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New Considerations for Wearable Technology Data: Changes in Running Biomechanics During a Marathon

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The purpose of this study was to use wearable technology data to quantify alterations in subject-specific running patterns throughout a marathon race and to determine if runners could be clustered into subgroups based on similar trends in running gait alterations throughout the marathon. Using a wearable sensor, data were collected for cadence, braking, bounce, pelvic rotation, pelvic drop, and ground contact time for 27 runners. A composite index was calculated based on the "typical" data (4–14 km) for each runner and evaluated for 14 individual 2-km sections thereafter to detect "atypical" data (ie, higher indices). A cluster analysis assigned all runners to a subgroup based on similar trends in running alterations. Results indicated that the indices became significantly higher starting at 20 to 22 km. Cluster 1 exhibited lower indices than cluster 2 throughout the marathon, and the only significant difference in characteristics between clusters was that cluster 1 had a lower age–grade performance score than cluster 2. In summary, this study presented a novel method to investigate the effects of fatigue on running biomechanics using wearable technology in a real-world setting. Recreational runners with higher age–grade performance scores had less atypical running patterns throughout the marathon compared with runners with lower age–grade performance scores.

Keywords*:* running, fatigue, performance, composite index, movement patterns

Running has become one of the most common sports and recreational activities around the world. The sport is also growing each year, where more people than ever are beginning to explore running trails for the first time due to the increased interest in more recreational, unorganized, and lighter forms of physical activity.[1] However, although there are many health benefits associated with this activity,[2] overuse running–related injuries are quite common, with annual incidence rates being as high as 50% to 79%.[3,4]

The risk of experiencing an overuse injury can increase due to a combination of many factors including alterations in running biomechanics, neuromuscular fatigue, and training errors.[5] Running in a fatigued state will affect a runner's gait, potentially increasing the stress, strain, and impact forces within the lower extremities.[6–8] For example, it is well documented that running-related fatigue can affect running kinetics,[9] kinematics,[8,10] and center of mass motion.[11] Thus, researchers have often studied runners in a fatigued state to better understand changes in running mechanics with the potential for injury. Unfortunately, these studies have used strict lab-based protocols, which do not necessarily reflect real-world long-distance running sessions characterized by progressive fatigue over the course of the run.

One of the most popular long-distance, fatigue-inducing running events is the marathon, which is a 42.2-km race.[12] Although previous studies have analyzed alterations in running biomechanics during a marathon using force platforms and video analysis, these methods only allow for the evaluation of discrete time points throughout the race.[13–15] In contrast, with their portable nature, affordable cost, and recent improvements in accuracy, sensitivity, and computing power,[16] wearable sensors have the potential to be an effective tool to measure the effects of fatigue on running biomechanics in the field,[17–20] but the research in this area is still in the early stages of development.[21,22]

Reenalda et al[19] presented preliminary evidence for the use of multiple sensors to quantify running mechanics throughout the duration of a marathon race for 3 male competitive runners. Interestingly, these authors reported that the biomechanical changes were highly individualized suggesting that subject-specific analyses may be more appropriate to quantify each runner's biomechanical changes associated with running-related fatigue. This premise is supported by other research investigations showing that subgroups of runners with different training backgrounds based on weekly mileage or race performance exhibit specific "typical" movement patterns[23–26] and appear to adjust their running patterns differently in response to fatigue.[10] Specifically, more recreational or novice runners demonstrate greater kinematic alterations at the end of a fatigue-inducing run, whereas competitive runners can maintain more consistent biomechanical patterns during prolonged running.[10]

Therefore, the first purpose of this study was to quantify subject-specific alterations in running patterns, using wearable technology data, throughout a marathon race. The second purpose of this study was to determine if runners could be clustered into separate subgroups based on similar trends in the changing running patterns throughout the marathon. It was hypothesized that more than one subgroup would exist, and these subgroups would differ in race performance and training characteristics (ie, running experience and weekly mileage), where more competitive runners would exhibit more consistency in their running patterns throughout the race.

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Methods

This study was carried out in accordance with the recommendations of the University of Calgary's Conjoint Health Research Ethics Board as part of 2 larger research projects (REB16-1044 and REB16-2035) with written and informed consent from all subjects. A sample size calculation (2 × 14 [cluster × section] repeated-measures design, medium effect size, $\beta = 0.80$, and $\alpha = .05$) revealed a minimum sample size of 26 was required to adequately power the study. Thus, data from 27 healthy runners (12 males and 15 females) were used for this study. The inclusion criteria for all participants consisted of an age ≥18 years and official registration for a marathon race. Exclusion criteria included any self-reported cardiac risk, lower-extremity running-related injury within the previous 6 months, history of major surgery to the lower extremity, the use of foot orthoses, or medical conditions/medications that would impair postural control. Prior to race day, each participant provided informed consent, and participants' anthropometric and demographic information (age, height, mass, running experience, and weekly running mileage) were recorded (Table 1).

Running data for each runner were collected during one of 7 different marathon races (2017 Calgary Marathon [n = 13], 2017 Íslandsbanki Reykjavik Marathon [n = 2], 2017 Edmonton Marathon [n = 2], 2017 Okanagan Marathon [n = 1], 2017 Portland Marathon [n = 2], 2017 EDP Porto Marathon [n = 2], and 2018 Calgary Marathon [n = 5]). Each participant's official race time from their timing chip was recorded, and participants were given an age–grade performance score. The age–grade calculator adjusts a runner's performance based on age and sex and is the ratio of the sex-specific world-record time to the runner's sex- and age-adjusted time, expressed as a percentage (eg, 100% = approximate world-record level, 90%–99% = world class, 80%–89% = national class, 70%–79% = regional class, and 60%–69% = local class). The age–grade performance score can then be used to compare runners across sex and age, as runners with a higher age–grade score performed better in the marathon within the context of their age and sex.[27]

Immediately prior to the race, a commercially available inertial measurement unit (IMU) (Lumo Run®; Lumo Bodytech Inc, Mountain View, CA), sampling frequency at 100 Hz, was securely clipped to the back of each runner's shorts, aligned with the spine, and placed near the center of mass. Due to feasibility reasons, our research team was only able to attend the 2017 and 2018 Calgary Marathon events to equip the runners with the sensors. For the other races, runners were given the devices prior to the race and instructed on how to properly fit the equipment.

The Lumo Run® sensor is a body-worn 9-axis IMU that contains an accelerometer, gyroscope, and magnetometer. The sensor sends data to a Lumo Run® app, which contains built-in Lumo® MotionScience™ algorithms to calculate and output 6 biomechanical variables: (1) cadence (step frequency, in steps per minute); (2) braking (change in forward velocity, meters per second); (3) bounce (vertical oscillation, in centimeters); (4) pelvic rotation (side-to-side movement of the pelvis, in degrees); (5) pelvic drop (side-to-side drop of the pelvis, in degrees); and (6) ground contact time (time foot is in contact with the ground at each step, in milliseconds). The Lumo Run® variables were averaged over every 10 steps throughout the race for each output observation. Although the results have not been published, in-house validation studies by Lumo Run® were conducted. Separate experiments determined the within-day and between-day reliability during running in similar (outdoor uncontrolled) conditions. The results show that reliability of the 6 biomechanical variables was very good to excellent (within-day intraclass correlation coefficient (2,1) range: .90–.98; between-day intraclass correlation coefficient (2,2): range .96–.99).

Runners were also fitted with a GPS-enabled watch (Garmin vívoactive® HR; Garmin International Inc, Olathe, KS). The vívoactive® HR contains an optical heart rate sensor, accelerometer, and GPS capabilities, which sends data to the Garmin Connect® software to calculate and output measures of distance, cadence, and speed in 1-second intervals. Participants were instructed to run at their own desired race pace, and the 6 Lumo Run® biomechanical variables and 3 vívoactive® HR variables were continuously recorded throughout the entire marathon race.

Data processing was performed using customized MATLAB R2018a software (MathWorks Inc, Natick, MA). IMU data were aligned with the output of the watch via cadence so that the biomechanical output was known at each race distance. The Lumo Run® device only records steady-state running data. Nevertheless, if at any point, the runner's speed was slower than 1.8 m/s, which is approximately the minimum speed of the run–walk transition,[28] these data points were also removed from analysis. Running biomechanics are also affected by graded running,[29] so data pertaining to only level running (ie, $2\% < x < 2\%$ grade) were retained for analysis by calculating the elevation grade using altitude and distance data from the GPS watch. In addition, the first 4 km of the marathon race was potentially characterized by irregular running associated with a warm-up period[30] along with running in large cluster of people at the beginning of an organized race. As a result, the data corresponding to 0 to 4 km of the race were removed from each dataset. The next 10 km (4–14 km) were considered the typical run, and the remaining data were partitioned into 2-km test sections throughout the marathon (ie, 14–16, 16–18, 20–22, . . . 40 km—finish), resulting in 15 sections (1 typical and 14 test) for analysis.

To quantify subject-specific running patterns, a composite index was calculated based on methods described by Saisana and Tarantola.[31] The mean (μ_{Typical}) and SD (σ_{Typical}) of each Lumo Run® biomechanical variable for each runner in his or her typical

Table 1 Participant Characteristics

Parameter, units	Male (n = 12), mean (SD)	Female (n = 15), mean (SD)
Age, y	50.42 (12.99)	40.93 (10.27)
Height, cm	174.88 (10.25)	160.53 (4.31)
Mass, kg	79.03 (11.99)	58.23 (7.83)
Running experience, y	12.83 (9.33)	7.14 (5.13)
Weekly running mileage, km	45.04 (22.13)	45.13 (16.7)
Marathon time, h:min:s	4:26:23 (00:36:05)	4:30:18 (00:45:42)
Age–grade performance score, %	53.83 (8.26)	55.83 (7.76)

run section were first calculated. Then, for each test section, the biomechanical index (z) was created for each observation (x) with μ_{Typical} and σ_{Typical} (Equation 1).

$$z_i = \frac{1}{6}\sum_{j=1}^{6}\frac{|x_{ij} - (\mu_{\text{Typical}})_j|}{(\sigma_{\text{Typical}})_j},$$
$$i = \text{each observation;}$$
$$j = \text{each biomechanical variable.} \quad (1)$$

The biomechanical index represents the number of SDs by which the observation was above or below the mean value from the typical run, averaged across all 6 biomechanical variables. The biomechanical indices were averaged for each test set of each runner. A higher biomechanical index would indicate a more "atypical" running pattern.

All statistical analyses were performed using SPSS Statistics (version 24; SPSS, Inc, Chicago, IL). A repeated-measures analysis of variance (ANOVA) was performed on the composite indices for each test section to determine the effect of race section on biomechanical index. Overall significance was determined at $P < .05$, with follow-up Bonferroni pairwise comparisons tests. Note that only comparisons to the first test set were evaluated to detect at what point the running patterns became significantly atypical.

Cluster analysis was performed using customized software in MATLAB R2018a software (MathWorks Inc). For each participant, the mean biomechanical indices for each test section were used as input data for the analysis, totaling 14 input variables for each participant. Calinski–Harabasz criterion values were first used to evaluate the optimal number of clusters (k) within the sample data. An unsupervised *k-means clustering* algorithm was then used to assign all 27 participants to exactly one cluster based on the cluster centroids. In brief, the *k-means clustering* algorithm chooses k initial cluster centers (centroids) using the *k-means++ algorithm*[32] based on the input data, where k is the number of clusters determined previously. The algorithm then computes point-to-cluster-centroid distances for all observations to each centroid, assigns each observation to the cluster with the closest centroid, computes the average of the observations in each cluster to obtain 2 new centroid locations, and repeats these steps until cluster assignments do not change.

One-way ANOVA tests with Bonferroni adjustments were used to compare participant characteristics (age, height, mass, running experience, and weekly running mileage) and race performance (race time and age–grade performance score) between clusters (Bonferroni $p_{\text{adjusted}} = .05/7 = .007$). A cluster × section, mixed ANOVA ($P < .05$) with follow-up Bonferroni pairwise comparisons was used to determine the effect of cluster and section of the race on biomechanical index.

Even though reduced running speed is an expected result of fatigue,[14] speed has also been shown to influence running biomechanics[33,34]; therefore, we sought to determine whether the subject-specific changes in speed were similar to the subject-specific changes in biomechanics over the course of the marathon. To test this null hypothesis, the composite index for each subject's running speed (*speed index*) for each test section was calculated with similar methods to the biomechanical index described earlier (Equation 2).

$$\text{Speed index}_i = \frac{|x_{ij} - (\mu_{\text{Typical}})_j|}{(\sigma_{\text{Typical}})_j},$$
$$i = \text{each observation;}$$
$$j = \text{speed.} \quad (2)$$

A cluster × section, mixed ANOVA ($P < .05$) with follow-up Bonferroni pairwise comparisons was used to determine the effect of cluster and race section on the speed index.

Results

Subject-specific alterations in running patterns, based on the biomechanical indices, were quantified and compared throughout a marathon race. On average, the 10-km typical runs had 980.11 (101.96) observations and the 2-km test runs had an average of 187.38 (46.9) observations each. For the repeated-measures ANOVA to compare biomechanical indices throughout the race, Mauchly test of sphericity indicated that the assumption of sphericity had been violated; therefore, a Greenhouse–Geisser correction was used. There was a significant effect of race section on biomechanical index, $F_{(4.28,111.16)} = 13.78$, $P < .001$. Follow-up comparisons indicated that the biomechanical index was significantly different from the first test section (14–16 km) for the 20- to 22-km test section and all sections from 24 km until the end of the race (Figure 1).

Using the k-means cluster analysis, runners were clustered into separate subgroups based on similar trends in the changing running patterns throughout the marathon. With a Calinski–Harabasz criterion value of 16.86 for our sample data, the optimal number of clusters was 2. Therefore, based on the biomechanical indices for the 14 test sections of the marathon, 19 runners were assigned to cluster 1 and 8 runners were assigned to cluster 2 (Tables 2 and 3). Runners in cluster 1 had a significantly greater age–grade performance score compared with runners in cluster 2, $F_{(1,25)} = 10.46$, $P = .003$. There were no significant differences between clusters with respect to age, height, mass, running experience, weekly running mileage, or marathon time (Ps > .007).

When comparing the biomechanical indices for cluster 1 and cluster 2 over the course of the marathon, a Greenhouse–Geisser correction was first used on the mixed ANOVA due to violations of sphericity. The interaction effect between race section and cluster was not significant, $F_{(4.29,107.36)} = 2.24$, $P = .07$ (Figure 2). There was a significant main effect of race section on biomechanical index, $F_{(4.29,107.36)} = 15.79$, $P < .001$. There was also a significant main effect of cluster on the biomechanical index, $F_{(1,\ 25)} = 43.43$, $P < .001$, in which the average biomechanical indices for cluster 1 (mean = 1.17 [0.33]) were significantly lower than cluster 2 (1.79 [0.59]) throughout the marathon. Follow-up comparisons indicated that the biomechanical index was significantly different for both groups ($P < .05$) at race section 20 to 22 km until the end of the race compared with the first test section (14–16 km) (Figure 2).

The changes in speed index were analyzed, and it was determined that speed was not a significant confounding factor for the changes in biomechanical indices. Using the Greenhouse–Geisser correction, the interaction effect between race section on the speed index was not significant, $F_{(2.43,60.65)} = 1.37$, $P = .26$. There was a significant main effect of race section on the speed index, $F_{(2.43,60.65)} = 13.83$, $P < .001$ (Figure 3). However, there was no significant main effect of cluster on the composite index of speed, indicating that the average speed index between cluster 1 (mean = 1.42 [0.94]) and cluster 2 (1.95 [1.79]) was not significantly different, $F_{(1,\ 25)} = 2.14$, $P = .16$. Follow-up comparisons indicated that the speed index was significantly different ($P < .05$) from the first test section (14–16 km) at 30 to 32 km until the end of the race (Figure 3).

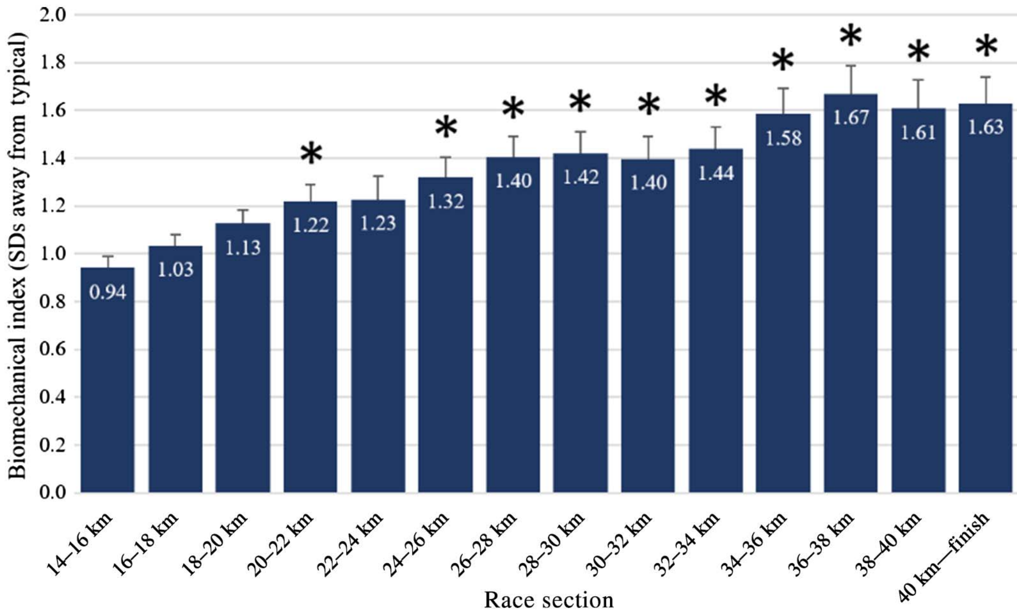

Figure 1 — Mean biomechanical index for all runners throughout the marathon race. Error bars denote SEs. *Significant difference compared with 14- to 16-km test section ($P < .05$).

Table 2 Participant Characteristics for Each Cluster

Parameter, units	Cluster 1	Cluster 2	*P*
Age, y	45.95 (11.2)	43.25 (15.29)	.61
Height, cm	164.87 (7.23)	171.75 (15.01)	.12
Mass, kg	65.47 (11.95)	72.24 (18.88)	.27
Running experience, y	8.67 (4.83)	12.25 (12.2)	.29
Weekly running mileage, km	43.79 (17.08)	48.19 (23.69)	.59
Marathon time, hh:mm:ss	4:25:28 (00:38:50)	4:56:29 (00:41:52)	.04
Age–grade performance, %	57.39 (6.12)	48.12 (8.29)	.003*

Cluster 1: 7 males and 12 females; cluster 2: 5 males and 3 females. Values are represented as mean (SD).
*Significant difference between cluster 1 and cluster 2 with Bonferroni correction: $p_{\text{adjusted}} = .05/7 = .007$.

Table 3 Marathon Race Participation for Clusters 1 and 2

Date	Event	Location	Cluster 1 (n = 19)	Cluster 2 (n = 8)
May 28, 2017	Scotiabank Calgary Marathon	Calgary, Canada	10	3
August 19, 2017	Íslandsbanki Reykjavik Marathon	Reykjavik, Iceland	2	0
August 20, 2017	Servus Edmonton Marathon	Edmonton, Canada	2	0
October 8, 2017	Okanagan Marathon	Kelowna, Canada	1	0
October 8, 2017	Portland Marathon	Portland, USA	1	1
November 5, 2017	EDP Porto Marathon	Porto, Portugal	2	0
May 27, 2018	Scotiabank Calgary Marathon	Calgary, Canada	1	4

Discussion

The first purpose of this study was to present a novel method to quantify subject-specific typical running patterns from wearable technology data and detect if the patterns became atypical throughout the marathon. We were able to quantify the subject-specific running patterns using a composite index based on data from 6 biomechanical variables and detect a progressive increase in atypical running patterns throughout the marathon race. At approximately the midway point of the marathon (20–22 km), biomechanical indices were significantly different compared with the first test section, indicating that fatigue-induced changes in subject-specific

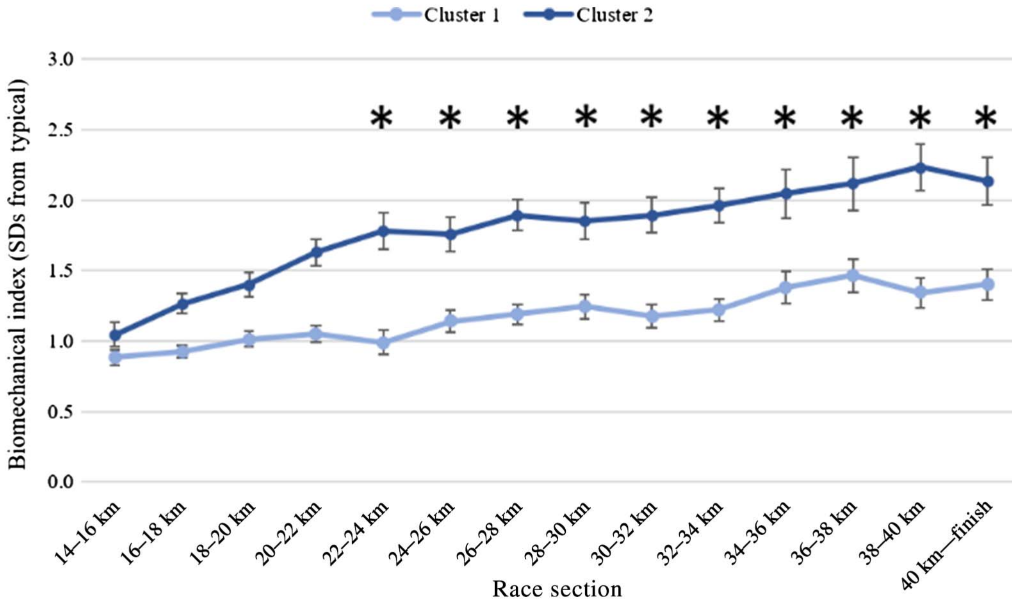

Figure 2 — Biomechanical indices throughout marathon race for cluster 1 versus cluster 2. Error bars denote SEs. *Significant difference compared with 14- to 16-km test section ($P < .05$).

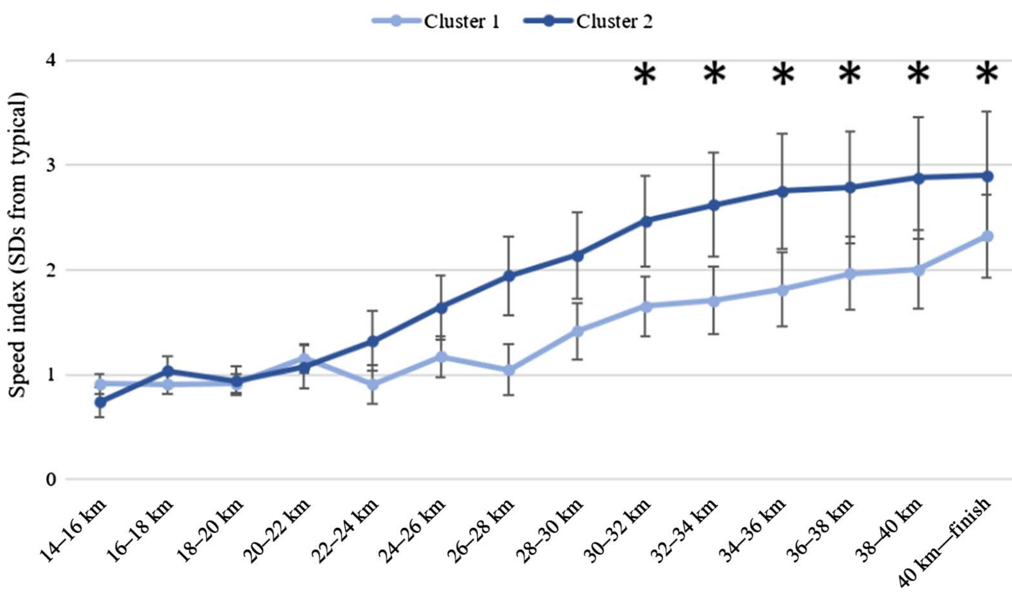

Figure 3 — Speed indices throughout marathon race for cluster 1 versus cluster 2 runners. Error bars denote SEs. *Significant difference compared with 14- to 16-km test section ($P < .05$).

running biomechanics were evident in the second half of the race. Previous research has also found significant changes in running biomechanics over the course of a marathon race,[14,15] but with the limitations of traditional measurement devices (eg, 2-dimensional video analysis and force platforms), only a few distinct time points have been analyzed. In the current study, we were able to record considerable amounts of data using wearable technology and quantify the subject-specific changes in running biomechanics associated with fatigue throughout a marathon race. This adds to the growing body of evidence using wearable technology to better understand the effects of training and fatigue on changes in running biomechanics in the field.[17–20,35] In particular, our novel methods' ability to reduce subject-specific multidimensional data may then be combined with markers of training load (eg, ratings of perceived exertion, heart rate, and blood lactate) to better characterize the complete training workload of recreational and competitive athletes. This can then be used to alert the runner with his or her training runs if their running biomechanics become significantly atypical due to risk factors for running-related injuries, such as fatigue. Nonetheless, more running gait research using wearable technology in real-world settings is needed to identify appropriate biomechanical variables and proper analyses in order to provide effective clinical interventions or coaching practices to reduce injuries and improve performance for runners in natural environments.[22]

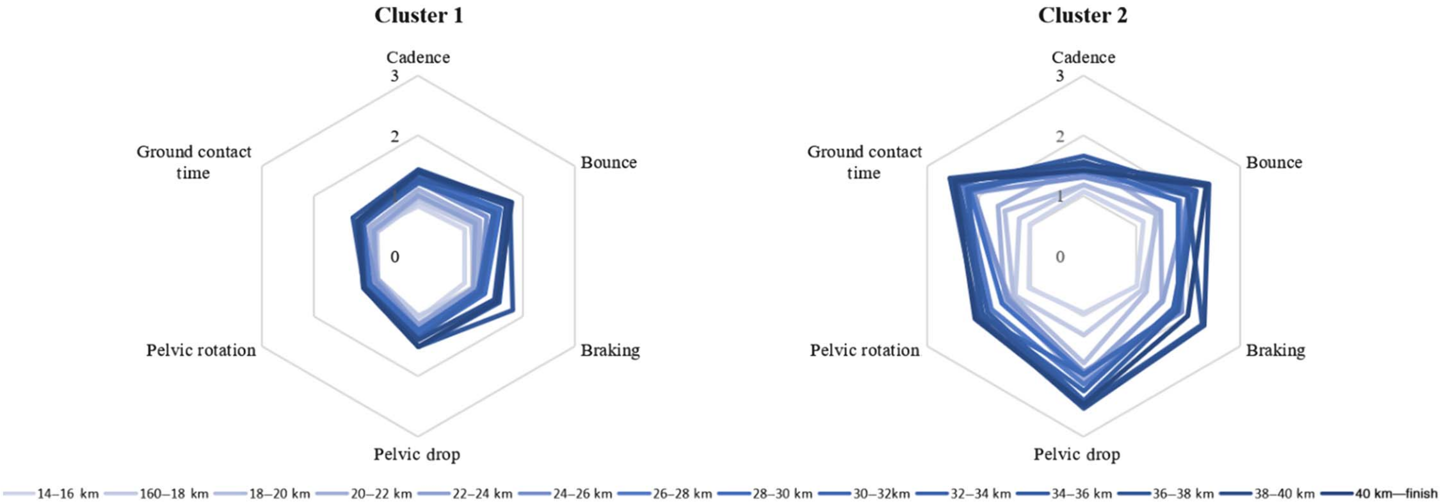

Figure 4 — Standard scores for all biomechanical variables throughout the marathon between clusters.

Although it is important to understand the changes in running mechanics within a prolonged, fatigue-inducing race, it may be more clinically relevant to assess running mechanics in the days or weeks following a marathon in order to better evaluate the effects of overreaching and overtraining on injury.[36] Inadequate recovery periods can lead to overtraining, prolonged maladaptation in the musculoskeletal structures, and an increased risk of injury. Therefore, a longitudinal research design with large data sets that evaluates runners throughout a training block of several months leading up to a marathon race using wearable technology with the biomechanical indices would add value to the scientific and running communities to determine typical healthy running patterns and atypical patterns that may lead to injury. Regardless, the current study provides a novel method and new biomechanical approaches for runners, coaches, and health care professionals to potentially evaluate the effects of fatigue, overtraining, and injury on gait biomechanics and training workload in real-world scenarios.

For the second purpose of our study, and in support of our hypothesis, we were able to cluster our sample of runners into 2 subgroups based on similar trends in the changing running patterns throughout the marathon. The only significant difference in participant characteristics between clusters was the age–grade performance score, where cluster 1 had a higher score than cluster 2 (57.39% [6.12%] vs 48.12% [8.29%]). This result indicates that cluster 1 runners had better race performance within their respective age and sex groups. Although the interaction effect between race section and group for the biomechanical index was only approaching significance, it suggests that the running patterns for cluster 1 were relatively more consistent in the second half of the race, whereas the running patterns for cluster 2 appeared to be more "atypical." Interestingly, runners with higher age–grade performance scores demonstrated less atypical running patterns as the race progressed and thus a more consistent gait pattern in the second half of the marathon.

As speed has been shown to influence running biomechanics,[33,34] one could argue that the changes in running patterns may be attributed to differences in running speed throughout the race rather than the runners' characteristics and performance levels. Contrary to this notion, the current study found no significant differences in the subject-specific changes of speed between clusters, meaning runners in both clusters slowed down in a similar way in the later stages of the marathon. Therefore, the difference in atypical running patterns between clusters 1 and 2 was more likely associated with the differences in performance level rather than their changes in running speed alone.

Previous research has also found differences in running profiles between competitive and recreational runners using biomechanical data and the same age-grade calculator in this study.[25,26,37] Specifically, data from center of mass acceleration patterns revealed that competitive runners with higher age–grade performance scores had a more consistent running pattern than recreational runners (ie, greater step and stride regularity in the acceleration signal).[26] Although the competitive group in the previously mentioned studies had a higher average age–grade performance score than this study, it appears that more competitive runners not only exhibit more consistent running patterns within a short bout of exercise, but they are also able to better maintain this consistency over the course of a prolonged run compared with more recreational runners.

The biomechanical index used in the current study is a combination of the standard scores for all 6 biomechanical variables, and Figure 4 illustrates the multidimensional changes throughout the race for clusters 1 and 2. As can be observed, the changes in running patterns for cluster 1 were generally related to the bounce and braking variables, whereas the most notable changes for cluster 2 were related to bounce, pelvic drop, and ground contact time. Although it is possible to quantify the atypical changes for each variable and inspect them visually, as with Figure 4, it is important to note that each runner's biomechanical changes were highly individual throughout the race. Therefore, specific increases or decreases in biomechanical variables were not analyzed statistically. A backward analysis can be performed to identify each runner's changes in biomechanical data that contributed to his or her atypical running patterns, but this would be more useful in commercially available wearable technology with personalized coaching and is beyond the focus of the current study.

A significant strength of the current study was the use of a novel subject-specific method with wearable technology in a real-world setting to quantify the effects of fatigue on running biomechanics. Other applications could include, but are not limited to, monitoring performance and training of athletes, predicting musculoskeletal injuries for other cyclical-type sports such as cycling and swimming, and monitoring rehabilitation of patients as they begin to restore a more "typical" gait pattern. Despite these strengths, some study limitations must be taken into consideration. First, although there was a significant difference in age–grade performance scores between clusters, runners in this study were considered, on average, "recreational" according to previous research using the same age–grade performance calculator to subgroup the runners.[25,26] The results from this study still indicate that runners with higher age–grade performance scores have more consistent running mechanics with fatigue, but further research should use the same a priori 60% cutoff as selected in previous work to subgroup runners and compare "competitive" and "recreational" runners over the course of a marathon race.

Second, we acknowledge that data from several different races were combined and the 2017 Calgary Marathon included the most runners in the study. Differences in altitude, temperature, elevation changes, and so forth may be considered confounding variables to the analyses. However, we conducted a post hoc course × section mixed ANOVA to determine whether the biomechanical indices differed between data from the 2017 Calgary Marathon and the other pooled courses, which revealed no significant difference between courses, $F_{(1,25)} = .90$, $P = .35$. Therefore, we are confident that there was no uncontrolled race effect on our results, and the combination of several races in our analyses only improves the ecological validity of our results. The race sections were also chosen subjectively based on the authors' combined knowledge and experience of running biomechanics, sports medicine, and data science using wearable technology data. Previous studies have selected different points in a marathon race to quantify the biomechanical changes associated with fatigue.[14,15,19] We chose the 4- to 14-km section as the "typical" run in order to include many prefatigued observations (~5000 running strides) while accounting for the within-subject variance of typical movement patterns. The 2-km test sections were chosen to also include many observations (~1000 running strides) while partitioning the race into several sections for the analysis of progressive biomechanical changes with fatigue. Nonetheless, future work should use objective statistical analyses to identify a stability point for the amount of running data needed to establish a stable movement pattern based on biomechanical data prior to running-related fatigue.

Third, although the marathon race was expected to be a prolonged, fatigue-inducing run, no measurements for markers of fatigue were recorded. Previous lab-based research examining the effects of volitional exhaustion on running mechanics has used some measurements, such as oxygen uptake and ratings of perceived exertion, to identify a fatigue-inducing speed threshold or point of fatigue within the running trial.[10,11,38,39] However, the goal of this study was to use a more ecological type of fatigue-inducing run protocol and to avoid the lab-based setting. Nevertheless, future research should collect markers of fatigue during prolonged running while collecting wearable technology data to determine if our analyses quantify the changes in running patterns due to neuromuscular fatigue, specifically.

Finally, we acknowledge that only one IMU was used to collect biomechanical data. Additional IMUs placed on various anatomical locations may yield more information about changes in running biomechanics associated with fatigue. However, it is important to consider that the current study collected data during a real-world marathon race, and we had to strike a balance between each runner's comfort for IMU placement along with the biomechanical data to be collected. The use of wearable sensors for analyzing running biomechanics outside of the lab is in very early stages of development.[21] Thus, we encourage future research to collect as much gait-related data with multiple IMUs that can be tolerated by the research participants for marathon racing. This will not only provide more information about the changes in running biomechanics from different anatomical locations, but it will also determine the optimal configuration of IMUs to deliver the most important information while still being comfortable for runners. Furthermore, due to proprietary algorithms from the commercially available device, only 6 variables were used for the current study, and we were not able to access the raw signal from the IMU to calculate any other variables. Future research should include additional or more complex variables from one or more wearable sensors to potentially detect more subtle biomechanical changes associated with fatigue, but the simplicity and translatability of the methods used with commercially available technology we used in our study should not be overlooked.

This study adds to the growing body of literature using wearable technology to monitor changes in running biomechanics associated with fatigue and performance in the field. More specifically, this study was able to monitor subject-specific changes in running gait biomechanics over the course of a marathon race using wearable technology in a real-world setting. We have proposed a novel method with a composite index to quantify subject-specific alterations in running patterns compared with a "typical" gait pattern. The overall results show that subject-specific running gait biomechanics become significantly "atypical" later in the marathon race as fatigue accumulates, but more competitive runners exhibit greater consistency in their running patterns throughout the race compared with recreational runners. This information may be used to quantify subject-specific "typical" running biomechanics for competitive and recreational runners and monitor alterations that may occur due to fatigue, training, and/or injury development.

Acknowledgments

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