International Journal of EXERCISE SCIENCE

Original Research

The Determinants of Marathon Performance: An Observational Analysis of Anthropometric, Pre-race and In-race Variables

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ABSTRACT

International Journal of Exercise Science 13(6): 1132-1142, 2020. Researchers investigating the determinants of marathon performance have previously focused on pre-race (e.g. training) or in-race (e.g. pacing) variables, but not both. This cross-sectional study, therefore, sought to elucidate the relationship between training behaviours, in-race pacing and anthropometric variables with eventual marathon finish time. A self-report questionnaire collecting athletes' anthropometrics, training behaviours and recent race times was administered to 260 participants in the 2018 Dublin Marathon. Participants' race numbers were cross referenced with in-race split times and finish times to determine their race performance. The accuracy or pragmatism of participants' target finish time was calculated using a 'predicted' time based on their training and previous race performances and subtracting this value from their eventual finish time. Multiple regression analysis examined the influence of age, body mass index (BMI), marathon experience, training history, target finish time pragmatism and in-race pace variance on marathon performance. The model was statistically significant and predicted marathon finish time $F(7,252) = 217.761$, $p < 0.0005$, adj. $R^2 = 0.858$. Marathon experience ($p = 0.01$, Beta = 0.06), a pragmatic target finish time ($p < 0.0005$, Beta = -0.36), training history ($p < 0.0005$, Beta = 0.76) and in-race pace variance ($p < 0.0005$, Beta = 0.26) made statistically significant contributions to the overall regression model. A marathoners' training history accounts for the greatest variance in their overall performance, followed by the pragmatism of their target finish time and their in-race pace variance. This study provides the first indication of the combined relative importance of anthropometric, training and pacing variables to marathon performance.

KEY WORDS: Running, endurance training, physical fitness, sports

INTRODUCTION

The marathon remains one of the most popular worldwide mass sporting events, with over 2.1 million global annual participants (4), a figure that has grown considerably in recent decades (36, 26). This increasing popularity has coincided with a greater number of recreational runners competing each year (2, 18, 22). As a result, a large body of research has sought to investigate the potential determinants of marathon performance, or 'finish time' (20). This research can be leveraged by runners and coaches alike to adapt and enhance their training and race strategies.

Traditionally, the determinants of marathon performance have been categorised to include: (1) anthropometrics (age, sex, height, weight and body mass index [BMI]), (2) training behaviours (such as average weekly running distance or average training pace), (3) previous race performances (such as a runner's 10km or half-marathon times) and (4) pacing. Variables such as weekly training volume (29), average training speed (5, 21, 29) and previous race times (3) explain between 23% and 66% of the variance in marathon performance. Similarly, advancing age (8, 12, 15, 32) and increasing BMI (6) are associated with slower finish times, while performance is also linked with in-race factors such as nutritional strategies (17) and pace variance (3). Indeed, studies have shown that, independent of sex and ability, the majority of marathoners adopt a positive pacing pattern, decreasing their speed in the second half of the race relative to the first (30). This reduction in speed coincides with a depletion of fuel (nutrition), increased perceived fatigue and greater effort to maintain a consistent pace (27), which is likely to lead to decreased performance (1). Therefore, pace variance is likely an important determinant of marathon performance (16), yet this not yet been included in prediction equations (20). Furthermore, a runner's self-selected target time may be primarily selected based on personal goals and ambitions. Whether a runner selects a realistic, pragmatic target time will influence their training, their pacing and, by association, their eventual finish time. However, to date, no study has investigated the pragmatism of a runner's target finish time on their marathon performance.

Whilst the relationship between these variables and marathon finish-time have been investigated independently, to date, no study has evaluated their combined relative contribution to marathon performance. Therefore, despite the volume of studies, a lack of clarity as to the precise determinants of marathon performance exists, and thus the recipe for success remains somewhat elusive. Furthermore, existing literature is limited by an over reliance on male runners, elite athletes, poorly reported measures of predictive accuracy, and an extensive range of variables (20).

An assessment of the combined contribution of all potential determinants of performance, would benefit runners and coaches seeking to enhance their performance. Therefore, the aim of this study was to analyse the relationship and relative contribution that pre-race determinants, pace variance and anthropometric characteristics have in determining marathon finish time. We hypothesized that anthropometric, pre-race factors (such as target time pragmatism, training history and previous race times) and in-race factors (specifically, pace-variance) would each explain some of the variance in marathon performance within a multiple regression model.

METHODS

Participants

Participants in this study were runners taking part in the 2018 Dublin Marathon. Excluding the participants recruited for this study, 16126 runners partook in the 2018 Dublin Marathon, the average finish time was 256 minutes (4 hours 16 minutes) +/- 50 minutes. Based on the publicly available race data (19), the mode finish time (i.e. the finish time that occurred most often across all race participants) was 238 minutes (3 hours 58 minutes). Participants were recruited using convenience sampling during the 2018 Dublin Marathon Exposition event (Expo). All runners intending to take part in the marathon were required to attend this event to collect their race number. The Expo took place during the two days preceding the race (26-27th October 2018). Data from 260 marathon runners (157 male & 103 female) aged between 19 and 75 was collected to be used for analysis. Participants under the age of 18 were not eligible to partake in the study. No other exclusion criteria existed.

Protocol

Data were collected via an open answer self-report questionnaire (Table 1). Included questions were based on previous research identifying their respective contributions to marathon performance: anthropometrics (including age, sex and BMI), training history and previous race times (including average weekly running distance, previous 10km race time, previous 10-mile race time, previous half-marathon race time and the number of previously completed marathons), and their self-reported race day target time.

This cross-sectional observational study was undertaken alongside the SSE Airtricity Dublin Marathon 2018 (28th October 2018). Ethical Approval was granted by the affiliate Review Board of the institution at which the authors are based (Reference: LS-17-77). This work adheres ethical guidelines of the journal (25).

The authors of this study had rented space at the Expo. Runners who approached the tent were asked if they would like to participate in the survey. In addition, members of the study team directly approached runners as they walked through the event and invited them to take part. The protocol and purpose of the research study was outlined to participants and informed verbal consent was garnered prior to data collection.

The Marathon started at 9:00 am on the 28th October 2018. The temperature during the race was between 3°C (9.00am) and 10°C (1.30pm). Wind conditions were northerly 11-17 km/h, humidity was at 76-87% with scattered clouds throughout. The course is reasonably flat taking runners through the centre of Dublin city.

Finish times for the 2018 Dublin Marathon were retrieved using the publicly available race data (19). Participants' race numbers were used to identify the respondents to the pre-race questionnaire so that their in-race splits and overall finish times could be extracted. The time in each split (10km, 21.1km, 30km, 42.2km) was normalised to the distance covered, such that each split could be compared for a distance of 10km. Specifically, the time spent in segment 2 was divided by 1.10975 (21.0975-10), in segment 3 was divided by 0.89025 (30-21.0975) and in segment 4 was divided by 1.2195 (42.195-30). Pace variance was then calculated as the standard deviation of the normalised split times.

To reduce data dimensionality and the redundancy of the pre-race determinants that were likely to be correlated, average weekly running distance, most recent half marathon time, most recent 10 mile race time and most recent 10km race time were used to calculate a 'prediction time' for each marathoner using the equations described by Vickers and Vertosick (35). This collapsed these multiple training variables into a single variable ('predicted finish time'), which was considered for input into our regression model. The pragmatism of each marathoner's target time was then determined by subtracting their predicted time from their self-reported target time (in minutes); negative values represented marathoners who's predicted finish times were slower than their target times.

The final list of variables for potential inclusion in the multiple regression analysis included each marathoner's pace variance of their normalised split times during the race, their predicted finish time, the difference between their target and predicted finish times, their anthropometrics (age, sex and BMI) and their marathon experience.

Table 1. Questionnaire implemented with participants.

Questions
What is your race number?
Male or female?
What is your age?
What height are you?
What weight are you?
How many marathons have you previously completed?
What is your best previous marathon finish time?
What is your target finish time?
Can you tell me your pacing plan for race-day?
What is the average number of kilometers you run per week?
What was the maximum distance you covered in a week in the previous 8 weeks?
What was the minimum distance you covered in a week in the previous 8 weeks?
What is the longest run you preformed during training for this race?
What is your best 5km time?
What is your best 10km time?
What is your best 10-mile time?
What is your best half-marathon time?
How many days have you been injured during training?

Statistical Analysis

To prepare the predictor variables for preliminary testing, the dataset was first filtered to remove participants who did not finish within 10% of their reported target time. This method of filtering was employed to reduce the potential heterogeneity of the data sample and prevent the potential prediction inaccuracy associated with including participants who may have sustained injury or illness during the race. Such events are difficult to control for experimentally, and thus, our attempt to limit the variability of the included sample was deemed appropriate. This process resulted in the exclusion of 59 subjects from the regression analysis (leaving 200 in total).

Following data aggregation, 8% of the dataset for the dependent variables were found to be missing. Missing cases arose in instances where it was not possible to calculate the dependent variable of interest (for instance, predicted finish time could not be calculated if participants did not know a 5km, 10km, 10-mile or half marathon race time). To accommodate missing data values, a multiple imputation procedure was implemented. A chi-squared statistic ['Little's

Missing Completely at Random (MCAR) test'] was utilised to determine whether values were MCAR and therefore suitable for imputation. The Little's MCAR test obtained a chi-square value of 23.058 ($p = 0.235$), indicating that the data were indeed missing at random (i.e., no identifiable pattern exists to the missing data) and suitable for imputation. The multiple imputation method adopted here is based on data augmentation (31). Five imputations were obtained giving an efficiency of 99% compared to using an infinite number of imputations (28). After imputation, a representative missing data value was calculated as per Rubin's rules (28) as the average of estimates from each of the five MI data sets for that value. After imputation, outliers were identified via visual inspection of scatterplots. One outlier was identified and was deemed to be caused by measurement error and was therefore excluded from further analysis. Due to the hypothesis-confirming nature of our research aims, all outcomes (sex, age, BMI, marathon experience, predicted finish time, the difference between predicted finish time and target finish time and pace variance) were entered into a multiple regression analysis in one block to predict marathon finish time (in minutes). The *a-priori* p-value for the regression analysis was set at $p <$ 0.05. IBM SPSS Statistics 24 was used for all statistical analysis.

RESULTS

The characteristics of the respondents are presented in Table 2. Participant's normalised split times for each race segment is depicted in Figure 1.

Table 2. Participant characteristics.

	Mean	SD	Range
Age (yrs)	40	10	19 to 75
Height (m)	1.7	0.1	1.4 to 1.9
Body mass (kg)	72	11	45 to 108
BMI (kg/m2)	24.3	3.3	17.5 to 36.9
Marathon experience (N)	4.1	7.2	0 to 46
Predicted finish time (min)	252	40	167 to 382
Target time (min)	248	46	162 to 420
Predicted-Target time (min)	4	29	-105 to 191
Pace variance	4.7	4.6	0.14 to 32.28
Finish time (min)	259	51	169 to 427

Preliminary assumption testing for the multiple regression analysis revealed linearity as determined by partial regression plots and a plot of studentized residuals against predicted values. There was independence of residuals, as assessed by a Durbin-Watson statistic of 1.63. There was homoscedasticity as assessed by visual inspection of a plot of studentized residuals versus unstandardized predicted values. There was no evidence of multicollinearity, as assessed by tolerance values greater than 0.1. There were no studentized deleted residuals greater than +/- 3 standardized deviations, no leverage values greater than 0.2, and values for Cook's distance above 1. The assumption of normality was met, as assessed by a Q-Q plot.

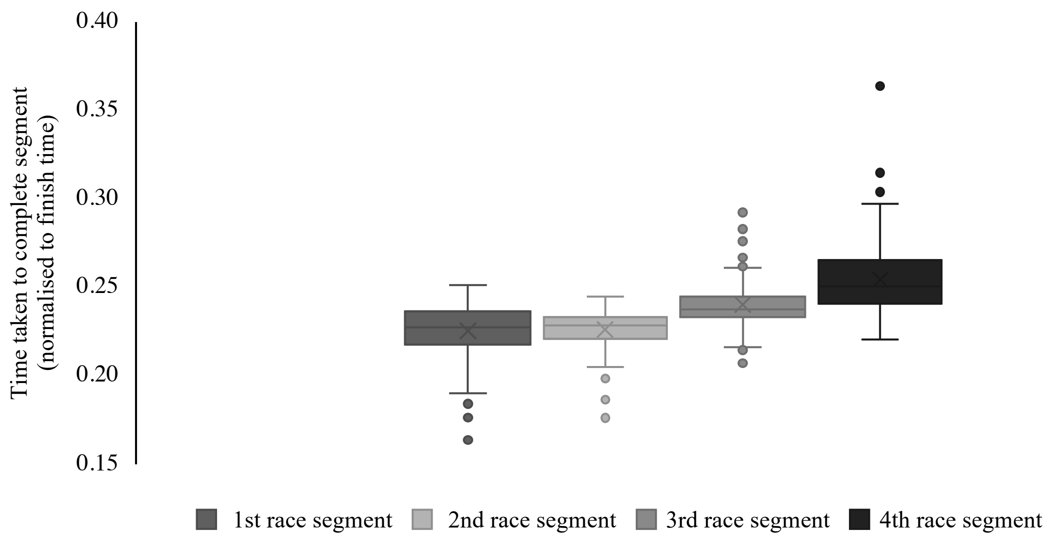

Figure 1. Participants normalized split times per race segment.

The multiple regression model was statistically significant, and predicted marathon finish time $F(7,252) = 217.761$, $p < 0.001$, adj. $R^2 = 0.858$. Marathon experience ($p = 0.01$, Beta = 0.06), a pragmatic target finish time ($p < 0.001$, Beta = -0.36), training history ($p < 0.001$, Beta = 0.76) and in-race pace variance ($p < 0.001$, Beta = 0.26) each made statistically significant contributions to the overall regression model. Regression coefficients and standard errors are presented in Table 3. The final prediction equation was:

Time(mins) = -5.252 + (0.162 x age) + (0.319 x BMI) + (0.451 x marathon experience) + (0.947 x Predicted finish time) + (-0.636 x Difference between predicted finish time and target finish time) + (2.925 x pace standard deviation) + (-3.232 x sex)

Table 3. Model outputs of multivariate analysis of significant anthropometric, pre-race and in- race variables.

Coefficients Model	Unstandardized coefficients		Standardized coefficients			95% Confidence intervals	
	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
(Constant)	-5.252	11.564		-0.454	0.65	-28.027	17.522
Age	0.162	0.127	0.033	1.276	0.203	-0.088	0.412
BMI	0.319	0.396	0.021	0.803	0.423	-0.462	1.099
Marathon Experience	0.451	0.181	0.064	2.49	0.013	0.094	0.808
Predicted Finish Time	0.947	0.04	0.757	23.842	0	0.868	1.025
DiffPredicted Target	-0.636	0.047	-0.36	-13.469	0	-0.729	-0.543
PaceStDev	2.925	0.303	0.264	9.654	0	2.329	3.522
Sex	-3.232	2.818	-0.031	-1.147	0.253	-8.783	2.318

DISCUSSION

The aim of this study was to analyse the relationship and combined relative contribution that pre-race determinants (through training and past performances), pace variance and anthropometric characteristics have in determining marathon finish time. Anthropometrics, training and pacing all uniquely explain some of the variance in marathon performance (R-squared = 0.858), albeit to different extents based on the semi-standardised beta weights. By incorporating an amalgamation of anthropometric, pre-race and pace variance factors, the resultant regression model provides a unique and novel insight into the determinants of marathon performance.

This study supports previous research in demonstrating that both training behaviours and previous race times are strong determinants of finish time. Indeed, these findings confirm those of a recent meta-regression, which highlighted that multiple training variables (for example number of runs >32km completed in the pre-marathon training block, average running pace during training and hours of running per week), are all associated with eventual finish time (11). However, while these specific variables were not included in the model of this study, each of them are highly correlated with a runner's average weekly distance, which was included in the model through the Vickers prediction equation. Therefore, this variable alone may account for a significant portion of marathon success. Indeed, even in non-academic writing, the widely recognised 'Theory of Collapse' suggests that the point in which runners break down in a race will be approximately one twentieth of their total mileage in the previous eight weeks (13). Though limited empirical data supporting the precision of this threshold exists, it is clear that runners need to carefully plan their training schedule to ensure that they reach their necessary mileage in a safe timeframe.

The strong predictive capacity of a formula derived from training behaviours and recent race performances may seem self-evident, however it may nonetheless be belied by marathoners with overly or underly-ambitious target times. Herein lies a strength of the current investigation, as to our knowledge, this is the first analysis to incorporate marathoners' target times within a prediction time. The analysis revealed that marathoners with disparate target and predicted times, or those who's target time was faster than their predicted time, were more likely to finish slower than those who did not (semi-standardized beta weight = -0.36). Marathoners with target times for which they have not trained adequately to achieve, likely pace their race incorrectly resulting in significant slowing during the latter stages of the race and slower associated finish times (33). The strength of the relationship between training behaviours, previous race performances and eventual finish time assumes that marathoners' target times are realistic, however these variables are likely to be related. This assumption is corroborated in the current analysis, whereby experience was associated with faster finish times (semi-standardized beta weight = 0.06). Pacing, by extension, would likely be more even in this group, and this was confirmed in the current analysis, whereby lower pace variance over the four normalised race splits was associated with faster finish times (semi-standardized beta weight = 0.26).

Pacing is another modifiable variable of performance and various pacing strategies have been investigated for improving finish time. Santos-Lozano et al., illustrated that even-split pacing (or less pace variance) was associated with faster finish times (30), which is in agreement with our findings. "Hitting the wall" is a phenomenon that often occurs during long-duration endurance events and is associated with high levels of perceived exertion. Hitting the wall is associated with a significant slowdown in running pace (7, 34). Training, previous race-times, a marathoner's target time and their eventual pacing are all likely to be interdependent; to the authors' knowledge, this is the first analysis to formally define their relationship, and we would conjecture that appropriate training, a realistic target time and aiming for minimal pace variance on race-day are likely to reduce the potential for hitting the wall occurrence, thus maximising performance potential.

A further strength of this study was the inclusion of sex in the model, as previous research has focused on male runners (11). It has been shown that men and women perform differently during race events (33, 10) a difference attributed to both physiological (10) and psychological (9) factors. For example, it has been suggested that men are motivated by status and outcome, whereas women will persevere when social support is either provided to them or required by them. The suggestion therefore is that women run more even races because they are motivated by different factor compared to their male counterparts. However, this traditional view of sex differences is perhaps too simplistic. Additionally, it is suggested that a lower BMI is beneficial to finish time due to a lower mass and the likely associated higher training volumes that are seen in runners with a lower BMI (14). Interestingly however, neither sex nor BMI made a significant contribution to the regression model. When pacing variance and pre-race variables are considered together, it appears that these more easily modifiable variables diminish the influence of both sex and BMI.

Despite these strengths, this study is not without limitations. First, the results were derived from a single marathon, thus their external validity is not clear. Environmental factors such as the temperature and altitude have demonstrated an association with marathon finish time in the literature (23, 24), however, this study cannot elucidate the influence of such factors, due to the logistical and resource demands of conducting a multi-marathon study. Nonetheless, given that the conditions on the day were not 'extreme' in terms of temperature, humidity or wind strength, the environment is unlikely to have significantly influenced performances. Secondly, the precision of the estimate of pace variance may have been compromised. It was not possible for us to confidently ascertain whether any athlete finished the race without being affected by a range of performance limiting events such as illness, injury, poor race execution, a fall, or any other event that would bely suitable data aggregation. However, as all participants were planning on running within 48 hours following recruitment, it was reasonable to assume that no significantly debilitating injuries or illnesses existed. Additionally, runners who finished 10% slower than their reported target time were excluded from the final analysis in an attempt to acknowledge the potential for this to occur. Finally, although the sample size of 200 runners may initially appear small, it is in line with all previously published prediction research (20). Furthermore, the heterogeneity of the participants should be seen as a positive given the previously highlighted limitations of prediction research which has focused on elite, male runners (20). Nonetheless, this model is best suited to recreational runners due to the profile of the participants recruited in this research.

Coaches and runners, both male and female, may utilise the results of this study to plan their marathon strategy in line with the relative contribution that training variable and pace variance have been shown to have in this study. Previously, a lack of research combining anthropometric, training variables and pace variance resulted in a sustained lack of clarity regarding marathon performance. This study is the first to bridge that gap by evaluating the determinants of finish time in a cohort of male and female recreational marathon runners.

In summary, a marathoners' training history accounts for the greatest variance in their overall performance, followed by the pragmatism of their target finish time and their pace variance. This research seeks to guide and inform recreational runners on the predictive value associated with modifiable performance variables, thus placing finish time firmly in the hands of the individual. With pacing highlighted as a primary determinant of marathon finish time, future research should investigate pacing interventions within a variety of marathon courses.

ACKNOWLEDGEMENTS

This Research is funded by the European Regional Development Fund (ERDF) under Ireland's European Structural and Investment Funds Programmes 2014-2020, as part of the RunAId (Pace-Man) project.

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