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Prediction equations for marathon performance: A systematic review

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Abstract

Purpose: Despite the volume of available literature focusing on marathon running and the prediction of performance, no single prediction equations exists that is accurate for all runners of varying experiences and abilities. Indeed the relative merits and utility of the existing equations remains unclear. Thus, the aim of this study was to collate, characterise, compare, and contrast all available marathon prediction equations.

Methods: A systematic review was conducted to identify observational research studies outlining any kind of prediction algorithm for marathon performance.

Results: Thirty-six studies with 114 equations were identified. Sixty-one equations were based on training and anthropometric variables, while 53 equations included variables that required laboratory tests and equipment. The accuracy of these equations was denoted via a variety of metrics; r^2 values were provided for 68 equations (r^2 = 0.10 to 0.99), while a standard error of the estimate was provided for 19 equations (SEE 0.27-27.4 minutes).

Conclusion: Heterogeneity of the data precludes the identification of a single 'best' equation. Important variables such as course gradient, sex, and expected weather conditions were often not included, while some widely used equations did not report a r_2 value. Runners should therefore be wary of relying on a single equation to predict their performance.

Keywords: marathon; prediction; performance; running; training

INTRODUCTION

'*Prediction is very difficult, especially about the future'*. These words from Danish writer Robert Peterson highlight not only why prediction equations are problematic, but also the biggest question facing most athletes of any kind prior to competition; 'How will I do?'. This is especially pertinent for the 2.1 million people who run the marathon footrace each year[1], a figure that has grown exponentially in the last 50 years[2]. The majority of this growth has come from an increase in non-elite recreational runners who participate in the marathon for a variety of reasons including health, fundraising, or a sense of personal achievement[3,4], as the marathon remains one of the foremost symbols of a runner's endurance capabilities. Many novice runners lack the knowledge and experience to optimally prepare for the marathon and rely on heavily of third-party advice (clubs, apps, experts) to ensure that they adequately prepare for their race. One important judgement that novice runners in particular struggle with is predicting their likely finish-time, which is important in order for them to judge their pacing and maximise the likelihood that they will finish safely[5]. Getting their finish-time wrong can have real consequences: too conservative and a runner may feel disappointed with their race while too ambitious a time may see them 'hitting the wall' and struggling to finish.

Recent research into marathon performance has demonstrated how too fast a start is likely to result in a slower finish, while conservative pacers will speed up at the end of the race, and may not reach their full potential[6]. To avoid this, runners may use predictive equations as a guide in order to help them to set a target, devise a training plan, monitor their progress, and review their finish times if required. One of the first freely available prediction equations was published in a 1973 edition of Runner's World Magazine[7]. Paul Slovic provided a series of anthropometric and training variables which could be used by elite and recreational endurance runners to identify a realistic target finish time[7]. The availability of this system empowered runners to more accurately judge their likely finish time, and by association, allowed them to plan a pacing strategy to meet this predicted target[7] in an attempt to avoid 'Hitting the Wall'. However, no accuracy results were presented alongside this system, thus, while it was an innovative and promising tool for its time, its utility was unclear.

Since then, a range of equations have been developed in an attempt to most accurately predict marathon finish times in a manner that is cost-effective and simple to understand[8]. Specifically, two methods of prediction have been employed. The first is based on observational studies whereby runners' ages, sex, backgrounds and training histories are correlated with marathon finish time, and prediction equations are developed using linear regression models[9]. In addition laboratory tests may be implemented to measure physiological variables, such as maximum volume of oxygen (VO_2max), and are associated with higher prediction accuracies[10], however most recreational runners do not have access to the expensive equipment, or the necessary expertise needed to complete this level of testing[8]. The second method produces prediction equations through a power law which extrapolates a relationship between different race distances, finish times and future races at different distances[9]. This approach models historical performance in a prudent manner as predictions are based on data gathered from other runners with similar performance abilities in the same distance (e.g. 10km race, half-marathon etc.). However, though this may be accurate for elite runners, the SEE is once again high for recreational runners, while the accuracy of the prediction decays over time, unless the runner continually updates the equations with their most recent performance variables.

Therefore, despite the increasing availability of large datasets for this population, to date, no single prediction equation has proven to be accurate for all runners of varying abilities and experience. Additionally, equations may need to be identified as accurate for specific sub-cohorts. Identifying which prediction equation is most suitable for runners depending on their experience or other factors may be of significant value to the athlete seeking to identify a realistic marathon finish time around which they can devise a suitable pacing strategy to achieve this time. Consequently, the aim of this study was to conduct a systematic review of non-interventional studies which sought to develop marathon prediction equations in different cohorts of runners, and collate these equations for the benefit of prospective marathon participants and coaches.

MATERIALS AND METHODS

Design

The protocol for this review was not deemed eligible for registration in PROSPERO as it related primarily to athletes and athletic performance (14/09/2018). This review was performed in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement. The available literature was systematically searched for observational research studies outlining prediction equations and/or power laws for marathon footrace (42.2km) performance time. Specifically, studies were included if they proposed a formula of any kind that can be used to predict a marathon time based on clearly definable input parameters, or if they developed a prediction formula modelled on participants who were not subjected to an intervention as part of the experimental protocol that could affect their marathon performance. Studies were excluded if they were not published in English, if they included injured or impaired participants, and if they did not take place on marathon distances. Both published and unpublished trials were eligible for inclusion if data were available.

Methodology

In January 2019, a computerized literature search of the following databases from inception was completed: PEDro, PubMed, Scopus and SPORTDiscus. The database search was further supplemented with a single related-citation search on PubMed (National Centre for Biotechnology Information, U.S. National Library of Medicine. Home page: http://www.ncbi.nlm.nih.gov/pubmed. Accessed October 2018). The search strategy was constructed for Medline and completed in a stepwise manner using the Boolean operators as follows: marathon OR long distance run* OR endurance run*, AND, predict* OR equation* OR math* OR formul* OR calculate* OR determin*, AND, performanc* OR pac* OR "finish time" OR speed OR velocity. The search strategy was adapted for each database. No restrictions (including time and language) were applied in any of the databases when the search was completed. The following grey literature databases were also searched: Open Grey (http://www.opengrey.eu/), Runner's World Magazine (https://www.runnersworld.com/) and Road Runner's Club (http://www.rrca.org/).

Two authors (X and X) reviewed all titles and abstracts and obtained the full texts of potentially eligible trials. Following this, the same two authors read full-text content and independently assessed eligibility by applying the inclusion criteria described previously. In instances of disagreement, a consensus meeting was organised with the wider author group.

A standardised data extraction sheet was used by two authors (X and X) to power law models and/or prediction equations, and their associated accuracies, from the included studies. Additionally, the following data were extracted for each study: design, sample characteristics, protocol, outcomes, findings and descriptive anthropometric/training/performance inputs relevant to the prediction equation(s) described.

Two reviewers (X and X) independently assessed the quality of the included studies. An adapted version of the STROBE guidelines was developed for rating observational studies (11). The adapted form was developed by group consensus to improve rating specificity for the profile of studies that were expected to be identified via the search strategy. All included studies were rated on nine specific criteria which were derived from the original checklist; 1) title includes description of study, 2) aims and objectives stated, 3) description of marathon, 4) details of sex of participants, 5) participants anthropometrics, 6) inclusion and exclusion criteria; 7) sufficient description of statistical analysis, 8) results reflective of methods, 9) any missing data explained/reported. Each item was scored as to be at low (+), high (–) or unclear (?) risk of bias. Studies were considered at low risk of bias when all domains were scored as low risk of bias or if one item was scored as high risk or unable to determine. If two domains were scored as high or unable to determine risk of bias, the study was considered at moderate risk of bias. Finally, when more than two domains were scored as high risk of bias, the study was regarded as being at high risk of bias. In case of disagreement between assessors, consensus was sought during a consensus meeting. If no consensus was reached, a third assessor (X) was asked to give a final verdict.

Statistical analysis

Meta-analysis was deemed inappropriate in the fulfilment of the primary experimental aim, which was to collate prediction equations for marathon performance time. Prediction equations were extracted from each study deemed eligible for inclusion in this review. Each prediction equation was contextualised by the sample used to generate it. Where available, standardised beta weights were extracted for each included variable within a prediction equation.

RESULTS

A total of 10872 articles were identified. Following the removal of duplicates, 10022 singular articles were found. After title and abstract selection 96 articles were selected for full-text evaluation (Figure 1), of which 36 met the inclusion criteria[8, 10, 12-40].

The characteristics of the included studies are summarised in Table 1. Year of publication ranged from 1973 to 2017. Five studies were conducted between 1973-1979, 10 between 1980 and 1989, five between 1990 and 1999, two were completed between 2000 and 2009, while the remaining 13 were conducted from 2010 to date. Studies included an average of 113.8 participants (standard deviation [SD]= 179.6), ranging from elite marathon runners (20%; n=7), recreational runners (48.6%; n=17) or a mix of the two (25.7%; n=9). Two studies did not report the backgrounds or experience of the runners used within their analysis (5.7%). Of the total number of participants included in studies (n=3368), 75.8% (n=2554) were male and 24.2% (n=814) were female. The majority of the studies (71.4%; n=25) were prospective-cohort studies, nine were cross-sectional studies (25.7%), with one study using a hybrid design (2.9%).

Included equations and variables

Fifteen studies detailed a single equation (41.7%) while the majority (n=21; 58.3%) listed multiple equations, therefore a total of 114 equations in total were identified (Supplemental file 1). Of these, 61 equations were based variables that did not require laboratory-grade equipment or the expertise of a trained professional to measure (e.g. a time in a previous race, Body Mass Index; 53.5%), while 53 equations (46.5%) included tests that required either laboratory equipment, or a trained practitioner to help the runner measure them (e.g. VO_2max, skinfold thickness; Table 2). In total, 26 (22.8%) equations contained anthropometric variables, 67 (58.8%) equations contained training variables, 49 (43.0%) equations contained laboratory-based variables and 41 (36.0%) equations contained a previous race time variable (Figure 2; Table 2).

Within the reported equations, the level of prediction accuracy was conveyed for 68 equations (59.6%) via a r^2 value, ranging to 0.10 to 0.99, while 19 equations listed a SEE (16.7%), ranging from 0.27 to 27.4 minutes (Table 2). A total of 43 equations did not report any measure of accuracy for the prediction estimate (37.7%). Only three studies included standardised beta weights for each of their included variables[14, 22, 37].

A total of 50 independent variables were identified within the 114 equations (Table 3). Of these, 50% (n=25) required access to laboratory equipment or a skilled practitioner. Of the 50 identified variables, 11 (22%) were used in more than two studies, of which eight variables were based on a runner's training data or previous race performance data. Eighteen variables (36%) were used in single instances (i.e. in one equation and in one study). Of these single instance variables, 12 required either access to laboratory equipment or a trained practitioner to help measure them.

Study quality

The results of the quality assessment are presented in Table 4. Based on the modified STROBE scale, six studies were considered to be at a low risk of bias, six were at a moderate risk of bias, while the remaining 24 studies were at a high risk of bias, with scores ranging from one to nine. A majority of studies (63.9%, n=23,) did not outline the design of the study in the title or abstract, while 80.5% of studies did not provide adequate detail around potential 'missing data' (unclear risk of bias; n=29). Most studies (86.1%, n=31) provided adequate detail around the 'statistical analysis'.

DISCUSSION

This study aimed to identify and collate the available literature describing prediction equations and power law models for marathon performance. This review identified 114 independent equations across 36 different studies, with a wide variety of reported 'fit' ranging from r^2 values of 0.10 to 0.99. It was not possible to identify 'the best' equation due to the heterogeneity of participants and the variety of outcomes used. However, runners, coaches and researchers may use this list of equations contextually depending on the characteristics of the runner(s), and the tools available to them.

To the authors' knowledge, this is the first study to collate all available marathon prediction equations for marathon performance. With 114 equations containing 50 independent variables, it is clear that there are a wide variety of factors that may influence marathon performance. However, given the high error associated with these equations (as evidenced by the r^2 and SEM values), and the requirement of access to expensive laboratory equipment to measure input parameters of half of these variables, there is clear difficulty associated with marathon performance prediction. The wide variety of included variables, combined with the inconsistencies in what was reported about participants (i.e. their marathon experience, training histories, the sex-distribution of the sample), and (for some equations) the small sample sizes used, makes practical implementation of these equations difficult. Indeed, the lack of adequate reporting as to the type of runner that the equations were tested on (six studies did not report the sex of participants, while two did not report their experience), compounded this difficulty and precluded meta-analysis or meta-regression, in determining whether prediction accuracy was associated with some demographic of the studied sample, or a characteristic of the experimental report. Future studies that seek to validate existing, or produce further marathon equations therefore need to explicitly state the characteristics of their participants. In addition, a prospective validation of these equations in a wide variety of both runners and marathon courses is necessary to improve our understanding of the accuracy of these equations. Indeed the heterogeneity of the variables included in the predictive models precludes our ability to analyse which are predictive across various cohorts of runners, and which are predictive simply by chance.

This point is demonstrated by the fact that only 22% of the 50 variables identified within this review were used in more than two studies, while 36% were used in only one equation. Much of the research identified via this review was undertaken to advance theoretical understanding of the mechanistic underpinnings of marathon performance, without much consideration for the practical value this may have in the 'real-world'. While the importance of such research cannot be questioned, it is not surprising that the most commonly used variables primarily focused on training variables or previous race results, as they are simple to implement and collect irrespective of the experience of the runner, thus allowing larger samples of runners to use them, generating greater statistical power. However, just because a variable is commonly used does not mean that it is effective. Indeed, the use of previous performance and training characteristics often relies on self-report recall from runners, which is potentially associated with recall bias[41]. However, logs and diaries are frequently used to accurately determine exercise levels[42] and so this is unlikely to be a significant barrier to prediction. Nonetheless, the equations with the best 'fit' all contained variables that were measured in a laboratory setting (like blood lactate accumulation during exercise testing) albeit in very homogenous cohorts of runners (elites). While this would initially suggest that these parameters and their associated performance models effectively predict eventual marathon performance (with r_2 values higher than 0.9), that they were evaluated on a small number of elite runners (the largest sample of elite runners included in a study was 30) limits their external validity and likely artificially inflates the predictive value[43]. Indeed it is the authors' contention that it would be unlikely that laboratory metrics would explain as much variance in marathon performance in a more diverse, recreational cohort of athletes. Elite runners are likely to display similar characteristics when it comes to their anthropometrics, lifestyle and training habits, especially when compared to more recreational runners, thus they be more likely to demonstrate accurate predictions[44]. Therefore, while the advancement of the theoretical underpinnings of marathon research is important, the focus on a range of different, difficult to calculate characteristics in a homogenous group may not be helpful to a 'real-world cohort. Future prediction equations should perhaps aim to investigate whether sex, in-race variables such as pacing strategies, or the gradient of a marathon course, are important predictors to include. Previous research has identified a clear role for these factors in determining eventual performance[6,45,46], yet they remain unaccounted for in the equations identified through this review, however it must be acknowledged that they are challenging to control experimentally, and by association, to include within equations.

Due to the heterogeneity of the data, it is not possible to compare between equations. Indeed, the limitations of this work are heavily influenced by the limitations of previous research. For instance, the lack of reported standardised beta weights is a significant limitation of these equations as it precludes an assessment of which individual variables are strongly correlated with marathon finish time. The observed low r_2 values may be therefore be the result of variables that are not strongly correlated or, alternatively, variables that are unaccounted for within the models (e.g. sex; marathon course characteristics such as gradient). Future research should also consider the potential utility of aggregating 'weak', uncorrelated prediction equations to create more accurate predictions. For example, machine learning analysis uses 'ensemble learning'[47], a strategy in which the use of combination of multiple weak predictors may improve prediction accuracy more than any of the individual predictions. However, it should also be considered that those equations with high values may have lower predictive capacity when applied to more heterogenous groups of runners. In particular, the equations with high fit in elite runners, all used 30 participants or less, thus undermining whether these are representative samples of the wider population of elite and sub-elite runners. In addition, some of the most commonly used equations (e.g. Reigel) did not report either a SEE or a r_2 value, and so their validity is unknown despite its comprehensive use. Future studies therefore need to ensure that they test the accuracy of their equations on a wide variety of runners and with large numbers.

PRACTICAL APPLICATIONS

While this study is the first to collate all available marathon equations, it is limited by the lack of ability to perform a meta-analysis. Nonetheless, the results of this study have demonstrated some important information for runners to be aware of, including:

- Prediction equations should only ever be used as a guide for marathon participants.
- The limitations of these equations are likely to result in practically relevant rates of error that runners should be wary of. For instance, an r-squared value of 80% for the runner targeting a 4-hour marathon is associated with a potential error of +/-24 minutes, resulting in a potentially large window in which runners may finish.
- As a result, runners, or their coaches, should consider using a variety of equations to best evaluate their most likely performance.
- Specifically, combining multiple, weaker, uncorrelated prediction equations may help coaches and athletes to identify the most accurate set of predictors, or a more accurate set than any of the individual equations.

CONCLUSIONS

A diverse range of prediction equations exist within the field of marathon running. The result of this diversity is a lack of clarity as to what variables work best and for whom. As a result, it is difficult, to be definitive as to which equation, or group of equations, are most useful, as previous research has focused on advancing the theoretical underpinnings of marathon prediction than the development of a better predictor. Consequently, runners and coaches should utilise a number of different equations in order to come up a 'window' of prediction that may best reflect their ability.

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DECLARATION OF INTEREST

The authors confirm that they have no conflicts of interests to declare.

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Table 1: Characteristics of the included studies

Study	Year	Study design	Cohort studied	Participants (n=)	Gender^
Bale et al.,	1985	Cross-sectional	Elite and recreational marathon runners	36	M=0; F=36
Barandun et al.,	2012	Prospective	Recreational marathon runners	126	M=126; F=0
Billat et al.,	2001	Prospective	Elite marathon runners	20	M=10; F=10
Brown et al.,	2016	Cross-sectional	Recreational marathon runners	185	M=0; F=185
Davies et al.,	1979	Cross-sectional	Elite marathon runners	22	M=13; F=9
Di Prampero et al.,	1986	Prospective	Recreational marathon runners	36	M=36; F=0
Dotan et al.,	1983	Prospective	Elite and recreational marathon runners	16	NR
Emerick et al.,	1997	Prospective	Recreational marathon runners	19	M=0; F=19
Florence et al.,	1997	Prospective	Recreational marathon runners	12	M=6; F=6
Fohrenbach et al.,	1987	Multiple study	Elite marathon runners	24	M=11; F=13
Foster and Daniels	1975	Prospective	Elite and recreational marathon runners	176	NR
Foster	1983	Prospective	Elite and recreational marathon runners	23	M=25; F=0
Franklin et al.,	1978	Prospective	Recreational marathon runners	124	M=124; F=3
Gianoli et al.,	2012	Prospective	Recreational marathon runners	81	M=81; F=0
Hagan et al.,	1981	Prospective	Experienced and recreational marathon runners	50	M=50; F=0
Hagan et al.,	1987	Prospective	Experienced and recreational marathon runners	35	M=0; F=35
Haney et al.,	2011	Cross-sectional	Recreational marathon runners	285	NR
Karp et al.,	2007	Cross-sectional	Elite marathon runners	93	M=37; F=56
Legaz Arrese et al.,	2016	Cross-sectional	Elite marathon runners	18	M=10; F=8
Mckelvie et al.,	1985	Prospective	Recreational marathon runners	126	M=105; F=21
Noakes et al.,	1990	Prospective	Not reported	28	NR
Riegel et al.,	1981	Cross-sectional	Elite runners (mixed distance)	NR	NR
Rust et al.,	2012	Prospective	Recreational marathon runners	126	M=126; F=0
Salinero et al.,	2017	Prospective	Recreational marathon runners	84	M=84; F=0
Schmid et al.,	2012	Prospective	Recreational marathon runners	29	M=0; F=29
Slovic et al.,	1973	Cross-sectional	Elite and recreational marathon runners	184	M=178; F=6
Slovic et al.,	1977	Prospective	Elite and recreational marathon runners	359	M=359; F=0
Takeshima et al.,	1995	Prospective	Recreational marathon runners	51	M=51; F=0
Tanaka et al.,	1984	Prospective	Elite marathon runners	12	M=12; F=0

Tanaka et al.,	1990	Cross-sectional	Recreational marathon runners	48	M=48; F=0
Tanda & Knechtle	2013	Prospective	Recreational marathon runners	126	M=126; F=0
Tanda & Knechtle	2015	Prospective	Recreational marathon runners	126	M=126; F=0
Till et al.,	2016	Prospective	Recreational marathon runners	40	M=28; F=12
Vickers et al.,	2016	Prospective	Elite and recreational runners (mixed distance)	1022	M= 656; F= 366
Williams	2018	Not reported	Elite and recreational runners (mixed distance)	1000	NR
Zillmann et al.,	2013	Prospective	Not reported	126	M = 126; F= 0

^: M=male; F= female; NR= not reported

Table 2: Commonly reported variables per equation

Study	Anthropometric variable	Laboratory based variable	Training variable	Race time variable
Bale et al.,	x	x	√	x
	√	x	√	x
	√	x	√	x
Barandun et al.,	√	x	√	x
Billat et al.,	x	x	√	x
	x	√	x	x
	x	x	√	x
Brown et al.,	√	x	x	x
Davies et al.,	x	√	x	x
DiPrampero et al.,	x	√	x	x
	x	√	x	x
	x	√	x	x
	x	√	x	x
	x	√	x	x
Dotan et al.,	√	√	√	x
Emerick et al.,	x	√	x	x
	x	√	x	x
	x	√	√	x
Florence et al.,	x	√	x	x
	x	√	x	x
	x	√	x	x
Forenbach et al.,	x	√	x	x
	x	√	x	x
	x	√	x	x
	x	√	x	x
	x	√	x	x
	x	√	x	x
	x	√	x	x
	x	√	x	x
	x	√	x	x
Foster & Daniels	x	√	√	x
	x	√	√	x
	x	√	x	x
Foster	x	√	x	x
Franklin et al.,	x	x	√	x
	x	x	√	x
	x	x	√	x
Gianoli et al.,	√	x	√	x
Hagan et al.,	x	x	√	x
	x	√	√	x
	√	√	√	x

	√	√	√	x
	√	√	√	x
	x	√	x	x
	x	√	√	x
	x	√	√	x
	x	√	√	x
Hagan et al.,	x	x	√	x
	√	x	√	x
	x	x	√	x
Haney et al.,	x	√	x	x
	x	√	x	x
Karp et al.,	x	x	√	x
Legaz Arrese et al.,	x	√	x	x
	√	√	x	x
McKelvie et al.,	x	√	√	√
Noakes et al.,	x	√	x	√
	x	√	x	√
	x	√	x	x
	x	√	x	x
Riegel et al.,	x	x	x	√
Rust et al.,	√	x	√	x
Salinero et al.,	√	x	x	√
	√	x	x	√
Schmid et al.,	√	x	√	x
Slovic et al.,	x	x	x	√
	x	x	√	√
	x	x	√	√
	x	x	√	√
	√	x	√	√
	√	x	√	x
	√	x	√	x
	√	x	√	x
Slovic et al.,	x	x	√	√
	x	x	√	√
	x	x	√	√
	x	x	√	√
	√	x	√	√
	√	x	√	√
	x	x	√	√
Takeshima et al.,	x	√	x	x
	√	√	√	x
	√	x	√	x
Tanaka et al.,	x	√	x	x
	x	√	x	x
Tanaka et al.,	√	√	x	x

Tanda & Knetchle	√	x	√	x
Tanda & Knetchle	√	x	√	x
Till et al.,	x	x	x	√
Vickers et al.,	x	x	x	√
	x	x	√	√
	x	x	√	√
	x	x	√	√
	x	x	√	√
	x	x	√	√
	x	x	√	√
	x	x	√	√
	x	x	√	√
	x	x	√	√
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	x	x	√	√
	x	x	√	√
	x	x	√	√
	x	x	√	√
	x	x	√	√
	x	x	√	√
	x	x	√	√
Williams	x	x	x	√
Zillman et al.,	√	x	√	x

Table 3: Variables included in the equations based on their frequency of use

Variable	Frequency (n=number of studies; %)	Frequency (n= number of equations)
Previous race result	10 (27.8%)	40 (35.1%)
Average workout/training pace	10 (27.8%)	15 (13.2%)
VO_2max	8 (22.2%)	20 (17.5%)
Age	7 (19.4%)	20 (17.5%)
Average weekly distance	6 (16.7%)	28 (24.6%)
Body fat %	6 (16.7%)	7 (6.1%)
Total miles within the last 8 or 9 weeks	4 (11.1%)	12 (10.5%)
Previously completed marathons	3 (8.3%)	15 (13.2%)
Longest training run	3 (8.3%)	13 (11.4%)
Maximal distance covered per week	3 (8.3%)	7 (6.1%)
Skin folds (any site)	3 (8.3%)	3 (2.6%)
Number of workouts (in a timeframe)	2 (5.6%)	7 (6.1%)
Ponderal index	2 (5.6%)	4 (3.5%)
Body Mass Index	2 (5.6%)	2 (1.8%)
Duration of workouts (minutes)	2 (5.6%)	2 (1.8%)
Mean distance per day/workout	2 (5.6%)	2 (1.8%)
Years training	2 (5.6%)	2 (1.8%)
Velocity at various blood lactate levels	1 (2.8%)	9 (7.9%)
Number of runs above 32km	1 (2.8%)	4 (3.5%)
Velocity at lactate turnpoint	1 (2.8%)	4 (3.5%)
Number of days of workouts (in a timeframe)	1 (2.8%)	3 (2.6%)
Number of sessions per week	1 (2.8%)	3 (2.6%)
Critical velocity	1 (2.8%)	2 (1.8%)
Coefficient of variation of running velocity during the marathon	1 (2.8%)	2 (1.8%)
Difference in VO_2 between baseline and lactate increase	1 (2.8%)	2 (1.8%)
Ectomorphy	1 (2.8%)	2 (1.8%)
Energy cost of running	1 (2.8%)	2 (1.8%)
Lactate concentration at turnpoint	1 (2.8%)	2 (1.8%)
Maximal sustainable fraction of VO_2max	1 (2.8%)	2 (1.8%)
Velocity where lactate goes above baseline	1 (2.8%)	2 (1.8%)
Ventilatory threshold	1 (2.8%)	2 (1.8%)
VO_2max at Lactate Threshold	1 (2.8%)	2 (1.8%)
Annual training distance	1 (2.8%)	1 (0.9%)
Artherogenic Index	1 (2.8%)	1 (0.9%)
Breast mass	1 (2.8%)	1 (0.9%)
Calf circumference	1 (2.8%)	1 (0.9%)
Cortisol	1 (2.8%)	1 (0.9%)
Creatine phosphokinase	1 (2.8%)	1 (0.9%)
Days lost	1 (2.8%)	1 (0.9%)
Katsura Index	1 (2.8%)	1 (0.9%)
Lactate at specific velocity	1 (2.8%)	1 (0.9%)
Left ventricular telediastolic diameter	1 (2.8%)	1 (0.9%)
Max sustaining race speed	1 (2.8%)	1 (0.9%)
Peak treadmill velocity	1 (2.8%)	1 (0.9%)

Relative power output	1 (2.8%)	1 (0.9%)
Repression sensitisation	1 (2.8%)	1 (0.9%)
Ruffier test	1 (2.8%)	1 (0.9%)
Serrum ferritn	1 (2.8%)	1 (0.9%)
VO_2 peak	1 (2.8%)	1 (0.9%)
vVO_2max	1 (2.8%)	1 (0.9%)

Table 4: Risk of bias assessment

	1	2	3	4	5	6	7	8	9
Bale et al.,	-	+	+	+	+	?	+	+	?
Barandun et al.,	-	+	+	+	+	+	+	+	?
Billat et al.,	-	+	+	+	+	+	+	+	?
Brown et al.,	-	+	+	+	+	+	+	+	+
Davies et al.,	-	+	-	+	+	-	-	+	?
Di Prampero et al.,	-	+	+	+	+	-	+	+	?
Dotan et al.,	-	+	-	+	+	-	+	+	?
Emerick et al.,	-	+	-	+	+	+	+	+	?
Florence et al.,	-	+	+	+	+	?	+	+	?
Fohrenbach et al.,	+	+	+	+	+	-	+	+	?
Foster and Daniels	-	+	-	-	-	-	-	-	?
Foster	+	+	-	+	+	-	+	-	?
Franklin et al.,	-	+	+	+	-	+	-	+	+
Gianoli et al.,	+	+	+	-	+	-	+	+	?
Hagan et al.,	+	+	+	+	+	-	+	+	?
Hagan et al.,	+	+	+	+	+	+	+	+	?
Haney et al.,	-	+	+	-	-	-	+	+	+
Karp et al.,	-	+	-	+	+	?	+	+	?
Legaz Arrese et al.,	-	+	-	+	+	+	+	+	?
Mckelvie et al.,	+	+	+	+	+	+	+	+	+
Noakes et al.,	+	+	-	-	+	-	+	+	?
Riegel et al.,	-	-	-	-	-	-	+	+	?
Rust et al.,	+	+	+	-	+	-	+	+	?
Salinero et al.,	-	+	+	+	+	-	+	+	?
Schmid et al.,	-	+	+	+	+	+	+	+	?
Slovic et al.,	-	-	+	+	-	-	-	-	+
Slovic et al.,	-	-	+	+	+	+	+	-	?
Takeshima et al.,	-	+	-	+	+	-	+	-	?
Tanaka et al.,	-	+	-	+	+	-	+	+	?
Tanaka et al.,	+	+	-	+	+	-	+	+	?
Tanda et al.,	+	+	+	+	+	+	+	-	?
Tanda et al.,	+	+	+	+	+	+	+	-	?
Till et al.,	+	+	+	+	+	+	+	+	+
Vickers et al.,	-	+	+	+	+	+	+	+	+
Williams	-	-	-	-	-	-	-	-	?
Zillmann et al.,	+	+	+	+	+	+	+	-	?

1:Title includes description of study; 2: Aims and objectives stated; 3: Description of marathon; 4: Details of sex of participants; 5: Participants anthropometrics; 6: Inclusion and exclusion criteria; 7: Sufficient description of statistical analysis; 8: Results reflective of methods; 9: Any missing data explained/reported.

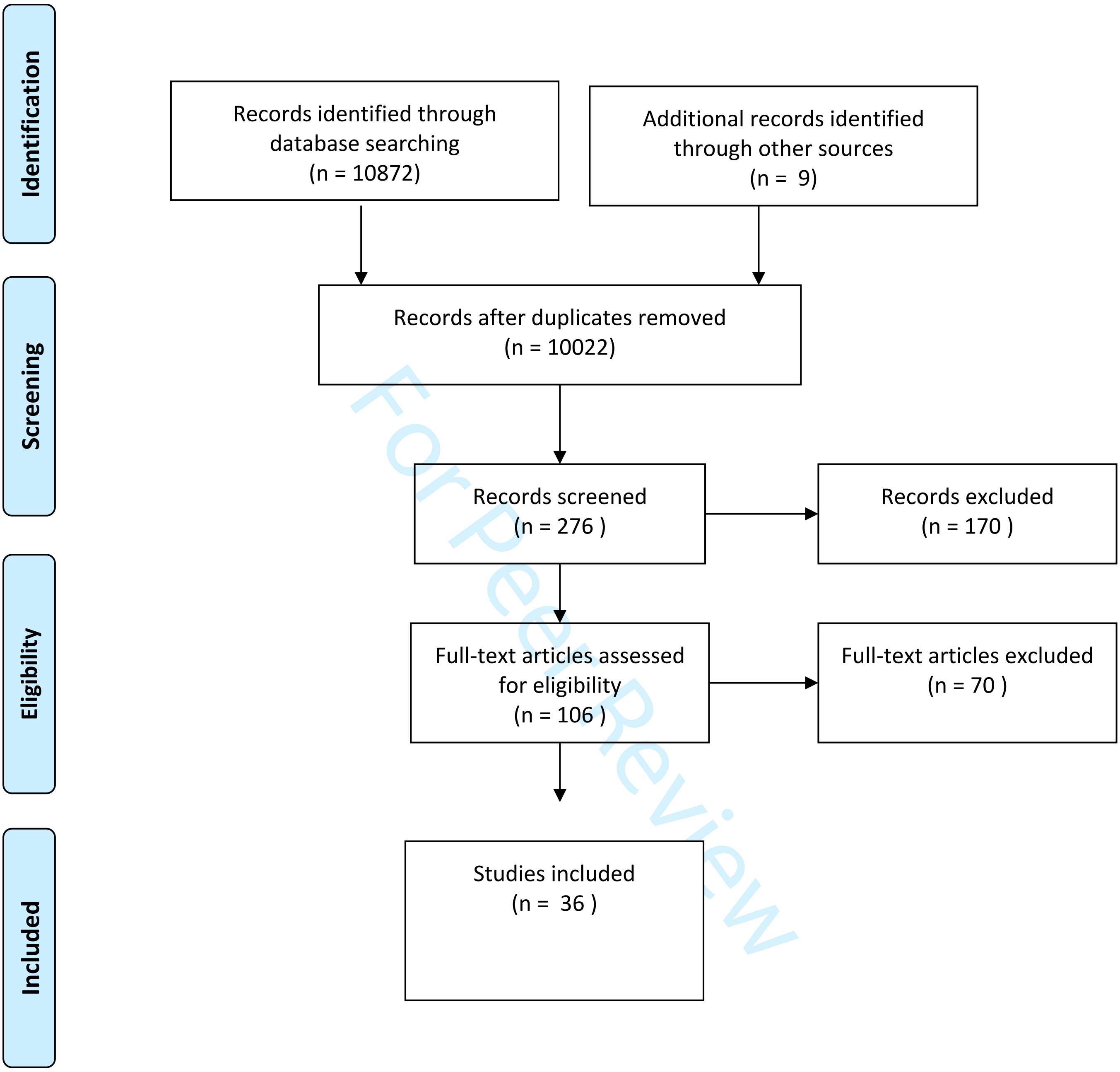

Figure 1: Flowchart of study selection within the systematic review

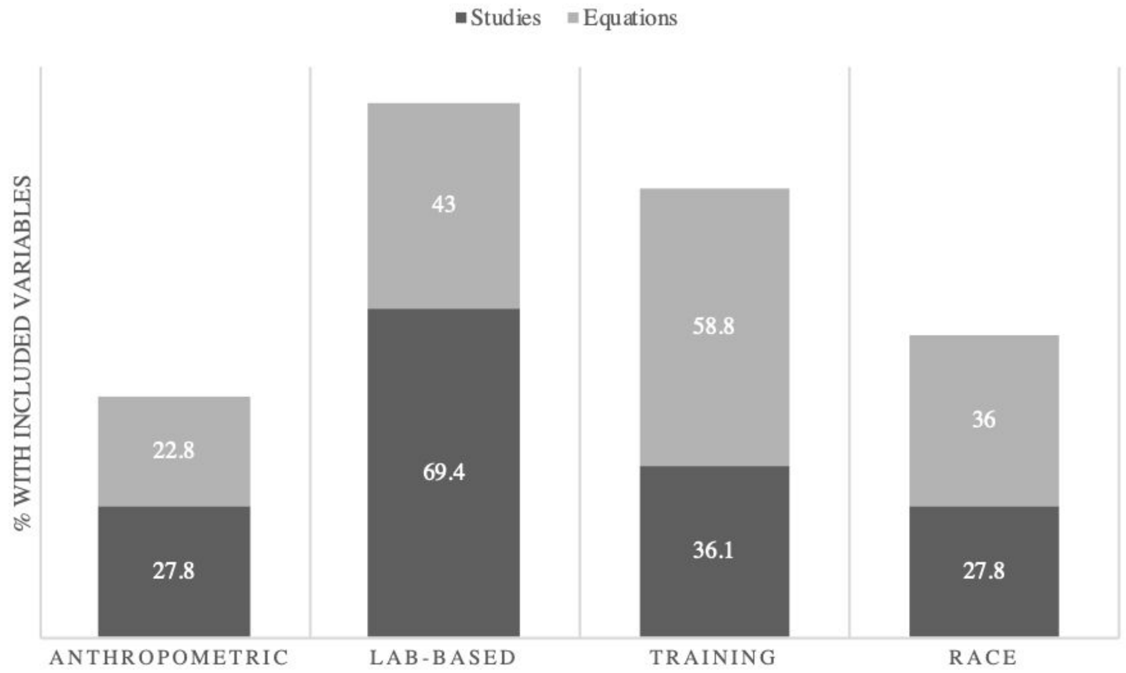

Figure 2: Categories of variables used in predictive equations

Table: Prediction equations and accuracy results

Study	**Prediction equation (Equation time in minutes unless specified)**	**Cohort studied[a]**	**R^2**	**Standard error of the estimate (in minutes)**
Bale et al.,	218.5 - 4.42*(sessions per week).	Females	0.39	14.2
	242.6 - 3.72*(sessions per week) - 7.02*(ectomorphy).	Females	0.52	12.9
	240.6 - 3.32*(sessions per week) - 6.05*(ectomorphy)-0.85*(years training).	Females	0.60	11.9
Barandun et al.,	326.3 + 2.394*(Body fat [%]) - 12.06*(Running speed in training [km.hour^{-1}])	Males	0.44	NR
Billat et al.,	278.4 - 6.63*(V1000)[b]	Mixed	NR	NR
	145.2 - 0.19*(VO_2max)	Males	NR	NR
	216.67 - 3.33*(V1000)[b]	Females	NR	NR
Brown et al.,	27 + 6.14*(BMI)[c] + 0.04*(breast mass [g]).	Females	0.28	NR
Davies et al.,	446.7 - 2.028*(VO_2max) - 1.818*(relative power output [%VO_2max])	Mixed	0.98	NR
Di Prampero et al.,	(Maximal fraction of VO_2max that can be sustained during the race [ml.kg^{-1}.min^{-1}])*(Energy cost of running [ml.kg^{-1}.km^{-1}])	Males	NR	NR
	42.195/((60/1000)*(1.15+0.044*[VO_2max]).	Males	0.52	NR
	42.195/((60/1000)*1.43(VO_2max [ml.kg^{-1}.min^{-1}])/(Energy cost of running per unit distance [mlO_2.kg^{-1}.km^{-1}]).	Males	0.63	NR
	42.195/((60/1000)*(0.79 + 0.0625*(maximal sustainable fraction of VO_2max)*VO_2max).	Males	0.58	NR
	42.195/((60/1000)*(1.12 + 0.643(maximal sustainable racing speed [m.sec^{-1}])).	Males	0.72	NR

Dotan et al.,	120.611 + 5.796*(subscapular skinfold [mm]) - 0.216*(annual training distance [km]) - 1.170 *(Age [yr]) + 3.757*(creatine phosphokinase, [SIGMA U.ml]$^{-1}$) - 3.078*(Cortisol levels)	NR	NR	6.83
Emerick et al.,	4.1*(VO_2max) + 456.3.	Females	0.55	22.9
	-0.86*(vVO_2max)[d] + 446.4.	Females	0.40	26.3
	-2.1*(weekly mileage) + 312.1.	Females	0.40	26.6
Florence et al.,	445.3 - 50.3*(Critical velocity)[e].	Mixed	0.76	14.1
	390.7 - 2.73*(VO_2peak)[f]	Mixed	0.51	20.1
	353.5 - 30.1*(Ventilatory threshold [m.sec^{-1}])[g]	Mixed	0.28	27.4
	443.5 - 78.9*(Critical velocity [m.sec^{-1}]) + 34.3*(Ventilatory threshold [m.sec^{-1}]).	Mixed	0.88	10.7
Fohrenbach et al.,	42.195/(0.27+1.02*(running velocity [m.s^{-1}] at a blood lactate concentration of 4mmol.l^{-1}))*60.	Females	0.88	NR
	42.195/(0.072+0.96*(running velocity [m.s^{-1}] at a blood lactate concentration of 3mmol.l^{-1}))*60.	Females	0.88	NR
	42.195/(0.47+0.889*(running velocity [m.s^{-1}] at a blood lactate concentration of 2.5mmol.l^{-1}))*60.	Females	0.88	NR
	42.195/(-0.529+1.073*(running velocity [m.s^{-1}] at a blood lactate concentration of 4mmol.l^{-1}))*60.	Males	0.98	NR
	42.195/(-0.416+1.08*(running velocity [m.s^{-1}] at a blood lactate concentration of 3mmol.l^{-1}))*60.	Males	0.99	NR
	42.195/(-0.25+1.067*(running velocity [m.s^{-1}] at a blood lactate concentration of	Males	0.99	NR

	2.5mmol.l^{-1}))*60.			
	42.195/(-0.389+1.046*(running velocity [m.s^{-1}] at a blood lactate concentration of 4mmol.l^{-1}))*60.	Mixed	0.98	NR
	42.195/(-0.456+1.09*(running velocity [m.s^{-1}] at a blood lactate concentration of 3mmol.l^{-1}))*60.	Mixed	0.98	NR
	42.195/(-0.375 + 1.09*(running velocity [m.s^{-1}] at a blood lactate concentration of 2.5mmol.l^{-1}))*60.	Mixed	0.98	NR
Foster and Daniels	335.5 - 2.65*(VO_2max [ml.kg^{-1}.km^{-1}]) - 0.014*(total miles run in an 8 week training block) - 2.38*(largest training run [miles]) + 0.16*(training pace [sec.mile^{-1}] for steady runs 3-10miles in length).	Males	NR	NR
	319.4 - 2.75*(VO_2max [ml.kg^{-1}.km^{-1}]) - 0.022*(total miles run in an 8 week training block) - 1.0*(largest training run [miles]) + 0.146*(training pace [sec.mile^{-1}] for steady runs 3-10miles in length))	Males	NR	NR
	387.3 - 3.45*(VO_2max [ml.kg^{-1}.km^{-1}])	Males	NR	NR
Foster	435.8 - 3.85*(VO_2max [ml.kg^{-1}.km^{-1}])	Males	0.91	11.01
Franklin et al.,	286.8 - 1.0*(training miles per week)	Males	0.17	NR
	256.9 - 0.78*(training miles per week)	Males	0.28	NR
	221.4 - 0.45*(training miles per week).	Males	0.10	NR
Gianoli et al.,	309.1 + 4.683*(thickness of the calf skin-fold [mm]) − 9.637*(speed in running training [km.hr^{-1}])	Males	0.44	NR
Hagan et al.,	283.7 - 0.089*(total workouts in the 9-week training block)	Males	0.67	NR

	397.6 - 0.064*(total workouts in the 9-week training block) - 2.05*(VO$_2$max [ml.kg^{-1}.km^{-1}])	Males	0.76	NR
	472.5 - 0.056*(total workouts in the 9-week training block) - 2.72*(VO$_2$max [ml.kg^{-1}.km^{-1}]) - 1.04*(age [yr]).	Males	0.80	NR
	515.6 - 0.055*(total workouts in the 9-week training block) - 2.28*(VO$_2$max [ml.kg^{-1}.km^{-1}]) - 1.27*(age [yr]) - 0.31*(average workout pace [m.min^{-1}]).	Males	0.83	NR
	525.9 - 0.17*(total workouts in the 9-week training block) - 2.01*(VO$_2$max [ml.kg^{-1}.km^{-1}]) - 1.24*(age [yr]) - 0.45*(average workout pace) + 7.09*(average km per workout).	Males	0.84	NR
	370.9 - 2.65*(VO$_2$max [ml.kg^{-1}.km^{-1}]).	Males	0.67	NR
	453.8 - 2.39*(VO$_2$max [ml.kg^{-1}.km^{-1}]) - 1.86*(total workout days over the 9 week training block).	Males	0.75	NR
	556.5 - 2.85*(VO$_2$max [ml.kg^{-1}.km^{-1}]) - 4.53*(total workout days over the 9 week training block) + 1.11*(total workouts over the 9 week training block).	Males	0.81	NR
	610.9 - 2.17*(VO$_2$max [ml.kg^{-1}.km^{-1}]) - 4.97*(total workout days over the 9 week training block) + 1.26*(total workouts over the 9 week training block)-0.41*(average workout pace [m.min^{-1}]).	Males	0.85	NR
Hagan et al.,	369.58 - 10.1*(Mean km.day^{-1}).	Females	0.48	22.2
	214.24 + 393.07*(BMI) - 0.68*(training pace [m.min^{-1}])	Females	0.76	12.4
	449.88 - 7.61*(Mean km.day^{-1}) - 0.63*(training pace [m.min^{-1}])	Females	0.68	18.4
Haney et al.,	09*(Velcov)[h] + 2.9	NR	0.46	NR

	- 0.0006*(Velcov race#2) + 0.11*(Velcov race#1) + 2.7	NR	0.46	NR
Karp et al.,	–0.135*(average weekly distance [km]) – 0.042*(peak weekly distance [km]) – 0.477*(number of years training) + 180.194	Females	0.45	NR
Legaz Arrese et al.,	8408.623 + 240.632*(lactate at 10 $km.h^{-1}$) – 18.255*(left ventricular telediastolic diameter) + 22.522*(lactate at 22 $km{\cdot}h^{-1}$)[i]	Males	0.98	NR
	7658.331 + 55.519*(subscapular skinfold [mm]) – 4.834*(serum ferritin) + 34.895*(sum of six skinfolds [mm])[i]	Females	0.98	NR
Mckelvie et al.,	20.23*(average training pace [$min.mile^{-1}$]) + 1.93*(10km time [in minutes]) - 0.34*(Maximum miles per week) - 0.47*(Repression Sensitization)[j] - 5.22*(marathon completions) - 11.16*(days lost) + 27.22.	Mixed	0.80	NR
	22.54*(average training pace [$min.mile^{-1}$]) - 0.57*(Maximum miles per week) - 5.08*(marathon completions) + 88.39.	Mixed	0.52	NR
Noakes et al.,	Half marathon time*(1.98) + (Lactate concentration at the lactate turnpoint)*(6.23) – (Speed at the lactate turnpoint [% of peak treadmill velocity, $km.hr^{-1}$])*(0.46) + 33.84.	NR	0.95	NR
	Half marathon time*(1.94) + (Lactate concentration at the lactate turnpoint)*(5.8) – (Speed at the lactate turnpoint [% of peak treadmill velocity, $km.hr^{-1}$])*(0.44) + VO_2max - 16*(0.39) + 16.79.	NR	0.95	NR
	(Speed at the lactate turnpoint [% of peak treadmill velocity, $km.hr^{-1}$])*(1.29) – (Speed at the lactate turnpoint [% of peak treadmill velocity, $km.hr^{-1}$])*(10.86) + 241.3.	NR	0.87	NR

	(Speed at the lactate turnpoint [% of peak treadmill velocity, km.hr^{-1}])*(-4.92) – (Peak treadmill velocity [km.hr^{-1}])*(4.46) + 337.8.	NR	0.87	NR
Riegel et al.,	Time achieved in a previous race of any distance*(Marathon distance/Distance of the previously listed race)$^{1.06}$	Mixed	NR	NR
Rust et al.,	326.3 + 2.394*(Body fat percentage [%]) - 12.06*(Running speed in training, [km.hr^{-1}])	Males	0.44	NR
Salinero et al.,	96.1 + 2.3*(body fat [%]) + 62.9*(Δ recovery Ruffier Test [%])^{k} + 0.023*(half-marathon performance [min])	Males	NR	NR
	104.3 + 3.1*(body fat [%]) + 67.3*(Δ recovery Ruffier Test [%])^{k} + 0.045*(10-km performance [sec]).	Males	NR	NR
Schmid et al.,	184.4 + 5.0*(circumference calf [cm]) – 11.9*(speed in running during training, [km.hr^{-1}]).	Females	0.50	NR
Slovic et al.,	0.69*(Fastest mile time [secs]) - 12.8.	Mixed	NR	NR
	0.51*(Fastest mile time [secs]) - 14.3*(Previously completed marathon [if yes, multiply by one. If no, multiply by 0]) - 0.5*(miles run in the 8-week training block preceding the marathon) - 1.22*(longest training run [miles]) + 94.0.	Mixed	NR	NR
	75.6 + 0.51(fastest 1 mile time [secs]) - 15.7*(Previously completed marathon [if yes, 1; if no, 0]) - 0.05*(total miles run in an 8 week training block) - 2.86*(number of runs greater than or equal to 20miles in an 8 week training block).	Mixed	NR	NR
	95.0 + 0.51*(fastest 1 mile time [secs]) - 14.9*(Previously completed marathon [if yes, 1; if no, 0]) - 0.27*(maximal miles per week in 8 week training block) -	Mixed	NR	NR

	1.34*(longest training run [miles]).			
	80.2 +0.51*(fastest 1 mile time [seconds]) - 16.0*(Previously completed marathon [if yes, 1; if no, 0]) - 0.31*(maximal miles per week in 8 week training block) - 3.31*(number of runs greater than or equal to 20miles in an 8 week training block).	Mixed	NR	NR
	503.5 - 18.3*(Previously completed marathon [if yes, 1; if no, 0]) + 0.7*(age [yr]) - 0.07*(total miles run in an 8 week training block) - 1.66*(longest training run [miles]) - 19.2*(ponderal index)[l].	Mixed	NR	NR
	511 - 21.2*(ponderal index) - 19.5*(Previously completed marathon [if yes, 1; if no, 0]) + 0.7*(age [yr]) - 0.07*(total miles run in an 8 week training block) -3.8*(number of runs greater than or equal to 20miles in an 8 week training block).	Mixed	NR	NR
	507 -19.2*(ponderal index) - 18.6*(Previously completed marathon [if yes, 1; if no, 0]) + 0.7*(age [yr]) - 0.5*(maximal miles per week in 8 week training block) - 1.4*(longest training run [miles]).	Mixed	NR	NR
	511 -20.7*(ponderal index) - 19.0*(Previously completed marathon [if yes, 1; if no, 0]) + 0.7(age [yr]) - 0.5*(maximal miles per week in 8 week training block) - 3.7*(number of runs 20miles or more in the 8 week training block preceding the marathon).	Mixed	NR	NR
Slovic et al.,	94.0 + 0.51*(fastest 1 mile time [seconds]) - 14.3*(Previously completed marathon [if yes, 1; if no, 0]) - 0.05*(total miles run in an 8 week training block) - 1.22*(longest training run [miles]).	Males	0.79	NR
	116.5 + 0.45*(fastest 1 mile time [seconds]) - 7.9*(Previously completed marathon	Males	0.85	NR

	[if yes, 1; if no, 0]) - 0.08*(total miles run in an 8 week training block) - 1.45*(longest training run [miles]).			
	42.8 + 6.62*(fastest 5 mile time [min]) - 0.05*(total miles run in an 8 week training block) - 1.45*(longest training run [miles]).	Males	0.89	NR
	46.6 + 2.98*(fastest 10 mile time [min]) - 0.04*(total miles run in an 8 week training block) - 1.3*(longest training run [miles]).	Males	0.87	NR
	503.5 - 18.3*(Previously completed marathon [if yes, 1; if no, 0]) + 0.7*(age [yr]) - 0.07*(total miles run in an 8 week training block) - 1.66*(longest training run [miles]) - 19.2*(ponderal index).	Males	0.72	NR
	260.0 - 17.2*(Previously completed marathon [if yes, 1; if no, 0]) + 1.0*(age [yr]) - 0.12*(total miles run in an 8 week training block) - 1.77*(longest training run [miles]).	Males	0.74	NR
	94.0 + 0.51*(fastest 1 mile time [seconds]) - 14.3 *(Previously completed marathon [if yes, 1; if no, 0]) - 0.05*(total miles run in an 8 week training block) - 1.22*(longest training run [miles]).	Males	0.79	NR
Takeshima et al.,	3.207 + 0.048*(VO_2 @Lactate Threshold [$ml.kg^{-1}.min^{-1}$])- 0.022*(age [yr])[m]	Males	0.91	0.22
	3.707 + 0.038*(VO_2@Lactate Threshold [$ml.kg^{-1}.min^{-1}$]) - 0.031*(age [yr]) + 0.005*(average running duration per workout [min])[m]	Males	0.93	0.20
	5.858 - 0.052*(age [yr]) + 0.067*(average running duration per workout [min]) [m]	Males	0.90	0.27
Tanaka et al.,	1.312*(the running velocity that corresponded to the level of the point at which blood lactate concentration exhibited a systematic increase above a resting base-line	Males	NR	NR

	value [m.sec^{-1}]) + 0.0346*(Difference between the %VO_2max at the onset of blood lactate accumulation and the %VO_2max at which blood lactate concentration exhibited a systematic increase above a resting base-line value [%treadmill speed]) - 0.0099*(VO_2max) - 1.272.[m]			
	1.145*(the running velocity that corresponded to the level of the point at which blood lactate concentration exhibited a systematic increase above a resting base-line value [m.sec^{-1}]) + 0.0333*(Difference between the %VO_2max at the onset of blood lactate accumulation and the %VO_2max at which blood lactate concentration exhibited a systematic increase above a resting base-line value [%treadmill speed]) - 1.214[m]	Males	NR	NR
Tanaka et al.,	-0.040*(age [yr]) - 0.324 (Artherogenic Index)[n] - 1.16 (Katsura Index)[o,m]	Males	0.95	NR
Tanda & Knechtle	11.03 + 98.46exponential(−0.0053*mean weekly training distance [km.week^{-1}]) + 0.387 *mean training pace [sec.km^{-1}] + 0.1exponential(0.23*body fat percentage [%])	Males	NR	14.3
Tanda & Knechtle	11.03 + 98.46exponential(-0.0053*mean weekly training distance [km.week^{-1}]) + 0.387 P + 0.1 exponential(0.23*body fat [%])	Males	NR	NR
Till et al.,	-3.85(treadmill time [mins]) + 351.57	Mixed	0.45	NR
Vickers et al.,	(((42195/60)/((0.16018617+(0.83076202*(42195/(21097.5/(21097.5/([Half-Marathon Time]*60)+0.0335971859175381)*(42195/21097.5)^1.07))+(0.06423826*([Average weekly training distance, miles]/1.60934)/10)))))).	Mixed	NR	NR

(((42195/60)/((0.16018617+(0.83076202*(42195/(21097.5/(21097.5/([Half-Marathon Time]*60)-0.0978322644420439)*(42195/21097.5)^1.07))+(0.06423826*([Average weekly training distance, miles]/1.60934)/10)))))).	Mixed	NR	NR
(((42195/60)/((0.16018617+(0.83076202*(42195/(21097.5/(21097.5/([Half-Marathon Time]*60))*(42195/21097.5)^1.07))+(0.06423826*([Average weekly training distance, miles]/1.60934)/10)))))).	Mixed	NR	NR
(((42195/60)/((0.16018617+(0.83076202*(42195/((16093.4)/((16093.4)/([10mile time*60)+0.103075553032855)*(42195/(16093.4))^1.07))+(0.06423826*([average weekly distance, miles]/1.60934)/10))))))	Mixed	NR	NR
(((42195/60)/((0.16018617+(0.83076202*(42195/((16093.4)/((16093.4)/([10mile time*60)-0.1358099643292151)*(42195/(16093.4))^1.07))+(0.06423826*([average weekly distance, miles]/1.60934)/10))))))	Mixed	NR	NR
(((42195/60)/((0.16018617+(0.83076202*(42195/((16093.4)/((16093.4)/([10mile-time*60)*(42195/(16093.4))^1.07))+(0.06423826*([average weekly distance, miles]/1.60934)/10))))))	Mixed	NR	NR
(((42195/60)/((0.16018617+(0.83076202*(42195/(10000/(10000/([10km-time]*60)+0.024557694615445)*(42195/10000)^1.07))+(0.06423826*([Average weekly training distance, miles]/1.60934)/10)))))).	Mixed	NR	NR
(((42195/60)/((0.16018617+(0.83076202*(42195/(10000/(10000/([10km-time]*60)-0.0780677777771365)*(42195/10000)^1.07))+(0.06423826*([Average weekly	Mixed	NR	NR

training distance, miles]/1.60934)/10)))))).			
(((42195/60)/((0.16018617+(0.83076202*(42195/(10000/(10000/([10km-time]*60))*(42195/10000)^1.07))+(0.06423826*([Average weekly training distance, miles]/1.60934)/10)))))).	Mixed	NR	NR
(((42195/60)/((0.16018617+(0.83076202*(42195/((8046.7)/((8046.7)/([5mile-time*60)+0.1089566001045939)*(42195/(8046.7))^1.07))+(0.06423826*([average weekly training distance, miles]/1.60934)/10))))))	Mixed	NR	NR
(((42195/60)/((0.16018617+(0.83076202*(42195/((8046.7)/((8046.7)/([5mile time*60)-0.1549942921949754)*(42195/(8046.7))^1.07))+(0.06423826*([average weekly training distance, miles]/1.60934)/10))))))	Mixed	NR	NR
(((42195/60)/((0.16018617+(0.83076202*(42195/((8046.7)/((8046.7)/([5mile time*60))*(42195/(8046.7))^1.07))+(0.06423826*([average weekly training distance, miles]/1.60934)/10))))))	Mixed	NR	NR
(((42195/60)/((0.16018617+(0.83076202*(42195/(5000/(5000/([5km-time]*60)+0.1129432382020499)*(42195/5000)^1.07))+(0.06423826*([Average weekly training distance, miles]/1.60934)/10)))))).	Mixed	NR	NR
(((42195/60)/((0.16018617+(0.83076202*(42195/(5000/(5000/([5km-time]*60)-0.0237814322487082)*(42195/5000)^1.07))+(0.06423826*([Average weekly training distance, miles]/1.60934)/10)))))).	Mixed	NR	NR
(((42195/60)/((0.16018617+(0.83076202*(42195/(5000/(5000/([5km-time]*60))*(42195/5000)^1.07))+(0.06423826*([Average weekly training distance,	Mixed	NR	NR

miles]/1.60934)/10)))))).			
(((ln((21097.5/(21097.5/([Half marathon time]*60)*(42195/10000)^(1.4510756+(-0.23797948*((ln((21097.5/(21097.5/([Half-marathon time]*60)/(10000/(10000/([10km time]*60)))/((ln(21097.5/10000))+(-0.01410023*[average weekly training distance, miles]))/60	Mixed	NR	NR
(((ln((21097.5/(21097.5/([Half-marathon time]*60)*(42195/10000)^(1.4510756+(-0.23797948*((ln((21097.5/(21097.5/([Half marathon time]*60)/(10000/(10000/([10mile time]*60)))/((ln(21097.5/10000))+(-0.01410023*[average weekly training distance, miles]))/60	Mixed	NR	NR
(((ln((21097.5/(21097.5/([Half marathon time]*60)*(42195/10000)^(1.4510756+(-0.23797948*((ln((21097.5/(21097.5/([Half-marathon time]*60)/(10000/(10000/([5mile time]*60)))/((ln(21097.5/10000))+(-0.01410023*[average weekly training distance, miles]))/60	Mixed	NR	NR
(((ln((21097.5/(21097.5/([Half-marathon time]*60)*(42195/10000)^(1.4510756+(-0.23797948*((ln((21097.5/(21097.5/([Half-marathon time]*60)/(10000/(10000/([5km time]*60)))/((ln(21097.5/10000))+(-0.01410023*[average weekly training distance, miles]))/60	Mixed	NR	NR
(((ln((21097.5/(21097.5/([10-mile time]*60)*(42195/5000)^(1.4510756+(-0.23797948*((ln((21097.5/(21097.5/([10-mile time]*60)/(5000/(5000/([5km time]*60)))/((ln(21097.5/5000))+(-0.01410023*[average weekly distance]))/60	Mixed	NR	NR
(((ln((21097.5/(21097.5/([10-miletime]*60)*(42195/10000)^(1.4510756+(-	Mixed	NR	NR

	0.23797948*((ln((21097.5/(21097.5/([10-miletime]*60)/(10000/(10000/([10km time]*60)))/((ln(21097.5/10000))+(-0.01410023*[average weekly training distance, miles]))/61			
Williams	(Half marathon time)*$2^{1.15}$	Mixed	NR	NR
Zillmann et al.,	326.3 + 2.394*(Body fat [%]) - 12.06*(Running speed in training [$km.hr^{-1}$])	NR	0.43	NR

a: NR=not reported; b:V1000= After a warm-up race, subjects ran 10 km on a level road at their target marathon velocity for the upcoming Olympics trials race; c: BMI= Body Mass Index; d: vVO_2max= velocity at VO_2max; e: Critical velocity = The regression of the distance run (distance limit; DL) versus the time limit (TL) at several exhaustive running velocities on the treadmill results in the generalized equation: DL =a + b(TL), where a is considered to be the anaerobic running capacity (ARC) and the slope (b) is termed CV (Housh et al. 1992); f: The VO_2peak was considered the highest VO2 attained during the incremental test; g: Ventilatory threshold determined using a computerized two-line segment linear regression program patterned after the procedure of Orr et al. (1982). The plots of minute ventilation (V ˙E) and CO2 output (V ˙CO2) versus time as well as V ˙CO2 versus V ˙O2 (V slope) were analyzed with the computer program. Visual inspection of the two plots was used to further delineate the Thvent from the differences between the two computerized analyses. It was then expressed as the velocity; h: Coefficient of variation of running velocity during the marathon, where velcov= (velstdev/velmean)*100, and velstdev = the standard deviation of velocity over the duration of the marathon. velmean = the average velocity over the duration of the marathon; i: equation time results in marathon time in seconds; j: Listed as a score derived from the Revised Repression Sensitization Scale by Byrne et al., 1963; k: Ruffier Test Index = ((resting heart rate + effort heart rate + recovery heart rate)-200)/10, then change from effort to recovery was calculated as a percentage; l: Ponderal index = weight/$height^3$; m: marathon time expressed as velocity in $m.sec^{-1}$; n: Artherogenic Index= log(triglyceride/HDL cholesterol); o: Katsura Index = mass/((height – 100)*0.9).

PRISMA 2009 Checklist

Section/topic	#	Checklist item	Reported on page #
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both.	1
ABSTRACT			
Structured summary	2	Provide a structured summary including, as applicable: background; objectives; data sources; study eligibility criteria, participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number.	2
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known.	3
Objectives	4	Provide an explicit statement of questions being addressed with reference to participants, interventions, comparisons, outcomes, and study design (PICOS).	4
METHODS			
Protocol and registration	5	Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number.	N/A
Eligibility criteria	6	Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.	4
Information sources	7	Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched.	4
Search	8	Present full electronic search strategy for at least one database, including any limits used, such that it could be repeated.	4
Study selection	9	State the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis).	5
Data collection process	10	Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators.	5
Data items	11	List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made.	5
Risk of bias in individual studies	12	Describe methods used for assessing risk of bias of individual studies (including specification of whether this was done at the study or outcome level), and how this information is to be used in any data synthesis.	5
Summary measures	13	State the principal summary measures (e.g., risk ratio, difference in means).	N/A
Synthesis of results	14	Describe the methods of handling data and combining results of studies, if done, including measures of consistency (e.g., I^2) for each meta-analysis.	5

PRISMA 2009 Checklist

Section/topic	#	Checklist item	Reported on page #
Risk of bias across studies	15	Specify any assessment of risk of bias that may affect the cumulative evidence (e.g., publication bias, selective reporting within studies).	NA
Additional analyses	16	Describe methods of additional analyses (e.g., sensitivity or subgroup analyses, meta-regression), if done, indicating which were pre-specified.	5
RESULTS			
Study selection	17	Give numbers of studies screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally with a flow diagram.	5
Study characteristics	18	For each study, present characteristics for which data were extracted (e.g., study size, PICOS, follow-up period) and provide the citations.	Table 1
Risk of bias within studies	19	Present data on risk of bias of each study and, if available, any outcome level assessment (see item 12).	Table 4
Results of individual studies	20	For all outcomes considered (benefits or harms), present, for each study: (a) simple summary data for each intervention group (b) effect estimates and confidence intervals, ideally with a forest plot.	5/6
Synthesis of results	21	Present results of each meta-analysis done, including confidence intervals and measures of consistency.	NA
Risk of bias across studies	22	Present results of any assessment of risk of bias across studies (see Item 15).	6/Table 5
Additional analysis	23	Give results of additional analyses, if done (e.g., sensitivity or subgroup analyses, meta-regression [see Item 16]).	NA
DISCUSSION			
Summary of evidence	24	Summarize the main findings including the strength of evidence for each main outcome; consider their relevance to key groups (e.g., healthcare providers, users, and policy makers).	6/7
Limitations	25	Discuss limitations at study and outcome level (e.g., risk of bias), and at review-level (e.g., incomplete retrieval of identified research, reporting bias).	7
Conclusions	26	Provide a general interpretation of the results in the context of other evidence, and implications for future research.	6/7
FUNDING			
Funding	27	Describe sources of funding for the systematic review and other support (e.g., supply of data); role of funders for the systematic review.	8

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