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PACING STRATEGY AFFECTS THE CARDIAC COST AND PERFORMANCE ON MARATHON

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ABSTRACT. The cardiovascular cost increases during prolonged exercise and we sought to establish the relationship between recreational marathoner's racing strategy,cardiovascular cost increase cardiac drift and performance.We started with looking for a trend in the speed time series (by Kendall's non-parametric rank correlation coefficient) in 280 runners(2:30-3:40 hrs) marathoners. We distinguished two groups,the one gathering the large majority of the runners(n=215,77%),who had a significant decrease of their speed during the race that appeared at the 26th km.We therefore named this group of runners the "fallers"one.The asymmetry indicator of the faller group runner's speed is negative, meaning that the average speed of this category of riders is below the median, indicating that they ran more than half marathon distance(56%) above their average speed before they "hit the wall" at the 26th kilometer. Furthermore,we showed that marathon performance was correlated with the amplitude of the cardiac drift (r=0.18,p=0.0018) but not with those of the increase in heart rate (r=0.01,p=0.80). In conclusion,we recommend utilizing the cardiac cost,which takes into account the running speed and that could be implemented in the future,on phone mobile application.

KEYWORDS AND PHRASES. Running; Endurance;Kendall,Strava;Big data.

1. INTRODUCTION

Endurance running capacity may have initially arisen in the genus Homo. Over the course of evolution, human physiology has been optimized for covering large distances every day, in order to find enough food to sustain the brain's metabolism.Indeed,the increasing popularity of marathon running in modern humans of all ages and abilities can be viewed as legacy of our species evolutionary capacity to run long distance ($> 5km$) using aerobic metabolism. The increasing popularity of road running is typified by the emergence of recreational marathon runners who complete the 42.195 km event in a time of between 2:40 hrs and 4:40 hrs. The marathon's potentially negative impact on cardiac status and the occurrence of sudden cardiac deaths during this type of event have prompted much debate. There is a progressive increase in fractional use of the maximum heart rate (HRmax) over the course of the race (from around 80%of HRmax at the start to around 90% at the finish). This HR increase was associated with a continuous speed decrease, starting halfway through the race (i.e., at 21 km). The upward drift in HR is one component of so-called "cardiovascular drift," which is also characterized by a decrease in stroke volume (SV) and in arterial and pulmonary pressures. Depending on the exercise intensity, cardiac output (CO) may or may not be maintained over time. An increasing number of recreational marathon runners are now using data from HR and speed monitors in an attempt to pace their effort. There are currently no guidelines on how to use these variables to optimize performance. Indeed, every year, the New York, London, Berlin and Paris marathons each attract around 30 to 50,000 adult runners of all levels.Most of these runners are recreational athletes. Indeed, many train alone and hope to progress by monitoring their heart rate and/or running speed. However, more and more studies showed that the self- pace exercise allow to get the best performance.

A prior study of our group working has registered the cardiac output (CO) during a marathon in 14 recreational runners ($3 : 30hrs \pm 45min$) have demonstrated that the marathon performance was inversely correlated with an upward drift in the CO/speed ratio (mL of CO $m^{-}1$) named the cardiac cost ([2],[4]and [5]). This cardiac cost drift was due to the decrease of speed mainly after the half marathon while heart rate, stroke volume and the cardiac output were not significantly different between the first and last 4 km ([2],[4]).Furthermore, a recent study performed on big data available on Strava®, a social fitness network, has shown that 80% of recreational (2:30hrs-3:40hrs) marathoners had a negative distribution of their speed since it drops after the half race. In probability theory and statistics, skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean. The skewness value can be positive or negative, or undefined. For a unimodal distribution, negative skew commonly indicates that the tail is on the left side of the distribution, and positive skew indicates that the tail is on the right side. In cases where one tail is long but the other tail is fat, skewness does not obey a simple rule. For example, a zero value means that the tails on both sides of the mean balance out overall; this is the case for a symmetric distribution, but can also be true for an asymmetric distribution where one tail is long and thin, and the other is short but fat. Hence, from a practical point of view, it means that they ran more distance (median speed) above their average speed ([3],[4]and [5]). This was in opposition with best world performance marathons ([3],[5]).

When the runners wear a cardio frequency meter in addition to a GPS, the heart rate is also indicated in the runners Strava® file. Therefore, it gives the possibility to highlight the relationship between speed strategy, heart dynamics and performance in real racing condition. Indeed, the Marathon race is considered as an extreme physical endurance demand and has provided a unique opportunity to study the limits of human thermoregulation for more than a century ([7]). Voluntary reduction in exercise intensity and/or duration is one of the most obvious behavioural thermoregulatory responses to hot environments and is done (at least partially consciously), in order to reduce heat production and the rate at which core body temperature rises([14]). Therefore, in That present study, we sought to establish whether their racing strategy affects the sub-elite marathoner's cardiac drift and performance. The aim of this study was then to check the hypothesis that, in recreational but already good marathoners (2:30hrs-3:40hrs), their racing strategy impacted their performance, in relation with a possible cardiac drift.

2. MATERIALS AND METHODS

1)Population

The 280 analyzed runs come from marathon runners who took part to the "Marathon de Paris" in 2018 (n=140) or to the "Marathon de Berlin" in 2017 (n=140). The chronometric performances were between 2h30 and 3h40 for each race. Every subject publicly shared his race data using the website Strava®, on which we proceeded to the gathering of data. Therefore, given that the study used the Strava public data, we neither got the gender and the age of the subjects.

2)Experiment protocol

Data sampling

In order to have a constant performance sample, we gathered them from the fastest run (2h30) to the slowest (3h40), with an interval of 30 seconds between each runner.

Observed variables

We had access to the running pace (time passed for each kilometer ran) and to the mean of the heart rate (HR) by kilometer. In our study, we did not consider the last 195 meters of the run.

Computed variables

The cardiac cost (CC) (which has an unit corresponding to the amount of heartbeat by meter ran) was computed with the mean of the heart rate (in $b.min^{-}1$) and the speed (in $km.min^{-}1$) by kilometer using the following formula:

$$\text{Mean cardiac cost}= \frac{HR(b.min^{-}1)}{speed(m.min^{-}1)}/6000$$

3) Statistical study

Defining the running strategy by the skewness of the pace distribution during the race.

In this study, we have characterized the running strategy by the skewness of the speed distribution during the race. The skewness was calculated from the number of kilometer ran above of the mean speed expressed in percentage of the forty-two kilometer of the marathon. In this study, we defined the running strategy as the skewness of the speed data by kilometer.

Modelling the time series tendencies

We used Mann Kendall's non parametric test of trend on the speed,HR and CC series. The result of this test,Kandell's τ, between -1 and 1 ,gives us the statistical trends of the studied series. The statistic of Kandell's τ is defined by the following formula:

$$\tau = \frac{2}{n(n-1)} \sum_{i<j} K(v_i, v_j)$$

Like all the statistic tests, Mann Kendall s trend lest is read with a p-value. The closer to 0 this one is, the stronger the significance of the trend is. On the opposite, the closer to 1 this p-value is, the weaker, the significance of the trend is. In order to get the range Δ of this trend, we used the evolution coefficient below, where μ_0 is the mean of the 4 first kilometers and μ_1 if the mean of the 4 last,

$$\Delta = \frac{(\mu_1 - \mu_0)}{\mu_0} \times 100$$

We chose to use the distance of the 4 kilometers because it represented nearly 10% of the marathon's distance. Determining a heterogeneity among time series We used Pettitt's non-parametric lest, which is an adaptation of Mann-Whitney's rank-based test, allowing to identify the time where a shift occurs. This statistic test is read with a p-value. Pettitt's statistic test is computed like the following: We set:

$$D_{ij} = -1 \text{ if } (x_i - x_j) < 0, D_{ij} = 0 \text{ if } (x_i - x_j) = 0,$$
$$D_{ij} = 1 \text{ if } (x_i - x_j) > 0$$

we then define:

$$U_{t,T} = \textstyle\sum_{i=1}^{t} \sum_{j=i+1}^{T} D_{ij}$$

The alternative bilateral assumption of pettitt's test is defined by:

$$K_T = max_{1 \leq t < T} |U_{t,T}|$$

Applied to the time series of speed by kilometer , Pettitt's test allowed us to class the runners in 2 categories, the "fallers" who have a slightly statistically heterogeneous speed, and the "non-fallers" who have a homogeneous speed during the whole run.We used the Pearson's correlation coefficient to correlate the performance with the racing strategy (asymmetry of speed), the speed decrease (%) and with the cardiac drift (cardiac cost increase). We then determined the significance level a $\alpha = 0.05$ for the interpretation of the statistical tests used, The entirety of the study has been conducted with the software XLSTAT® version 2019, developed by the Adinsoft society. All the results are presented with mean ± standard deviation. At the end, we can also use the coefficient of variation, another speed race characteristic of speed time series (CV i.e. standard deviation/mean %) that is appears to be an easy and high marker of the difference of running strategy between the two groups.

3. RESULTS

We started with looking for a trend in the speed time series (by Kendall's non-parametric rank correlation coefficient) and confirmed that almost 80%of the 280 marathoners (77%) had a decreasing trend in speed data. Then, we compared this group (n=215), that we named the "fallers", with the group of the "non-fallers" runners (n=65) who did not have a significant speed decrease.

The difference of performance between the falters and non-fallers group:

The ANOVA test showed that the fallers group had a significant lower performance (3h 01min 42s ± 18:10s: min vs 2h 54min 09s ± 17 min 13s, F= 15, p = 0.006) than the non-fallers.

The difference of speed strategy between the two groups

All the marathoners ran in "positive split" that is to say, with a speed decrease trend. However, the faller's group had a significant higher speed decrease than those of the non-fallers group (-0.49 vs. -0.25 for the Kendall's tau in the fallers vs. non fallers group, F = 15, p = 0.0001). In addition to this difference of the speed time course, the two groups had different speed race distribution. Indeed, the asymmetry indicator of the faller group runners' speed was negative in contrast with the non-fallers one whose speed distribution was normal (F=28, $p < 0.0001$ and F=11, p = 0.001, for speed and HR, respectively). Hence, the faller's group average speed was below their median speed, running 56% of the 42,195 km above their average speed. Then, they hit "the wall" as their speed fall sharply at the 26th kilometer. However, interestingly, we can underline the normality of the cardiac cost distribution in both groups (F=2.6, p = 0.1). It means that, whichever their speed profile, all the marathoners ran 50% of the time above and below their average cardiac cost. whichever their speed profile, all the marathoners ran 50% of the time above and below their average cardiac cost.

The correlation between speed strategy and Marathon performance:

The running asymmetry was significantly correlated with the performance (r= -0.15, p = 0.018).

The difference of heart rate and cardiac cost time courses between the fallers and non-fallers group:

The heart rate increase between the first and last 4 km of the marathon, was not significantly different between the two groups (F = 2.0, p = 0.15) and then not correlated with the performance (r = 0.01, p = 0.80). Given that the non-fallers did not decrease their speed, their heart rate increase significantly more than in in the fallers group (0.56 vs. 0.29 respectively, F=14, p = 0.002). When we indexed the heart rate by the speed, we saw that the fallers group, the cardiac cost increased, significantly at the 26,h kilometer, as the speed did (figure 3) and hence, the cardiac drift was then mainly associated to the speed decrease. Indeed, the cardiac cost increase between these first and last 4-km section was highly correlated with the marathon performance (r=0.18, p = 0.002). Furthermore, we showed that marathon performance was correlated with this the amplitude of the cardiac drift but not with those of the increase in heart rate (r=0.01, p = 0.80).

The relationship between heart rate and cardiac cost time course and the Marathon performance:

The increase in cardiac cost (cardiac drift) between the first and last 4 km part of the Marathon was highly correlated with the performance (%, F = 54, $p < 0.0001$) in the fallers group between the first and the last 4 km part of the marathon was highly inversely correlated with performance (r = -0.19, p = 0.001). The coefficients of variation of speed, heart rate and cardiac cost are high markers of difference of running strategy and performance. The coefficient of speed variation (CV) was highly different between the two groups (5.0 vs. 2.9 %, F = 36, $p < 0.0001$) and was highly correlated with the performance (r = 0.30, $p < 0.0001$). The coefficient of heart rate variation was also significantly higher in fallers (CV and F = p) than non-fallers but was not correlated with the performance (r=0.03, p =0.63). However, the cardiac cost's CV was significantly higher in the fallers than in the non-fallers group (F=36, $p < 0.0001$) and correlated with performance (r= 0.25, $p < 0.0001$).

4. DISCUSSION

The main finding of the present study was that the racing strategy affects the sub-elite marathoner s cardiac drift and performance. Other important results have been achieved: (i) two groups of marathon runners can be distinguish e according to their speed distribution and time series: the group of runners who have a drop in speed(77%)(called "speed-fallers"), and those (group 2) who maintained their speed at the finish; (ii) speed-fallers a a significantly higher cardiac drift and lower performance than non-fallers; (iii) cardiac drift was correlated with performance. Therefore, this study showed that the running strategy influences both performance and cardiac drift that covariate Most of the marathoners hit the marathon wall While the minority of these recreational (around 3-h) runners were able to sustain a constant speed with a low coefficient of variation until the arrival, the great majority of them (3/4) "hit the marathon wall "at the 26th km. Indeed, in accordance with prior studies ([1],[3],[4],[7],[9]and [15]).A change of the fractal scaling of heart rate and speed in a marathon race has even be detected, showing evidence of the . significant effect of fatigue induced by such long and intensive exercise on heart rate and speed variability ([5],[15]). Running strategy must be integrated as a factor of marathon performance. The majority of marathoners, which were already experimented, considered their performance given that our population average speed was around 3h00min considered to be the Grail by marathon runners who wish to qualify for the historic Boston Marathon. We can also notice that this lack of stability of the running speed makes it more difficult to estimate the final time when speed beyond the half marathon are not available. However, MIT mathematicians proposed a model to estimate the final time after the 2013 attack that prevented 6,000 marathon runners from reaching the finish line. A computational study has demonstrated that it was possible to predict the distance at which runners will exhaust their glycogen stores as a function of running intensity (Rapoport, 2010). They integrated several physiological variables including the muscle mass distribution, liver and muscle glycogen densities and running speed as a fraction of aerobic capacity i.e. the velocity at Vo2max (Rapoport, 2010). They have already in mind to shed the physiologically principle light on important standards in Marathon that until now have remained empirically defined; The qualifying times for the Boston Marathon (Raport 2010) The necessity to have an interdisciplinary approach of the complexity of marathon pacing strategy This can be achieved thanks interdisciplinary approach crossing disciplining as psychology neuroscience physiology and physics and mathematics allowing to think the speed and heart rate and other signals registered during the Marathon,in an entropy model control as a measure for non stationary signals([6]).Mathematics and statistics already allowed us better describing the kinematics of running tactics [8], [9] investigated marathon running at the highest competitive level by examining the velocity distribution during marathon running. To illustrate the difficulty for targeting the appropriate speed on the first 5-km, they gave us an example the female runner (in Berlin Marathon 2002), who attempted lo break the world record running (he first 5-km al a mean velocity higher than 5.00 m/s. This was too fast since it gradually decreased in the course of the race, resulting in a lower velocity during the second part of the run than during the first, as observed in 77% of our 280 marathon recreational marathon runners.

5. **CONCLUSION**

The increasing volume of data split available on running community websites allowed a recent study lo investigate a marathon running pacing strategy for the various levels of performance, it is our scientific responsibilities, to use these data base in addition to continue to apply experimental protocols, to better understand the personal runners optimal way, especially on such now popular and intensive exercise as the marathon. Here we show that the use of cardiac cost as an objective tool for targeting the marathon pace avoiding or at least minimizing the hitting wall could be a first step for learning how to sell-pace long-distance run which gather almost all-the metabolic and psychical limiting factors defining a sensory tolerance limit.

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