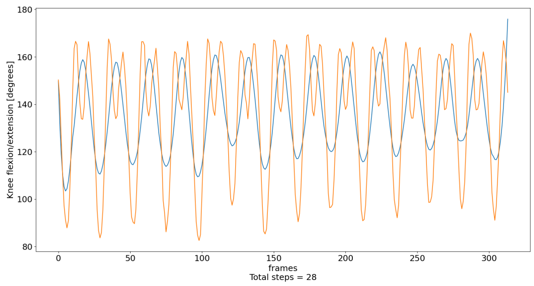


Fig. 3. A 10-second window video from a one-minute video of a subject running at 10 km per hour at her normal running form. The orange curve depicts the original data extracted from OpenPose. The blue curve depicts the smoothed data. Each high or low peak on the blue curve corresponds to a leg strike, enabling step count determination of one leg, in this case, 28 steps .

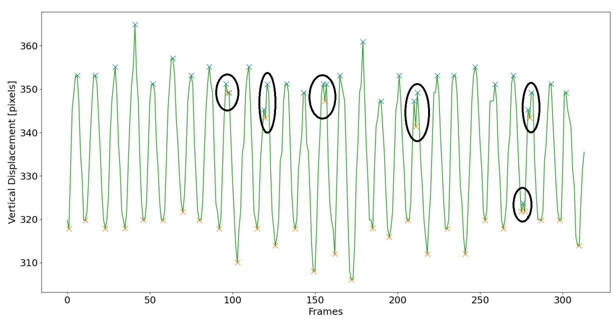


Fig. 4. Same video as in Figure First 3. Vertical displacement is plotted from the original data showing high peaks marked with blue x and low peaks marked with orange. Any noise present in the peaks is visually marked with black circles.

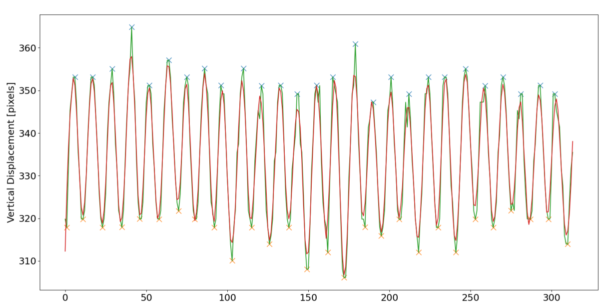


Fig. 5. The green curve indicates the vertical Displacement from Figure 4. While the orange curve depicts the original curve but is smoothed using the algorithm Savitzky-Golay smoothing filter. The number of high peaks is equal to 27, and low peaks are equal to 28

each peak of the original curve with the width of the peaks of the smoothed curve, the data may become more accurate since only one point of each peak is taken.

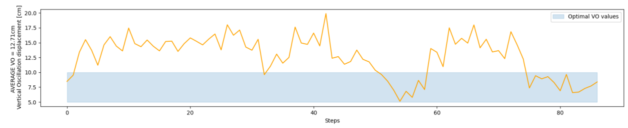


Fig. 6. The data Fig.4 was transformed into vertical oscillation (VO) per step, and the optimal range was defined with a minimum value of 5cm and a maximum value of 10cm [1]. This range signifies the safe zone within which the vertical oscillation should ideally fall.

Fig. 7. Green area represents the measured shank angle.

To calculate the vertical oscillation (VO) of a subject, it is necessary to make meaningful comparisons with average optimal VO values but to get there before; it is essential to establish a conversion from pixel measurements to centimeters. This conversion is achieved by incorporating known values into the system. In this case, the subject's thigh length (see Figure 2b) is measured and used to scale each frame's pixel values. The following formula defines the parameters used in the calculation of VO in centimeters:

$$VO^f = m^f_{pixels} * \frac{h_{cm}}{p^f_{pixels}} \tag{2}$$

Let 'h' represent the subject's thigh length in centimeters. The thigh length in pixels, denoted as 'p,' is computed using the Formula 1 with (hip - knee) key points as parameter at time f. The displacement of the middle hip coordinate, denoted as 'm', is defined as the position of m at time f. Upon implementation of Equation 2.

4.2.3 Overstriding extraction: The existing body of literature, specifically reference [22], highlights the significance of the shank angle as a valuable indicator for identifying instances of overstriding in runners. A detailed analysis of three specific key points is warranted to assess overstriding using the key point data provided by OpenPose. These key points include the ankle, knee, and the center of mass (COM), which can be conveniently derived by constructing an array with the x-coordinate equivalent to the x-coordinate of the knee and the y-coordinate equivalent to the y-coordinate of the ankle (Figure 7.

By extracting and analyzing these three keypoint values, it becomes possible to leverage Equation 4.2.1 to estimate the shank angle at the specific time point denoted as f. This estimation offers valuable insights into the extent of overstriding exhibited by the runner during that particular instance. Integrating these key

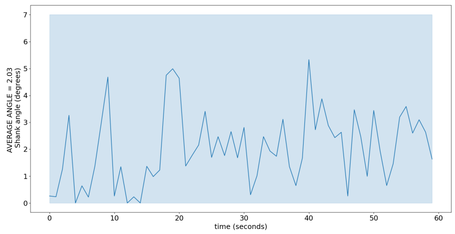


Fig. 8. One-minute video of subject running at moderate cadence depicting the shank angle cycle for 172 steps.

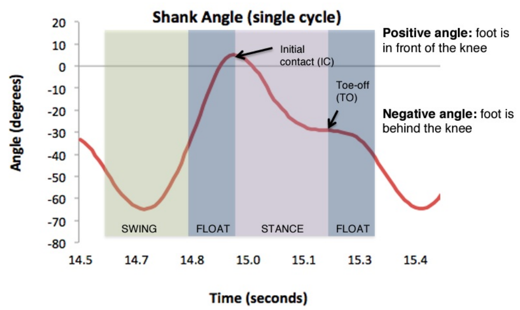


Fig. 9. The shank angle cycle for a single step. Adapted from [22].

point-based calculations into the research methodology enhances the ability to evaluate and estimate overstriding tendencies, facilitating a more comprehensive understanding of running biomechanics and potential performance limitations.

Figure 8 presents a visual representation of an approximately 10-second video segment, showcasing the locomotion of a subject engaged in running activity. The depicted running pattern exhibits a moderate degree of overstriding, falling within the angular range of $0°$ to $7°$. It is noteworthy that angles surpassing $7°$ can be regarded as indicative of high overstriding, based on established conventions [22].

4.3 Prescriptive Dashboard Implementation

Upon completion of the video analysis using the OpenPose library, the extracted parameters—namely cadence, vertical oscillation, and overstriding—are used to generate a comprehensive report. This report, presented in the form of a prescriptive dashboard, is designed to offer clear and actionable feedback to the user based on the post-analysis of their running video.

4.3.1 Dashboard Design and Features. The dashboard is organized into distinct sections, each dedicated to one of the three main parameters: Cadence, Vertical Oscillation, and Overstriding.

(1) **Overview Section:** This part briefly overviews the runner's performance, focusing on the average and standard deviation of cadence, vertical oscillation, and shank angles. It also includes a 'Targeted Achievement' section suggesting optimal benchmarks for cadence, vertical oscillation, and overstriding that the runner should aim for.
(2) **Graphs:** Three visual representations are employed, using color-coded bars to signify instances of elevated overstriding, low cadence, or excessive vertical oscillation throughout the run. A scatter graph is incorporated to enhance the accuracy of vertical oscillation data, featuring specific timestamps from the video. This empowers the runner to scrutinize and comprehend precise moments characterized by heightened vertical oscillation. The y-axis of the cadence graph represents step count, while the x-axis denotes time in minutes. In the case of overstriding, the y-axis represents degrees of the shank angle, while the x-axis corresponds to time in minutes. For vertical oscillation, the y-axis illustrates the runner's vertical movement in centimeters, with the x-axis indicating time in minutes.
(3) **Recommendations and Feedback Panel:**This section provides users with a brief performance summary. When instances of incorrect form are detected, it highlights potential associated risks. Within this section, suggestions are offered to the runner. Notably, a recommendation to increase cadence is provided to reduce occurrences of overstriding and minimize vertical oscillation. This advice was given to users as a response to situations characterized by high levels of overstriding, excessive vertical oscillation, and low cadence.

4.3.2 Dashboard Implementation. The dashboard is web-based, ensuring accessibility across various devices. It is built using a combination of Next.js, CSS, and JavaScript, with data visualization facilitated by the Chart.js library. The backend, responsible for processing the OpenPose data and generating insights, is developed using Python and Supabase (Figure 14).

To ensure the dashboard's effectiveness, an initial beta version can be tested with a small group of runners. Their feedback would be invaluable in refining the design, adding features, and ensuring that the presented information is both understandable and actionable.

A solution was implemented to prevent overwhelming the runner with excessive information by incorporating three buttons, each corresponding to a specific running parameter. Upon clicking a button, the screen will then display the relevant section pertaining to the chosen running parameter. This design ensures a focused and organized presentation of information for the user's convenience.

5 RESULTS

The primary objective of this research was to determine the effectiveness of feedback provided through a dashboard on key performance indicators (KPIs) of runners. The KPIs under investigation were Cadence, Overstriding, and Vertical Oscillation. Descriptive statistics, paired t-tests, and graphical visualizations were employed to analyze the data.

5.1 Descriptive Analysis

The initial investigation involved computing descriptive statistics, including the mean, median, and standard deviation for each metric both before and after feedback.

For the Cadence metric, mean values before feedback ranged from 149 to 188.2 steps per minute. Post-feedback, the range was from 160.4 to 196.4 steps per minute.

Overstriding showed mean values ranging from 4.26 to 14.04 degrees before feedback. After feedback, the range shifted from 1.61 to 16.27 degrees.

For Vertical Oscillation, the pre-feedback mean values ranged from 4.88 to 12.12 cms, while post-feedback values were between 4.89 and 10.06 cms.

5.2 Statistical Analysis

Paired t-tests were conducted to determine if there were statistically significant differences in the KPIs before and after the feedback. For data not conforming to normal distribution, the Wilcoxon signed-rank test was employed as a non-parametric alternative.

For Cadence, most participants exhibited statistically significant changes post-feedback. Notably, Participant 6 was the exception with no significant difference detected.

Overstriding also displayed significant changes for many participants, with Participant 7 and Participant 8 being the exceptions.

Vertical Oscillation changes were universally significant across all participants.

By glancing at the heatmap (Figure 10), you can quickly identify which participants had significant changes in their running metrics after viewing the feedback. Darker cells highlight these significant changes.

For example, most cells in the "Vertical Oscillation" row are dark, suggesting that changes in this metric were statistically significant for almost all participants.

Conversely, lighter cells, especially those with p-values above 0.05, indicate non-significant changes. For instance, the cell for "Participant 6" in the "Cadence" row is lighter, signifying that the change in cadence for this participant wasn't statistically significant post-feedback.

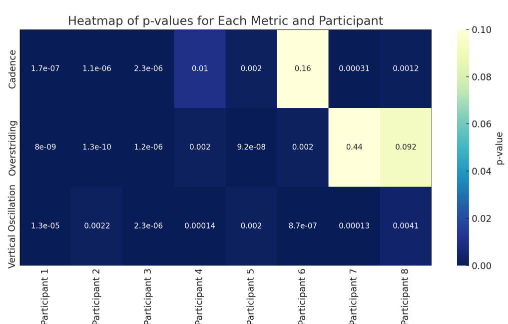


Fig. 10. Heatmap of p-values for each metric and participant. Darker shades indicate lower p-values, with values in cells providing precise p-values.

5.3 Graphical Evidence

Bar charts were constructed to visually represent the percentage of observations within ideal ranges for each metric before and after feedback.

For Cadence, participants like Participant 5 displayed a marked increase in observations within the ideal range[12, 13] (160-170 steps/min) post-feedback.

In the Vertical Oscillation chart, participants such as Participant 5 and Participant 6 showed noticeable changes, moving their metrics towards or away from the ideal range of 5-10 cms.

For Overstriding, while participants like Participant 2 displayed significant improvements in remaining within the ideal threshold of 7 degrees, others like Participant 5 and Participant 6 showed a decline.

5.4 Summary

The results suggest that the dashboard feedback had a discernible impact on the running metrics of most participants. The statistical tests and visualizations indicate a shift in KPIs after viewing the feedback, with varied effects depending on the participant and metric. Further research might delve into the factors influencing these changes and the potential long-term impacts of continuous feedback on performance.

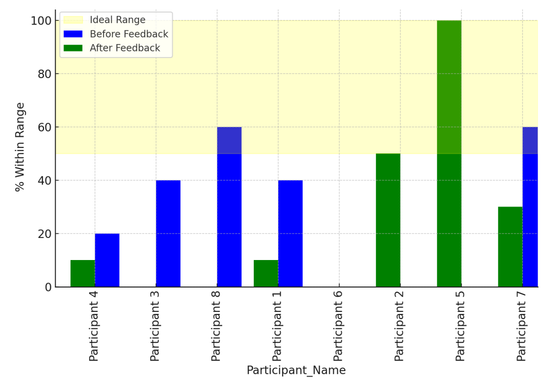


Fig. 11. Percentage of Observations within Ideal Cadence Range (160-170 steps/min) before and after feedback. The shaded yellow region represents the ideal range. As observed, participants like Participant 5 displayed a marked increase in observations within the ideal cadence range post-feedback.

6 DISCUSSION

6.1 Interpretation of Results

The primary objective of this investigation was to gauge the influence of feedback furnished via a dashboard on the running metrics of participants. Observations denote that for a majority of participants, the feedback precipitated discernible modifications in their subsequent running metrics.

6.2 Comparison with Existing Research

Numerous studies underscore the merits of feedback across diverse domains. This exploration, however, distinguishes itself by leveraging OpenPose in tandem with a tailored dashboard in a running milieu. The significant modifications in KPIs for a substantial portion of participants align with the overarching academic consensus emphasizing the potency of feedback in enhancing performance.

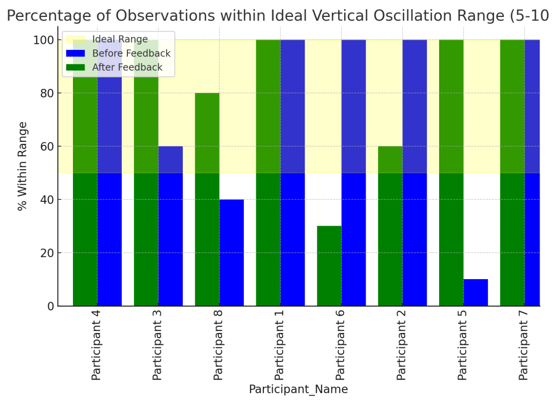


Fig. 12. Percentage of Observations within Ideal Vertical Oscillation Range (5-10 cms) before and after feedback. The shaded yellow region indicates the ideal range. Participants such as Participant 5 and Participant 6 showed noticeable changes, moving their metrics towards or away from the ideal range.

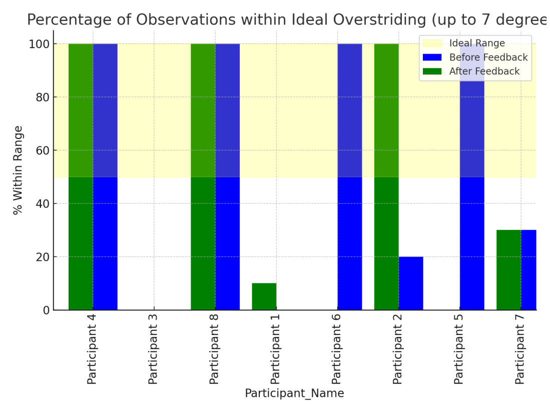


Fig. 13. Percentage of Observations within Ideal Overstriding (up to 7 degrees) before and after feedback. The shaded yellow region indicates the ideal threshold. Participants like Participant 2 displayed significant improvements, while others like Participant 5 and Participant 6 showed a decline.

6.3 Implications of Findings

The mechanism of post-run feedback manifests potential boons for a spectrum of individuals ranging from runners and coaches to rehabilitation professionals. The dashboard, with its capability to elucidate and guide, emerges as a potent instrument for technique refinement, prophylaxis against injuries, and augmentation of overall performance. Yet, understanding why certain participants did not exhibit marked improvements is pivotal, leading to a contemplation of potential limitations.

6.4 Limitations

- **OpenPose Accuracy:** While OpenPose is state-of-the-art for pose estimation, it might not always capture every movement accurately, especially during rapid or complex movements typical in the running.

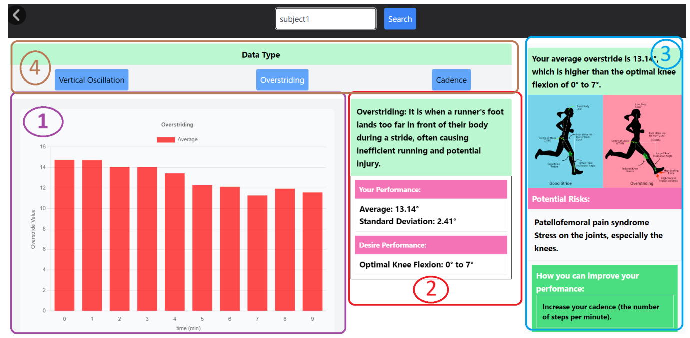


Fig. 14. The Prescriptive Dashboard highlights overstriding information. The first panel displays average knee flexion angles in a red color, indicating excessive overstriding by the participant. The second panel provides general information about the runner's performance and desired goals. The third panel presents feedback, while the fourth panel features buttons that allow users to switch between the three Key Performance Indicators (KPIs).

- **Camera Dependencies:** The efficiency of OpenPose can be influenced by the quality of the camera, its positioning, and ambient lighting conditions. Any inconsistencies in these elements can lead to variations in pose estimation.
- **Feedback Interval:** The lacuna between the initial run, the provision of feedback, and the ensuing run was relatively brief, potentially not allowing participants to assimilate and respond to the feedback.
- **Subjective Interpretation:** The feedback, articulated via bar charts on a dashboard, is inherently subjective. The thresholds for acceptability or the need for rectification might oscillate among participants.
- **Participant Pool:** The scope of the study was constrained to a select cohort of participants. An expansive and eclectic assembly of runners could offer a more panoramic perspective.

6.5 Recommendations and Future Research

In light of the tangible modifications observed in numerous participants, it becomes pertinent to delve into extended feedback sessions, more bespoke training regimens, and possibly amalgamating biomechanical analysis for a more enriched feedback spectrum. Probing the lasting repercussions of such feedback and melding qualitative feedback from participants can further hone the methodology.

7 CONCLUSION

This study evaluated the influence of post-run feedback on runners' key metrics, namely Cadence, Overstriding, and Vertical Oscillation, utilizing OpenPose for pose estimation and a prescriptive dashboard for feedback presentation.

The data revealed varying degrees of adjustment in these metrics among participants post-feedback. This suggests that providing insights through tools like OpenPose and analytical dashboards can affect certain running behaviors.

However, it's important to note that while some participants showed changes in their metrics, not all responded uniformly to the feedback. This underscores the complexity of individual responses and the challenges of universal feedback mechanisms.

OpenPose, despite its advanced capabilities, has its set of limitations, especially in the context of rapid movements like running. While effective for some, the dashboard might require further refinement to cater to a broader range of runners.

The goal moving forward is to refine and validate the system further, expanding its capabilities to provide real-time, individualized feedback that can help runners optimize their technique, enhance performance, and reduce injury risk. With the rising prevalence of wearable technologies and advanced motion tracking systems like OpenPose, the future holds great promise for providing runners with accessible and actionable insights into their running biomechanics.

In summary, the combination of OpenPose and the dashboard offers a new perspective on feedback provision in the running. The initial findings provide a foundation for future research, emphasizing the importance of iterative refinement and broader participant engagement.

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