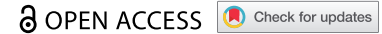





RESEARCH PAPER



Small changes in thermal conditions hinder marathon running performance in the tropics

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ABSTRACT

We examined marathon performance of the same group of runners in relation to small changes in dry bulb temperature (T_{db}) and wet bulb temperature (T_{wb}) across 3 consecutive years, and investigated whether performance was poorer during an evening marathon compared with morning marathons. Marathon results were obtained from the 2017, 2018, and 2019 Standard Chartered Singapore Marathons. T_{db} , T_{wb} , T_d , relative humidity, and absolute humidity were gathered for each marathon. K-means clustering and linear regressions were performed on 610 runners who participated in all three marathons. Analysis of the 610 runners' marathon performance was contrasted with T_{db} and T_{wb} . Linear regressions were also performed on 190 runners filtered by percentile, yielding similar results. For clusters with similar T_{db} from all runners K-means clustering, an increase in mean T_{wb} by 1.5°C coincided with an increase in finishing time by 559 s (9.3 min) ($p < 0.033$). T_{wb} hinders marathon performance more than T_{db} , with each percentage rise in T_{db} and T_{wb} resulting in an increase in net time by 7.6% and 39.1%, respectively ($p < 0.025$). Male and female runners' response to T_{db} and T_{wb} changes were similar (overlap in 95% confidence intervals for the respective regression coefficients). In conclusion, small variations in environmental parameters affected marathon performance, with T_{wb} impairing marathon performance more than T_{db} . Marathon performance was likely better in the morning than evening, possibly due to time of day differences, along with unfavorable T_{db} that superseded training effects and the effects of lower T_{wb} .

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Introduction

Runner's demographics, environmental conditions [1–3], training status [4,5], time of day [6], sunlight exposure [7,8], wind [9], and perceptual comfort [10] are some of the myriad of factors that could influence marathon performance. In particular, marathon performance suffers as temperature rises, especially if held in hot and humid climates [1,2,11]. Furthermore, the physiological challenge of running a marathon is vastly different than running shorter distance races [12]. In addition, running an actual marathon is different from completing one under laboratory settings [13–15], requiring runners to alter their pace to compensate for increased physiological demands [3,15]. Thus,

studies attempting to quantify the impact of environmental conditions on marathon performance should therefore adopt a multifactorial approach.

Climatic conditions can influence marathon performance [1–3]. The impact of temperature on marathon runners can be ascertained through measurements of dry bulb temperature (T_{db}), wet bulb temperature (T_{wb}), dewpoint temperature (T_d), and wet bulb globe temperature (WBGT). T_{db} is the ambient temperature of the air [16] and is often used as a measure to assess the impacts of environmental heat in both sporting or occupational activities [17,18]. T_{wb} and T_d are similar in the sense that both measurements relate to humidity [19,20], and are viable indicators of

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marathon performance capability [11,21]. A more commonly used measurement is WBGT, which is influenced by multiple factors and is utilized for both sports planning and as performance indicators [17,22,23]. Such measurements are hence paramount when attempting to evaluate the multifaceted effects of the environment on runners. Although the effects of different environmental conditions on marathon performance are well documented by prior studies, no previous research investigated the impact of small variations in environmental conditions on marathon performance.

In addition, previous analyses related to the impact of environmental conditions on marathon performance were based on the extraction of race results across the years for specific marathons [1–3]. Previous studies mostly examined the marathon performance of runners across the years based on placing [2,3], or the total number of finishers [1]. As such, the manner that studies analyzed marathon performance affects how the impact of environmental conditions are quantified and must be considered to ensure that an extensive range of runners' performance are covered. To our knowledge, no prior studies examined the impact of small variations in environmental conditions on the same cohort of runners' marathon performance across multiple years. Moreover, it is likely that the cohort of runners in our study would have been better heat acclimatized to running in the heat due to Singapore's persistent tropical climate, as compared to runners in studies that feature temperate or cooler conditions. This, alongside the underrepresentation of literature related to marathon performance in the tropics, showcases the novelty of our study.

The time of day also influences endurance performance [6,24], with previous literature on the topic reporting conflicting results. Hobson et al. [6] demonstrated in a laboratory setting that endurance performance in warm conditions was superior in the morning than the evening, while other laboratory studies conducted in cool conditions reported that endurance performance was better in the evening than the morning [24,25] or were the same for both the morning and evening [26,27]. As far as we know, no previous research

examined the small variations in environmental conditions at different times of day using the same cohort of runners.

The purpose of this study was to examine the marathon performance of the same large cohort of runners in relation to the small changes in T_{db} and T_{wb} across 3 y to (1) quantify the impact of T_{db} and T_{wb} on marathon performance and (2) investigate whether marathon performance was poorer during an evening marathon compared to morning marathons due to differing environmental conditions. We hypothesized that marathon performance would be affected by the small changes in T_{db} and T_{wb} and that marathon performance would be poorer in the evening marathon than in morning marathons.

Materials and methods

Participants

A total of 610 runners comprising 547 male runners and 63 female runners were subsequently identified by name, gender, and age category. Runners must have participated in at least two of the three Standard Chartered Singapore Marathons from 2014 to 2016, and in all three of the 2017, 2018, and 2019 marathons to be included in the study. Prior marathon experience was observed to affect runners' consecutive marathon performance [28], and Deaner et al. [29] showed that marathon pacing was more detrimentally affected amongst runners with $<$ or $=$ 3 y of marathon experience. Due to the lack of literature on the influence of training among the same cohort of runners for consecutive (similar) marathons, we choose to assume that the inclusion criteria would minimize the effect of training on average. This is because included runners would have some level of experience in running the Standard Chartered Singapore Marathon prior to 2017, and more highly trained runners experienced minimal performance improvements with training compared to less trained runners [4]. However, due to constraints in sample size if the inclusion criteria were narrowed to runners who participated in all six of the 2014 to 2019 marathons, the current inclusion criteria were used instead. Hence, runners who did not participate

in at least two of the three 2014, 2015, and 2016 marathons and all three of the 2017, 2018, and 2019 marathons were excluded. Marathon race results of the identified runners were extracted from the race results of each year. These data are in the public domain, therefore written and informed consent were not required from individual athletes.

Procedure

To examine the differences in the year-to-year marathon performance of each runner, each runner's net time was analyzed. The 2017, 2018, and 2019 Standard Chartered Singapore Marathons had similar routes consisting of urban and park areas alongside relatively flat terrain, with the 2017 marathon starting at a different location as compared to the 2018 and 2019 marathons, which shared the same starting location. Likewise, the 2017 marathon had a different finishing location in comparison to the same finishing location shared by the 2018 and 2019 marathons. Marathon distance and topography were the same throughout all three marathons, and all these marathons were certified as IAAF Gold Label Road Races. Starting times for each marathon were 0400 hr on both December 3, 2017 and December 9, 2018, and 1800 hr on December 30, 2019.

T_{db} , T_{wb} , T_d , and relative humidity (RH) measurements throughout the duration of each marathon were provided by the Meteorological Service Singapore. Because RH contained information on both T_{db} and T_{wb} which complicates the analysis (high RH could be caused by low T_{db} and/or high T_{wb}), T_{wb} was used as a proxy for moisture rather than RH (higher T_{wb} corresponds to higher moisture in the environment), and only T_{db} and T_{wb} were included subsequent analyses. Mean values of the environmental parameters (T_{db} and T_{wb}) experienced by each runner were calculated across the runner's marathon duration and across locations. Since the mean environmental parameters experienced by each runner were based on the runner's net time, and the environmental parameter measurements at locations throughout the duration of the marathon, different runners would hence experience different mean environmental

parameter values. As absolute humidity is often the main factor that influences marathon performance [30,31], mean values of absolute humidity experienced by each runner were also calculated to better elucidate the environmental parameters' influence on marathon performance. Specific humidity values for each minute were first derived from the T_d values for each minute via the MetPy Version 1.0 Python package and used to calculate the absolute humidity values for each minute based on the Ideal Gas Law, with the Individual Gas Constant of Air being 287.05 J/kg/K. Subsequently, the absolute humidity experienced by each runner was then averaged based on each runner's net time.

Statistical analyses

Data were analyzed using open-source packages in Python Programming Version 3.7.6 and statistical significance was accepted as $p < 0.05$ (before Bonferroni correction). Descriptive data are presented as mean \pm SD. Pairwise t -tests were used to compare net time across the years (2017 and 2018, 2017, and 2019, and 2018 and 2019, respectively) for all identified runners, male runners alone, and female runners alone. Two-sample z tests were used to examine the statistical significance of the differences in mean for net time, and the environmental parameters across all identified runners, male runners alone, and female runners alone. Standard deviations of the runners' net time were calculated by multiplying coefficient of variation (CV) and mean net times (for all runners, male runners and female runners, respectively). The CV value used in our analysis was 2.5%, as it was reported that $CV \leq 2.5\%$ should be employed when examining the smallest worthwhile changes in running performance for full marathons [32]. These standard deviations in net time were then used as proxies for the smallest effect size of interest (SESOI) for marathon performance. Equivalence tests (ET) via two-one sided test (TOST) with the SESOI set as 2.5% were then carried out for comparisons of marathon net time, and statistical equivalence was accepted as $p < 0.05$ (before Bonferroni correction).

The runner distribution of net time was not normal according to the Shapiro–Wilk test,

Kolmogorov–Smirnov (KS) test and KS test with Lilliefors correction. However, it was found that this was due to extreme data points (very small or very large runners’ net times) deviating from normality and causing the overall distribution to be not normal. Furthermore, this violation of the normality assumption would not have affected the parametric procedures used in this study as the sample size was large enough [33], and parametric tests should still be used for non-parametric or heavily skewed data [34].

Cluster analysis using K-means was implemented to separate runner characteristics into groups or clusters to better elucidate any possible relationship between the runners’ marathon net timings and environmental parameters. K-means is a clustering technique, which separates a dataset into K number of clusters such that the characteristics of members within each cluster are similar, while the characteristics of members across clusters are different. The similarity of members’ characteristics within a cluster is measured by the within-cluster sum of square distance, which is the total sum-of-square distance (Euclidean distance) between members of the cluster and the clusters’ centroid (mean of members in a cluster). K-means would iteratively select centroids with the lower within-cluster sum of square distance. K-means clustering was performed on 1830 data points (610*3 data points), with each runner’s data row for each year being an individual entry, for all runners, male runners alone, and female runners alone.

Pertaining to the K-means clustering algorithm, clusters were first initialized by randomly choosing samples within the dataset to be represented as its centroid, meaning that the starting value of centroids bears the value of the chosen sample. Subsequently, all samples within the dataset were allocated to the cluster with the nearest centroid based on Euclidean distance between the samples and the centroid. For each cluster, a new centroid was then created by taking the mean values of its members and the difference between the new and starting value centroid of each cluster was calculated. This generation of new centroids and differences was then repeated until the difference between the new and previous centroid of the

clusters was below a threshold or the number of iterations has exceeded a defined maximum number.

In our analysis, K-means was implemented using sci-kit-learn library with a maximum iteration of 500 and a threshold of 1×10^{-4} . Variables used for K-means were the runners’ marathon net timings and the T_{db} and T_{wb} experienced by the runners. Since K-means depends on Euclidean distance to perform clustering, it is critical that variables are of the same order of magnitude to ensure that clustering does not rely on variables with larger orders of magnitude. As the runners’ marathon net timings are a few orders of magnitude larger than T_{db} and T_{wb} , all variables were standardized to range from 0 and 1 using the Min-Max Scaler prior to K-means algorithm implementation as follows (Equation 1):

$$Z = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (1)$$

where Z is the scaled value based on the Min-Max Scaler and X is the original value of the variable.

An issue with implementing K-means is determining the appropriate K number of clusters to partition the dataset. This can be circumvented by iteratively implementing K-means with different K values and inspecting the changes in the within-cluster sum of squares as K increases. For our analysis, K value ranged from 2 to 14, and though using more clusters (higher K values) to partition the dataset will reduce the within-cluster sum of square distance (more coherent clusters), the large number of clusters would make cluster analysis and interpretation complex. This need to balance the choice of K value and the within-cluster sum of square distance can be addressed by using the “Elbow Method” [35]. The “Elbow Method” identifies the largest K value after which the decrease in within-cluster sum of square distance is significantly reduced, while disregarding subsequent K values that lead to marginal decreases in the within-cluster sum of square distance [35]. The result of K-means is clusters of runners with similar net time who experienced similar environmental parameters, and since a runner’s marathon year was not a variable for K-means, the same runner’s

data rows (i.e. 2017 and 2018 data rows) might appear within the same cluster.

The by-product of our cluster analysis is the observation of two distinct groups with different marathon performance levels (non-overlapping interquartile ranges in net time between both groups) across the clusters determined by K-means: High Marathon Performance level (HMP) and Low Marathon Performance level (LMP). Additionally, to account for the effect of training across the years, analysis of runners who were consistently in HMP and LMP respectively across the 3 y was performed.

The benefits of K-means clustering are twofold in our analysis. Firstly, naturally occurring groups within the data could be discovered and their characteristics summarized, so that the preliminary inspection of possible relationships between runners' net time and the environmental parameters could be performed. This is accomplished by comparing the distribution of these variables across the derived clusters. Moreover, the allocations of runners in the HMP and LMP could be done in an objective manner via K-means. Secondly, the environmental parameters' data was generated in a way that causes it to be dependent on runner timings since mean environmental parameters were calculated according to runners' net times. However, by performing K-means clustering that utilizes all variables (environmental parameters and net time), groups of runners with similar timings were segregated as seen in the separation of HMP and LMP. Thus, any variation in timing within HMP and LMP would then be likely due to the variations in environmental parameters.

Additionally, to further supplement the K-means clustering analysis, runners who were consistently below the 25th percentile or above the 75th percentile of each year's marathon, from 2017 to 2019, within the selected sample were also filtered to obtain another set of data pertaining to HMP and LMP, respectively. This method yielded 570 data points (190*3 data points). This is because despite the delineation of HMP and LMP via percentiles being clearer than that of K-means clustering, using percentiles to delineate HMP and LMP drastically limited the sample size and is more subjective than K-means clustering due to the arbitrariness of selecting percentile values.

Linear regressions were subsequently performed, using data from the 2017 and 2018 Standard Chartered Singapore Marathons, on all identified runners across HMP and LMP groups of runners to quantify the effects of environmental parameters on runners' marathon net time. This was done for both the K-means clustering derived HMP and LMP, and for the percentile derived HMP and LMP. Data from 2019 were excluded in the linear regression analysis to minimize confounding by time-of-day effects and differences between day (2017–2018) and night (2019) Standard Chartered Singapore Marathons.

Regression was performed using percentage changes in net time as the dependent variable and percentage changes in T_{db} and T_{wb} as the independent variables. Percentage changes in net time were calculated for each runner, using the year 2017 as the baseline for percentage change calculation as follows (Equation 2):

$$\Delta \text{time}_{2018}(\%) = (\text{time}_{2018} - \text{time}_{2017}) \div (\text{time}_{2017}) \times 100 \quad (2)$$

where time_{2018} was the runner's net time during the 2018 marathon, and time_{2017} was the runner's net time during the 2017 marathon. The same calculations were done for T_{db} and T_{wb} to derive the percentage change for the respective environmental parameters.

As multi-collinearity affects regression, the regression analysis was performed individually on the percentage changes in T_{db} and T_{wb} rather than on both variables in a multiple linear regression analysis. This is due to the strong correlation observed between T_d and T_{wb} , and between T_{db} and T_{wb} . This is because T_{wb} is the temperature of air that could be cooled to through evaporation, but given a fixed extent of evaporation, T_{db} and T_{wb} would likely move in tandem to one another (a strong correlation was observed). Furthermore, T_{wb} and T_d are both highly similar, as higher T_{wb} affects cooling temperature while higher T_d affects the extent that sweat evaporation can occur which affects cooling temperature.

The regression formulas relating the percentage change in net time with the percentage changes in T_{db} and T_{wb} respectively are as follows (Equations 3 and 4):

$$\Delta \text{time}(\%) = \alpha_{T_{db}} \Delta T_{db}(\%) + \text{intercept} \quad (3)$$

$$\Delta \text{time}(\%) = \alpha_{T_{wb}} \Delta T_{wb}(\%) + \text{intercept} \quad (4)$$

where $\alpha_{T_{db}}$ and $\alpha_{T_{wb}}$ are the coefficients of regression for T_{db} and T_{wb} , respectively; $\Delta \text{time}(\%)$ is the percentage change in net time; $\Delta T_{db}(\%)$ is the percentage change in T_{db} ; and $\Delta T_{wb}(\%)$ is the percentage change in T_{wb} .

For regression on data samples segregated by HMP and LMP groups, runners that were consistently in the same group for HMP and LMP every year were selected.

Results

Age distribution of runners

Figure 1 illustrates the age and sex distribution of runners in 2017. As of 2017 for female runners, 7 were aged 20–29, 14 were aged 30–39, 32 were aged 40–49 and 10 were aged 50–59. Likewise for male runners, 30 were aged 20–29, 138 were aged 30–39, 208 were aged 40–49, 152 were aged 50–59 and 19 were aged 60–69. The 2018 and 2019 distributions also consisted of the same 63 female runners and 547 male runners.

The age and sex distribution of the 190 runners consistently within the 25th and above the 75th

percentile each year was similar to that of Figure 1, with 23 female runners and 167 male runners.

Clustering results for all runners

Mean marathon performance between 2017 and 2018 was similar (mean difference = 65 ± 2181 s, ET $p < 0.017$). Mean marathon performance was slower in 2019 than in 2017 (mean difference = 320 ± 2306 s, $p < 0.017$) and 2018 (mean difference = 385 ± 2207 s, $p < 0.017$). Marathon performance for all runners in 2018 was the fastest of the 3 y (mean net time = $19,733 \pm 3748$ s). For male runners alone, mean marathon performance between 2017 and 2018 was similar (mean difference = 73 ± 2148 s, ET $p < 0.017$), but mean marathon performance was slower in 2019 than in 2017 (mean difference = 323 ± 2266 s, $p < 0.017$) and 2018 (mean difference = 396 ± 2158 s, $p < 0.017$). For female runners alone, mean marathon performance were similar between 2017 and 2018 (mean difference = -5 ± 2474 s, ET $p < 0.017$), between 2017 and 2019 (mean difference = -295 ± 2646 s, ET $p < 0.017$) and between 2018 and 2019 (mean difference = -291 ± 2616 s, ET $p < 0.017$). Figure 2 illustrates the environmental parameters experienced by runners across the years. Figure 3 illustrates the absolute humidity and relative humidity experienced by runners across the years. Noteworthy, a small difference

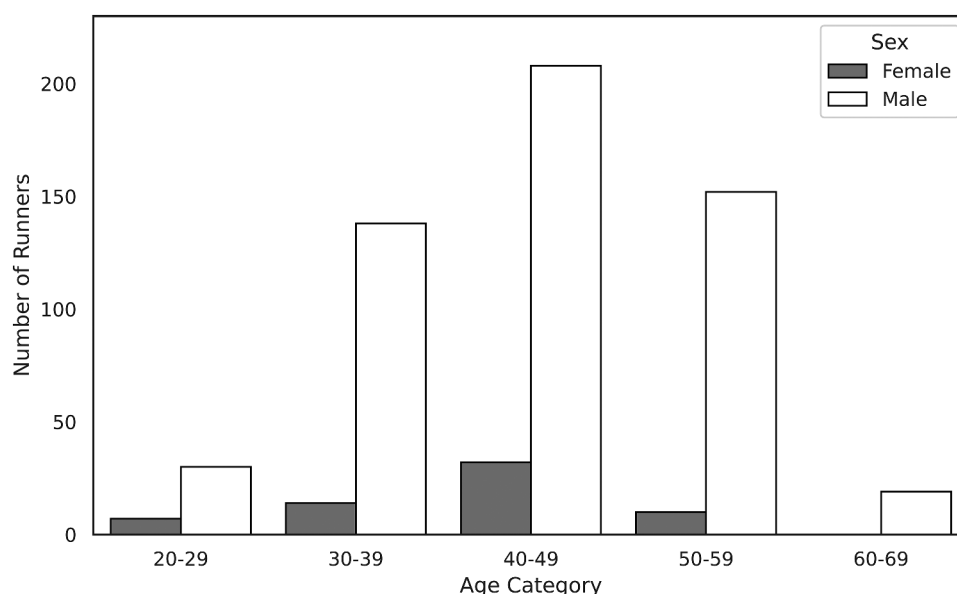


Figure 1. Distribution of age and sex of runners that took part in the 2017 Standard Chartered Singapore Marathon. This same sample of runners also participated in the 2018 and 2019 Standard Chartered Singapore Marathons.

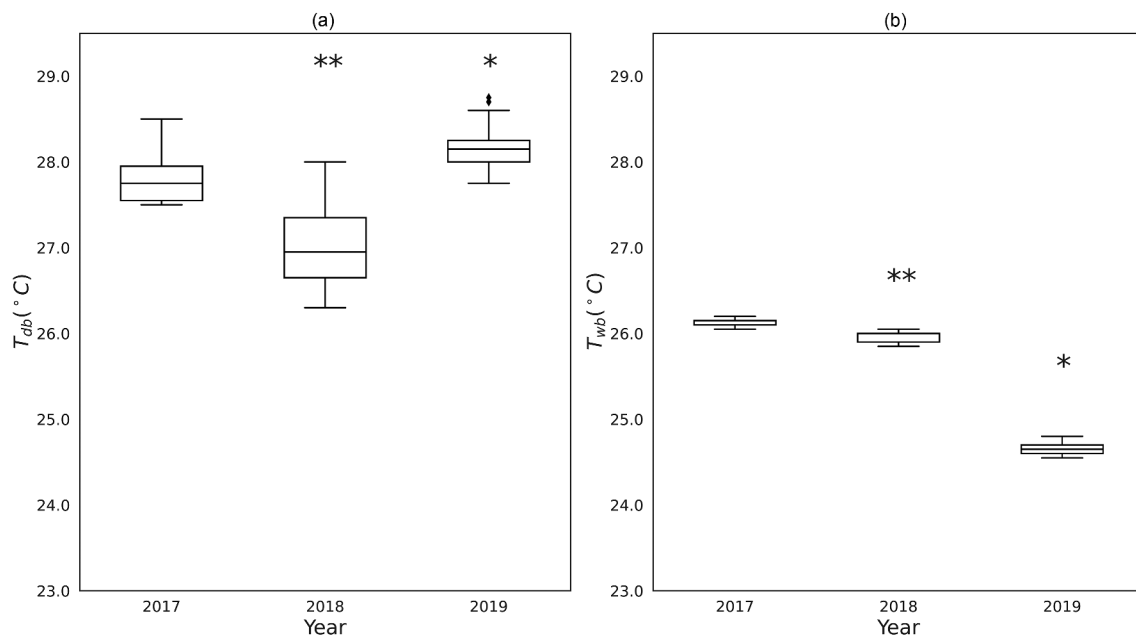


Figure 2. (a) T_{db} and (b) T_{wb} experienced by all runners across the years. * denotes difference ($p < 0.017$) between 2019 to 2017 and 2018. ** denotes difference ($p < 0.017$) between 2018 and 2017.

between the mean absolute humidity of 2017 and 2018 was observed (difference in mean = -0.11 g/m^3 , $p < 0.017$). This indicates that the mean absolute humidity of 2017 and 2018 were very similar to each other (mean absolute humidity = $23.86 \pm 0.083 \text{ g/m}^3$ and $23.96 \pm 0.12 \text{ g/m}^3$, respectively).

Performing K-means clustering on all runners and male runners alone, $K = 6$ was selected by observing the within-cluster sum of square for a range of number of clusters (2–14 clusters), and identifying the number of clusters after which the changes in the within-cluster sum of

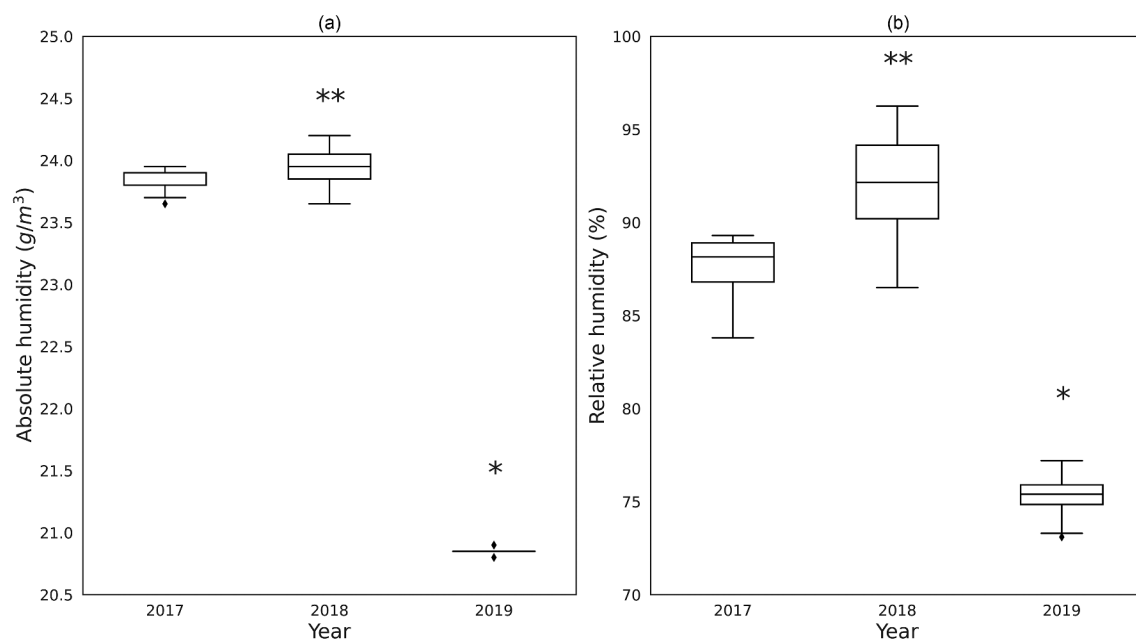


Figure 3. (a) Absolute humidity and (b) Relative humidity experienced by all runners across the years. * denotes difference ($p < 0.017$) between 2019 to 2017 and 2018. ** denotes difference ($p < 0.017$) between 2018 and 2017.

square becomes insignificant (in this case $K = 6$). For female runners alone, the K-means clustering resulted in $K = 5$ being selected, but a clear distinction between HMP and LMP clusters was still observed. When analyzing the clustering results for all runners, a total of 1830 data rows (derived from 610 runners) across 6 clusters were produced. Figure 4(a) illustrates clusters 1, 2, and 5 which were designated as HMP, and clusters 3, 4, and 6 which were designated as LMP. The largest difference between HMP and LMP clusters was between clusters 1 and 3, respectively (difference in mean = -7622 s, $p < 0.0033$), while the smallest difference between HMP and LMP clusters was between clusters 5 and 6, respectively (difference

in mean = -3942 s, $p < 0.0033$). Figures 4(b-c) illustrate the distribution of the environmental parameters across the six clusters for all runners.

The analysis performed on runners that were consistently in HMP or LMP across the 3 y yielded 218 runners in HMP and 228 runners in LMP, and runners that were not consistently in HMP or LMP each year were excluded. Table 1 illustrates the differences in mean net time and environmental parameters between 2017, 2018, and 2019 for HMP and LMP. There was greater improvement in mean marathon performance for HMP than LMP runners across 2017 and 2018 (difference in mean = 392 ± 1266 s $p < 0.017$ and 137 ± 2060 s ET $p < 0.017$, respectively). Conversely, mean marathon performance

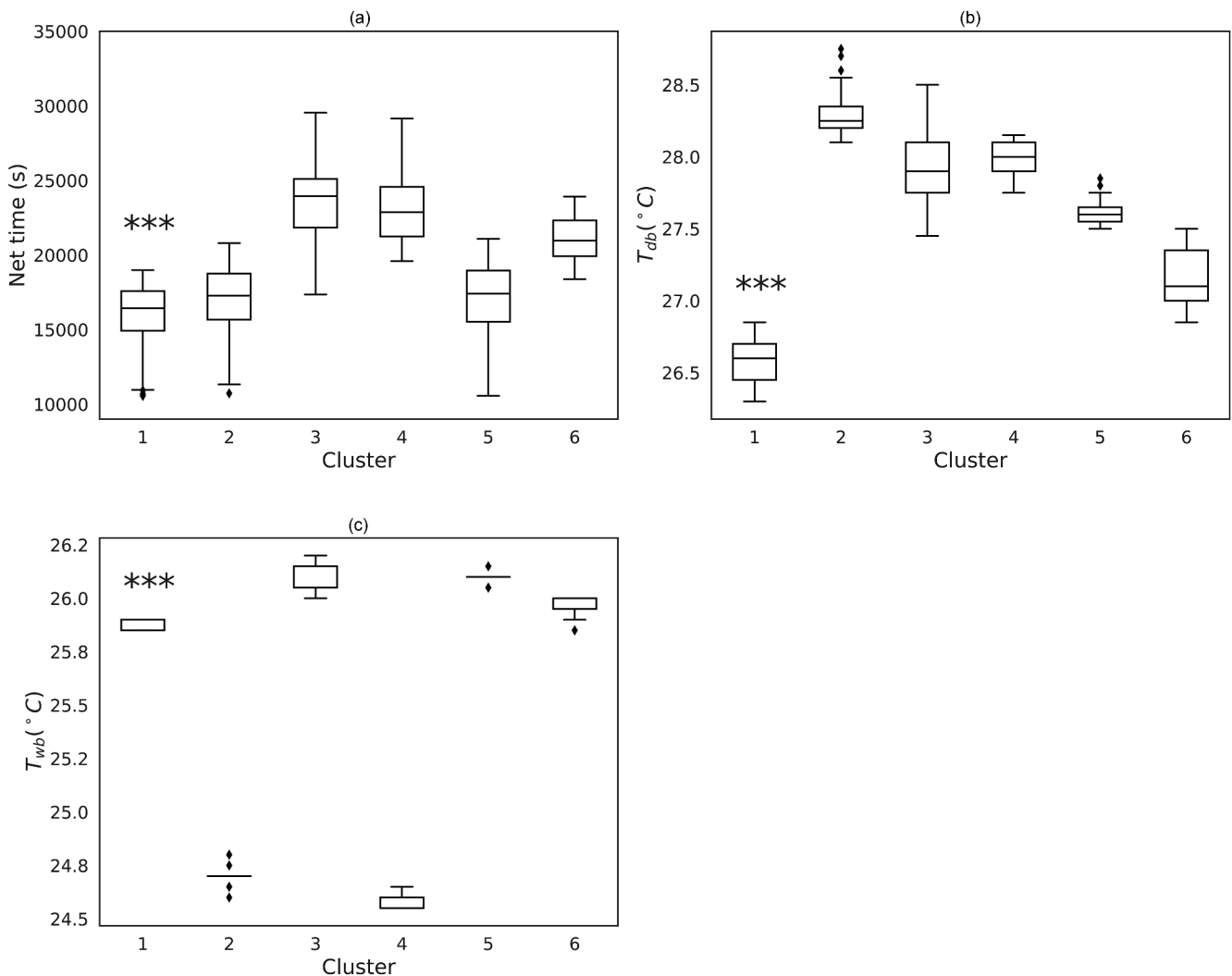


Figure 4. a) Marathon net time for all runners, b) T_{db} across experienced by all runners and c) T_{wb} experienced by all runners across the clusters generated from the all runners' K-means clustering analysis. The diamonds represent outliers with respect to the cluster's interquartile range. *** denotes difference ($p < 0.0033$) between cluster 1 to clusters 2, 3, 4, 5 and 6.

Table 1. Differences in mean for net time and environmental parameters between 2017, 2018 and 2019 for HMP and LMP, respectively.

		Net Time		T _{db}		T _{wb}	
		(s)	(%)	(°C)	(%)	(°C)	(%)
2017–2018	HMP	392	2.4	1.0	3.7	0.2	0.9
	LMP	138	0.6	0.6	2.2	0.2	0.6
2017–2019	HMP	–93	–0.6	–0.7	–2.7	1.4	5.3
	LMP	–284	–1.2	0.0	0.2	1.6	6.0
2019–2018	HMP	–485	–3.1	–1.8	–6.6	1.2	4.5
	LMP	–422	–1.8	–0.6	–2.1	1.4	5.4

For HMP, the difference in mean net time between 2017 and 2019 was similar (ET $p < 0.017$). For LMP, the difference in mean net time between 2017 and 2018 was similar (ET $p < 0.017$).

deteriorated from 2018 to 2019 for both HMP and LMP (difference in mean = -486 ± 1396 s $p < 0.017$ and -421 ± 2116 s $p < 0.017$). For HMP, the mean net times for 2017 and 2019 were similar (ET $p < 0.017$). For LMP, the mean net times between 2017 and 2018 was similar (ET $p < 0.017$).

Clustering results for male runners

When analyzing the clustering results for male runners alone, a total of 1641 data rows (derived from 547 male runners) across 6 clusters were produced. Clusters 2, 3, and 4 were designated as HMP, and clusters 1, 5, and 6 were designated as LMP. The largest difference between HMP and LMP clusters was between clusters 3 and 5, respectively (difference in mean = -7540 , $p < 0.0033$), while the smallest difference between HMP and LMP clusters was between clusters 4 and 1, respectively (difference in mean = -4018 , $p < 0.0033$).

Clustering results for female runners

When analyzing the clustering results for female runners alone, a total of 189 data rows (derived from 63 female runners) across 5 clusters were produced. Clusters 3, 4 and 5 were designated as HMP, while clusters 1 and 2 were designated as LMP. The largest difference between HMP and LMP clusters was between clusters 3 and 2, respectively (difference in mean = -7221 , $p < 0.005$), while the smallest difference between HMP and LMP clusters was between clusters 4 and 1, respectively (difference in mean = -6572 , $p < 0.005$).

Table 2. Differences in mean for net time and environmental parameters between selected cluster pairs.

	Net Time		T _{db}		T _{wb}	
	(s)	p -Value	(°C)	p -Value	(°C)	p -Value
Cluster 3 & 4 (All runners)	559	0.001	–0.1	0.000	1.5	0.000
Cluster 5 & 6 (Male runners)	558	0.002	–0.1	0.000	1.5	0.000
Cluster 1 & 2 (Female runners)	–447	0.421	–0.1	0.481	1.5	0.000

Cluster 3 from the all runners' analysis, cluster 5 from the male runners' analysis and cluster 1 from the female runners' analysis comprised of runners' performance in 2017 and 2018. Where else cluster 4 from the all runners analysis, cluster 6 from the male runners' analysis and cluster 2 from the female runners' analysis comprised of runners' performance in 2019 only.

Impact of environmental parameters on all runners

Table 2 illustrates the differences in mean for net time and environmental parameters for chosen pairs of clusters from the all runners, male runners, and female runners' K-means clustering analyses. Each pair of clusters was chosen because the differences in mean for T_{db} were similar (see Table 2). For all runners' and male runners' clusters, increases in T_{wb} when T_{db} were similar coincided with increases in net time ($p < 0.0033$). This observation was absent for the female runners' clusters.

Figure 5(a) illustrates the regression coefficients for T_{db} for all K-means clustering-filtered runners, with the regression coefficient for LMP being higher than that for HMP (no overlap in 95% confidence intervals). Figure 5(b) illustrates the regression coefficients for T_{wb} for all K-means clustering-filtered runners, with the regression coefficients for LMP and HMP being similar (overlap in 95% confidence intervals). Furthermore, the regression coefficient for T_{db} is ~ 7.6 and the regression coefficient for T_{wb} is ~ 39.1 across all performance groups ($p < 0.025$, see Figure 5), suggesting that each percentage rise in T_{db} and T_{wb} leads to an increase in net time by 7.6% and 39.1%, respectively. The findings generated by the regression analysis for T_{db} and T_{wb} for all percentile-filtered runners were similar to that of Figure 5. The regression coefficients for T_{db} for LMP, HMP and across all performance groups were 11.05, 7.03, and 7.64, respectively. The regression coefficients for T_{wb} for LMP, HMP, and across all performance groups were 50.04, 27.20, and 39.08,

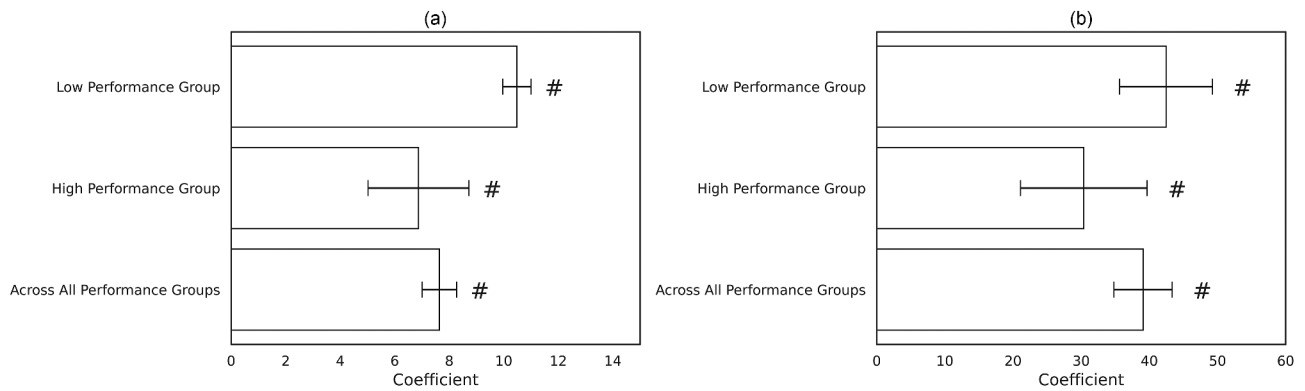


Figure 5. a) Regression coefficients for T_{db} for all performance levels of runners, b) Regression coefficients for T_{wb} for all performance levels of runners. The lines and dashes represent the range of values for the 95% confidence interval. # denotes statistical significance ($p < 0.025$) for 95% confidence interval within the group.

respectively. Notable differences compared to the regression analysis for all K-means clustering-filtered runners were that the regression coefficients for T_{db} for LMP and HMP were similar (overlap in 95% confidence intervals), while the regression coefficient for T_{wb} for LMP was higher than that for HMP (no overlap in 95% confidence intervals). Regardless, the influence of T_{db} and T_{wb} on net time was still observed for LMP, HMP, and across all performance groups.

Figures 6 illustrate the regression coefficients for T_{wb} for K-means clustering-filtered male and female runners. The regression coefficients for T_{wb} for male runners (between 34.33 and 43.41) and female runners (between 27.58 and 53.86) across all performance-level groups were similar

(overlap in 95% confidence intervals for male and female runners). For T_{db} , regression coefficients across gender and across all performance groups were similar (overlap in 95% confidence intervals). The findings generated by the regression analysis for T_{wb} for all percentile-filtered male and female runners were similar to that of Figure 6, with the exception of the regression coefficients for female LMP and HMP runners being less conclusive ($p > 0.025$). The regression coefficients for T_{wb} for male runners for LMP, HMP and across all performance groups were 47.34, 28.40, and 38.87, respectively, while the regression coefficient for T_{wb} for female runners across all performance groups was 40.72. As such, the influence of T_{wb} on net time across genders was still observed

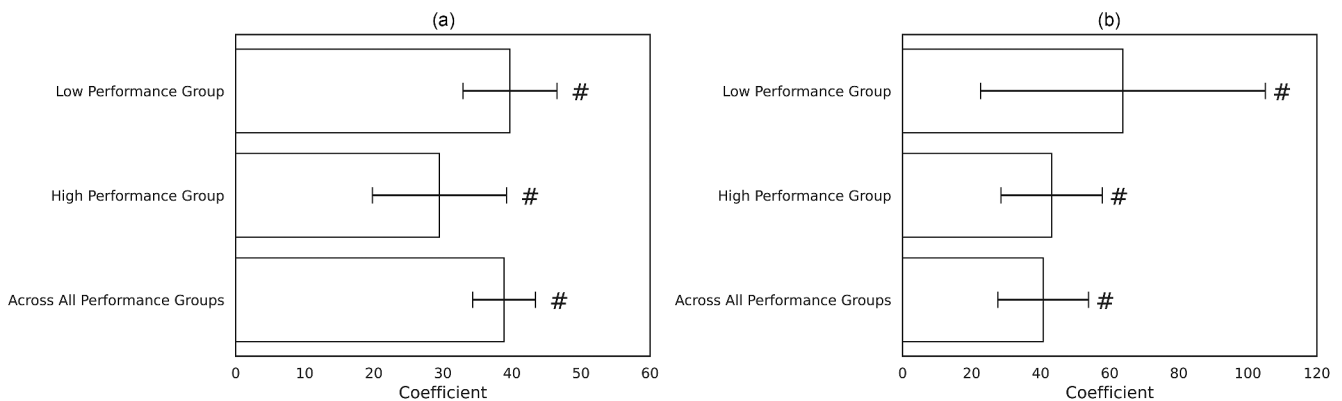


Figure 6. (a) Regression coefficients for T_{wb} for male runners, (b) regression coefficients for T_{wb} for female runners. The lines and dashes represent the range of values for the 95% confidence interval. # denotes statistical significance ($p < 0.025$) for 95% confidence interval within the group.

across all performance groups; however, the regression coefficients for T_{wb} for female LMP and HMP runners were less conclusive ($p > 0.025$).

Discussion

The principal finding of this study was that rising T_{db} and T_{wb} coincide with increases in net time, with the effect on marathon performance being greater for T_{wb} than T_{db} (see [Figure 5](#)). Our findings suggest that changes in T_{wb} have a greater impact on marathon performance than T_{db} , which differ from previous studies [1,36] that reported how T_{db} has the greatest influence on marathon performance as compared to other environmental parameters. The larger influence of T_{wb} on marathon performance could be attributed to the fact that T_{wb} as a parameter encompasses T_{db} , humidity, and wind conditions. T_{db} as a parameter directly influences heat exchange between the body and the environment, impacting skin and potentially core temperature. Rises in T_{db} increase the heat strain experienced by the body and the need for the body to dissipate this heat to prevent hyperthermia [37–39]. This, in tandem with how humidity and wind conditions can affect marathon performance [1,9], would suggest that T_{wb} (with its many variables encompassed within itself) would have a greater influence on marathon performance as compared to T_{db} . Additionally, the observations from [Table 2](#) also suggest the importance of evaporative heat loss for marathon performance among the all runners' and male runners' clusters. Since the body's evaporative heat loss capability is influenced by T_{wb} , and consequently RH as RH includes information from T_{db} and T_{wb} , higher T_{wb} would result in higher RH values given similar T_{db} values. High RH values impair the ability to evaporate sweat [40], which could lead to greater heat strain [41]. However, this observation was absent when observing the female runner clusters, which could be attributed to the smaller size of the female runner clusters.

The influence of running capability is ambiguous when determining the impact of T_{wb} on a runner's marathon performance. An overlap in 95% confidence intervals for the regression coefficients for T_{wb} for LMP and HMP was present when performing the regression analysis with K-means clustering-filtered runners (see [Figure 5\(b\)](#)), but absent when doing so with percentile-filtered runners. This is because

despite drastically reducing the sample size (as compared to K-means clustering), the delineation of percentile-filtered runners into HMP or LMP was clearer (no overlaps in net time between HMP and LMP groups were observed). It is likely that some slower HMP runners, who belong to LMP but were segregated into HMP via K-means clustering, contributed to higher variability within HMP and influenced the 95% confidence interval for HMP to be larger (and overlap with the 95% confidence interval for LMP). The impact of T_{db} on a runner's marathon performance was likely influenced by running capability. From the data, T_{db} has a greater impact on the LMP runners than the HMP runners (regression coefficient = 10.48 and 6.87, respectively, see [Figure 5\(a\)](#)). Similar findings were also observed when the regression analysis was carried out on percentile-filtered runners, with a notable difference being that the regression coefficient for T_{db} for LMP and HMP runners were similar (overlap in 95% confidence intervals). As mentioned prior, the delineation of percentile-filtered LMP and HMP runners was clearer than that of K-means clustering, but resulted in a drastic reduction in sample size (from 610 to 190 runners). This reduction in sample size could have led to the overlap in 95% confidence intervals for the regression coefficients of T_{db} for LMP and HMP. With respect to [Figure 5](#) and the results from the regression analysis performed on percentile-filtered runners, it is likely that HMP runners were more tolerant toward increasing temperature. This was supported by previous studies [2,36,42] that ascertained the influence of weather on both elite and non-elite marathon runners. Evidence also suggests that slower runners were exposed to environmental parameters for a longer duration [2] which prolongs the negative effects of increasing temperature. Slower runners also tended to run in closer proximity to other runners in clustered formations [43,44], which might result in greater heat stress and reduced heat loss ability for runners [45,46]. However, it should also be acknowledged that endurance performance in the heat can be attributed to the multifactorial regulation of factors such as athlete experience [47], perceived effort [10], endurance physiology [48] and heat acclimation status [49]. Hence, it is likely that running capability has the potential to influence the impacts of T_{wb} and T_{db} on runners' marathon performance.

The effects of T_{wb} on male and female runners across all marathon performance levels were similar. When comparing across all marathon performance levels of runners, both male and female runners showed no difference in regression coefficients (overlap in 95% confidence intervals for male and female runners for both K-means clustering-filtered and percentile-filtered runners), resulting in similar responses to T_{wb} among male and female runners. Male and female runners also showed similar responses to T_{db} (overlap in 95% confidence intervals for male and female runners for both K-means clustering-filtered and percentile-filtered runners). Our findings agree with previous studies [1,2,50] suggesting that there are minimal to no differences in the responses of male and female runners toward increasing heat stress. However, it is worth noting that factors such as menstrual cycle phase [51] and the heat acclimation differences among males and females [52,53] were not controlled for due to the present study's design. These factors could have affected the results obtained, though the influence of menstrual cycle phase would likely be eclipsed by the influence of environmental conditions [54]. It was also observed that the 95% confidence interval of the regression coefficients for T_{wb} for female LMP and HMP runners were inconclusive ($p > 0.025$). However, this is possibly due to the small sample size of 23 female runners when runners were filtered by percentile, and not because LMP and HMP female runners were more tolerant to temperature fluctuations. Regardless, there are minimal differences in the manner that male and female runners respond to T_{wb} and T_{db} changes.

Alongside environmental parameters, time of day and training effect also influences marathon performance. As it is challenging to ascertain the effects of time of day and environmental parameters separately, we focused on the 2017 and 2018 results to examine the environmental parameters' effect on marathon performance. First, this is due to training effect being potentially minimized following the initial inclusion criteria for runners. The initial inclusion criteria excluded runners who had 0 or 1 y of Standard Chartered Singapore Marathon experience prior to 2017, who might have experienced greater marathon performance improvements per year compared to runners with at least 2 y of Standard Chartered

Singapore Marathon experience prior to 2017. In tandem with the minimized training effect, time-of-day effects would also be at a minimum since both 2017 and 2018 marathons started at 0400 hr, hence differences in marathon performance would likely be attributed to the environmental parameters' influence. From Table 1, across 2017 and 2018, the improvement in marathon performance for runners consistently in HMP was greater than that for runners consistently in LMP (2.4%, $p < 0.017$ and 0.6%, ET $p < 0.017$, respectively, see Table 1). These improvements in marathon performance for HMP and LMP runners could be attributed to more favorable environmental parameters in 2018 than 2017 (see Table 1 and Figure 2), in conjunction with the minimized training effect. The 2.4% and 0.6% marathon performance improvements for HMP and LMP runners respectively were also similar to previous literature suggesting that endurance performance improves by approximately 1–3% per year with constant training [4,5,55]. Due to the observational nature of this study and the fact that the runners' data were extracted from a public domain, it is difficult to ascertain or control the training history of every runner prior to each marathon. Assuming that the 2.4% and 0.6% improvements for HMP and LMP runners respectively were entirely due to training effect, our findings still show that unfavorable environmental parameters hinder marathon performance more than training could improve performance. Each percentage rise in T_{db} and T_{wb} results in an increase in net time by 7.6% and 39.1%, respectively (see Figure 5), and it is likely that the 2.4% and 0.6% improvements for HMP and LMP runners respectively were due to training effect and the effect of favorable environmental parameters in tandem, rather than training effect alone. Additionally, the clinical difference in mean absolute humidity between 2017 and 2018 was unremarkable as seen from the small difference in mean of -0.11 g/m^3 ($p < 0.017$, see Figure 3(a)). This indicates that the 2.4% and 0.6% improvements for HMP and LMP respectively were largely unaffected by absolute humidity differences. Thus, the influence of environmental parameters on marathon performance potentially supersedes that of training effect.

In the case of time of day, we focused on the 2018 and 2019 results to examine the effects of time of day on marathon performance. It was observed that despite the lower T_{wb} in 2019 than 2018 and the additional year of training from 2018 to 2019, marathon performance in 2019 was worse than that in 2018 (mean difference = -385 ± 2207 s, $p < 0.017$). This worsened marathon performance in 2019, rather than an improvement, could possibly be attributed to the 2019 marathon being held at a different time of day. Our findings agree with the study by Hobson et al. [6], who reported that in thermally stressing conditions, exercise capacity was greater in the morning than in the evening likely because of a lower initial core temperature, which results in lesser heat stress experienced in the morning [37–39]. This suggests that the possible improvements in marathon performance due to training, the more favorable T_{wb} in 2019 as well as the more favorable absolute humidity in 2019 (see Figure 3(a)) were superseded by the reduced ability to exercise in the evening than in the morning [6]. Though it should be noted that T_{db} was higher in 2019 than 2018 (see Figure 2(a)) which might have contributed to the worsened marathon performance in 2019, the different time-of-day effect in 2019 would have arguably a larger role in affecting 2019's marathon performance. Furthermore, when comparing the current (2017 and 2018 data only) regression analysis with a regression analysis utilizing 2017 and 2019 data only, it was observed that the relationship between T_{wb} and net time, and the relationship between T_{db} and net time was no longer present. This highlights how it is possible that other factors, such as time of day, convolute the relationship between environmental parameters and net time.

With respect to restricting the study cohort of runners to those that took part in all Standard Chartered Singapore marathons from 2017 to 2019, by including race results prior to the 2017 marathon and comparing within the runners who participated in all marathons, the magnitude of confounders would be further exacerbated. Hence, the analysis was restricted to Standard Chartered Singapore marathons from 2017 to 2019 only, with race results from 2014 to 2016 being

used for the initial inclusion criteria for runners. The small variation in environmental parameters of the dataset within this study could be misinterpreted as a limitation since previous studies [2,3,21] on environmental parameters and marathon performance typically involve wider variations in environmental parameters. Noteworthy, apart from environmental parameters, factors not discussed in this study such as runners' behavior and physiology, also bear a profound role in influencing marathon performance [56]. For instance, running behavior, runners' behavior toward rehydration during a marathon, and their individual physiological differences can affect marathon performance [43,57–59]. Hence, future studies attempting to elucidate the management of heat strain for marathon performance should account for these factors.

Additionally, it should be noted that during exercise in the presence of heat stress, there is a prevalent dependency on sweat evaporation for heat exchange, which is influenced by the water vapor pressure gradient between the skin and air, alongside air movement and wetted area [60]. Thus, the environmental parameters used in this study would be limited in the sense that they do not directly determine the rate of sweat evaporation, which is instead influenced by absolute humidity [61,62]. However, it was observed that absolute humidity did not confound our findings of the environmental parameters and marathon performance across 2017 to 2019, hence elucidating the influence of the environmental parameters on marathon performance.

Consequently, this study did reveal that even small variations in temperature resulted in changes to marathon performance, suggesting that human performance could be affected by slight alterations to T_{db} and T_{wb} , with each percentage rise in T_{db} and T_{wb} resulting in an increase in completion time by 7.6% and 39.1%, respectively (see Figure 5). One limitation of this study is the difficulty in ascertaining the exact influence of time of day on runners' marathon performance due to the study's design. Although Hobson et al. [6] reported that exercise capacity was greater in the morning than in the evening,

more work is necessary to fully elucidate the effects of time of day on marathon performance, especially in thermally stressing conditions like the tropics.

Conclusions

Small variations in environmental parameters affect marathon performance, with T_{wb} having a larger impact than T_{db} . The running capability of runners could potentially influence how runners respond to T_{db} and T_{wb} changes. The responses of male and female runners to T_{db} and T_{wb} are similar. Marathon performance was observed to be better in the morning than evening, possibly due to the detrimental effect of a different time of day, as well as increases in T_{db} opposing the potential improvement in marathon performance from prior years of training and favorable T_{wb} . Despite the constraints faced by this study due to unknown variables such as the training history of runners, the present findings highlight how small variations in T_{db} and T_{wb} alter marathon performance. Time-of-day effects potentially supersede favorable environmental parameters and absolute humidity along with training effect. This enables future studies to factor in small variations in T_{db} and T_{wb} , and the influence of time of day, when investigating the impacts of other environmental factors on marathon performance, especially for marathons in the tropics.

Abbreviations

T_{db}	Dry bulb temperature
T_{wb}	Wet bulb temperature
T_d	Dewpoint temperature
WBGT	Wet bulb globe temperature
RH	Relative humidity
SD	Standard deviation
CV	Coefficient of variation
SESOI	Smallest effect size of interest
ET	Equivalence test
TOST	Two-one sided test
KS	Kolmogorov–Smirnov
HMP	High marathon performance level
LMP	Low marathon performance level

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References

- [1] El Helou N, Tafflet M, Berthelot G, et al. Impact of environmental parameters on marathon running performance. *PLoS One*. 2012;7(5):e37407.
- [2] Ely MR, Cheuvront SN, Roberts WO, et al. Impact of weather on marathon-running performance. *Med Sci Sports Exerc*. 2007;39(3):487–493.
- [3] Ely MR, Martin DE, Cheuvront SN, et al. Effect of ambient temperature on marathon pacing is dependent on runner ability. *Med Sci Sports Exerc*. 2008;40(9):1675–1680.
- [4] Legaz Arrese A, Serrano Ostariz E, Jcasajus Mallen JA, et al. The changes in running performance and maximal oxygen uptake after long-term training in elite athletes. *J Sports Med Phys Fitness*. 2005;45(4):435–440.
- [5] Jones AM. The physiology of the world record holder for the women's marathon. *Int J Sports Sci Coach*. 2006;1(2):101–116.
- [6] Hobson RM, Clapp EL, Watson P, et al. Exercise capacity in the heat is greater in the morning than in the evening in man. *Med Sci Sports Exerc*. 2009;41(1):174–180.
- [7] Henst RHP, Jaspers RT, Roden LC, et al. A chronotype comparison of South African and Dutch marathon runners: the role of scheduled race start times and effects on performance. *Chronobiol Int*. 2015;32(6):858–868.
- [8] Wright Kenneth P, McHill Andrew W, Birks Brian R, et al. Entrainment of the human circadian clock to the

- natural light-dark cycle. *Curr Biol.* 2013;23(16):1554–1558.
- [9] Knechtle B, Di Gangi S, Rüst CA, et al. The role of weather conditions on running performance in the Boston marathon from 1972 to 2018. *PLoS One.* 2019;14(3):e0212797.
- [10] Flouris AD, Schlader ZJ. Human behavioral thermoregulation during exercise in the heat. *Scand J Med Sci Sports.* 2015;25(S1):52–64.
- [11] Trapasso LM, Cooper JD. Record performances at the Boston marathon: biometeorological factors. *Int J Biometeorol.* 1989;33(4):233–237.
- [12] Krawczyk M, Wilamowski M. Task difficulty and overconfidence. Evidence from distance running. *J Econ Psychol.* 2019;75:102128.
- [13] García-Pérez JA, Pérez-Soriano P, Llana S, et al. Effect of overground vs treadmill running on plantar pressure: influence of fatigue. *Gait Posture.* 2013;38(4):929–933.
- [14] Edwards RB, Tofari PJ, Cormack SJ, et al. Non-motorized treadmill running is associated with higher cardiometabolic demands compared with overground and motorized treadmill running. *Front Physiol.* 2017;8(914). DOI:10.3389/fphys.2017.00914.
- [15] Morin JB, Tomazin K, Edouard P, et al. Changes in running mechanics and spring-mass behavior induced by a mountain ultra-marathon race. *J Biomech.* 2011;44(6):1104–1107.
- [16] Legg R. Chapter 1 - Properties of Humid Air. In: Legg R, editor. *Air conditioning system design.* Oxford, United Kingdom: Butterworth-Heinemann; 2017. p. 1–28.
- [17] James CA, Willmott AGB, and Dhawan A, et al. Increased air temperature decreases high-speed, but not total distance, in international field hockey. *Temperature.* 2021;1–16. doi:10.1080/23328940.2021.1997535.
- [18] Jay O, and Brotherhood JR. Occupational heat stress in Australian workplaces. *Temperature.* 2016;3(3):394–411. doi:10.1080/23328940.2016.1216256.
- [19] Razak AMY. 14 - Power augmentation. In: Razak AMY, editor. *Industrial gas turbines.* Sawston, United Kingdom: Woodhead Publishing; 2007. p. 376–408.
- [20] Camuffo D. Chapter 2A - theoretical grounds for humidity. In: Camuffo D, editor. *Microclimate for cultural heritage.* 2nd ed. Boston: Elsevier; 2014. p. 49–76.
- [21] Suping Z, Guanglin M, Yanwen W, et al. Study of the relationships between weather conditions and the marathon race, and of meteorotropic effects on distance runners. *Int J Biometeorol.* 1992;36(2):63–68.
- [22] Kjellstrom T, Lemke B, Venugopal V. 1.12 - occupational health and safety impacts of climate conditions. In: Pielke RA, editor. *Climate vulnerability.* Oxford: Academic Press; 2013. p. 145–156.
- [23] Vanos JK, Thomas WM, and Grundstein AJ, et al. A multi-scalar climatological analysis in preparation for extreme heat at the Tokyo 2020 olympic and paralympic games. *Temperature.* 2020;7(2):191–214. doi:10.1080/23328940.2020.1737479.
- [24] Bessot N, Nicolas A, Moussay S, et al. The effect of pedal rate and time of day on the time to exhaustion from high-intensity exercise. *Chronobiol Int.* 2006;23(5):1009–1024.
- [25] Reilly T, Baxter C. Influence of time of day on reactions to cycling at a fixed high intensity. *Br J Sports Med.* 1983;17(2):128–130.
- [26] Deschenes MR, Sharma JV, Brittingham KT, et al. Chronobiological effects on exercise performance and selected physiological responses. *Eur J Appl Physiol Occup Physiol.* 1998;77(3):249–256.
- [27] Dalton B, McNaughton L, Davoren B. Circadian rhythms have no effect on cycling performance. *Int J Sports Med.* 1997;18(7):538–542.
- [28] Slovic P. Empirical study of training and performance in the marathon. *Res Q Exerc Sport.* 1977;48(4):769–777.
- [29] Deaneer RO, Carter RE, Joyner MJ, et al. Men are more likely than women to slow in the marathon. *Med Sci Sports Exerc.* 2015;47(3):607–616.
- [30] Brotherhood JR. Heat stress and strain in exercise and sport. *J Sci Med Sport.* 2008;11(1):6–19.
- [31] Brocherie F, Girard O, Pezzoli A, et al. Outdoor exercise performance in ambient heat: time to overcome challenging factors? *Int J Hyperthermia.* 2014;30(8):547–549.
- [32] Hopkins WG, Hewson DJ. Variability of competitive performance of distance runners. *Med Sci Sports Exerc.* 2001;33(9):1588–1592.
- [33] Ghasemi A, Zahediasl S. Normality tests for statistical analysis: a guide for non-statisticians. *Int J Endocrinol Metab.* 2012;10(2):486–489.
- [34] Fagerland MW. t-tests, non-parametric tests, and large studies—a paradox of statistical practice? *BMC Med Res Methodol.* 2012;12(1):78.
- [35] Thorndike RL. Who belongs in the family? *Psychometrika.* 1953;18(4):267–276.
- [36] Vihma T. Effects of weather on the performance of marathon runners. *Int J Biometeorol.* 2010;54(3):297–306.
- [37] Hargreaves M. Physiological limits to exercise performance in the heat. *J Sci Med Sport.* 2008;11(1):66–71.
- [38] Bergeron MF. Heat stress and thermal strain challenges in running. *J Orthop Sports Phys Ther.* 2014;44(10):831–838.
- [39] Kenefick RW, Chevront SN, Sawka MN. Thermoregulatory function during the marathon. *Sports Med.* 2007;37(4):312–315.
- [40] Shi X, Zhu N, Zheng G. The combined effect of temperature, relative humidity and work intensity on human strain in hot and humid environments. *Build Environ.* 2013;69:72–80.
- [41] Kenefick RW, Sawka MN. Heat exhaustion and dehydration as causes of marathon collapse. *Sports Med.* 2007;37(4):378–381.

- [42] Montain SJ, Ely MR, Chevront SN. Marathon performance in thermally stressing conditions. *Sports Med.* 2007;37(4–5):320–323.
- [43] Alvarez-Ramirez J, Rodriguez E. Scaling properties of marathon races. *Phys A.* 2006;365(2):509–520.
- [44] Alvarez-Ramirez J, Rodriguez E, Dagdug L. Time-correlations in marathon arrival sequences. *Phys A.* 2007;380:447–454.
- [45] De Freitas CR, Dawson NJ, Young AA, et al. Microclimate and heat stress of runners in mass participation events. *J Clim.* 1985;24(2):184–191.
- [46] Wong P, Lai P-C, Hart M. Microclimate Variations between semienclosed and open sections of a marathon route. *Adv Meteorol.* 2013;2013:1–10.
- [47] Périard JD, Racinais S. Performance and pacing during cycle exercise in hyperthermic and hypoxic conditions. *Med Sci Sports Exerc.* 2016;48(5):845–853.
- [48] Nybo L, Rasmussen P, and Sawka MN. Performance in the heat—physiological factors of importance for hyperthermia-induced fatigue. *Compr Physiol.* 2014;4:657–689.
- [49] James CA, Hayes M, and Willmott AGB, et al. Defining the determinants of endurance running performance in the heat. *Temperature.* 2017;4(3):314–329.
- [50] Haymes EM. Physiological responses of female athletes to heat stress: a review. *Phys Sportsmed.* 1984;12(3):45–59.
- [51] McNulty KL, Elliott-Sale KJ, Dolan E, et al. The effects of menstrual cycle phase on exercise performance in eumenorrheic women: a systematic review and meta-analysis. *Sports Med.* 2020;50(10):1813–1827.
- [52] Mee JA, Gibson OR, Doust J, et al. A comparison of males and females' temporal patterning to short- and long-term heat acclimation. *Scand J Med Sci Sports.* 2015;25(S1):250–258.
- [53] Gagnon D, Kenny GP. Sex differences in thermoeffector responses during exercise at fixed requirements for heat loss. *J Appl Physiol.* 2012;113(5):746–757.
- [54] Lei T-H, Stannard SR, Perry BG, et al. Influence of menstrual phase and arid vs. humid heat stress on autonomic and behavioural thermoregulation during exercise in trained but unacclimated women. *J Physiol.* 2017;595(9):2823–2837.
- [55] Joyner MJ, Coyle EF. Endurance exercise performance: the physiology of champions. *J Physiol.* 2008;586(1):35–44.
- [56] Budd GM. Wet-bulb globe temperature (WBGT)—its history and its limitations. *J Sci Med Sport.* 2008;11(1):20–32.
- [57] Winger JM, Dugas JP, Dugas LR. Beliefs about hydration and physiology drive drinking behaviours in runners. *Br J Sports Med.* 2011;45(8):646.
- [58] Arrese AL, Ostáriz ES. Skinfold thicknesses associated with distance running performance in highly trained runners. *J Sports Sci.* 2006;24(1):69–76.
- [59] Maughan R, Shirreffs S. Exercise in the heat: challenges and opportunities. *J Sports Sci.* 2004;22(10):917–927.
- [60] Marriott BM, Marriott RW, Norris J. Nutritional Needs in hot environments: applications for military personnel in field operations. *J Med Primatol.* 1993;22(6):348–354.
- [61] Sawka MN, Leon LR, and Montain SJ, et al. Integrated physiological mechanisms of exercise performance, adaptation, and maladaptation to heat stress. *Compr Physiol.* 2011;1:1883–1928.
- [62] Lei T-H, Wang F. Looking ahead of 2021 Tokyo summer Olympic games: how does humid heat affect endurance performance? Insight into physiological mechanism and heat-related illness prevention strategies. *J Therm Biol.* 2021;99:102975.