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Validity of Treadmill-Derived Critical Speed on Predicting 5000-Meter Track-Running Performance

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Title: Predictive validity of two-parameter critical speed models on 5000 meter running performance

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Abstract

To evaluate different models of critical speed (CS) for the prediction of 5000-m running performance, 16 trained endurance athletes completed an incremental test on a treadmill to determine maximal aerobic speed (S_{max}) and three randomly ordered runs to exhaustion at the Delta70% intensity, at 110% and 98% of S_{max}. CS and the distance above CS (*D'*) were calculated using the hyperbolic speed-time model (HYP), the linear distance-time model (LIN) and the linear speed-inverse time model (INV). 5000-m running speed was determined on a 400-m running track. Individual predictions of 5000-m running speed and time were calculated across the three models. The agreement between predicted and actual performance was assessed with the 95% limits of agreement (LOA). 5000-m running speed (4.29 ± 0.39 $m \cdot s^{-1}$) was significantly higher than the predicted speeds from all three models ($F_{3,13} = 63.9$; $P < 0.001$). The bias and 95% LOA were 0.34 ± 0.20 $m \cdot s^{-1}$ for HYP, 0.31 ± 0.21 $m \cdot s^{-1}$ for LIN and 0.22 ± 0.22 $m \cdot s^{-1}$ for INV. Likewise, 5000-m time (1176 ± 117 s) was significantly faster compared with the predicted times ($F_{3,13} = 62.2$; $P < 0.001$) and the bias and 95% LOA were 99.4 ± 63.9 s, 90.3 ± 64.1 s and 62.3 ± 66.6 s for HYP, LIN and INV, respectively. None of the three models have a high predictive validity as the differences range from 5-9%. The two-parameter models from a single-visit laboratory test are not considered as strong predictors of 5000-m running performance.

Key words: running performance, anaerobic work capacity, performance prediction, exercise testing

Introduction

To maintain a fast yet comfortable pace over a given distance without early exhaustion is one of the principal objectives of endurance sports like running, swimming or cycling. A slight increase in pace can result in a substantial increase in perceived effort and reduce the tolerable duration of exercise. The speed-duration relationship was first described by Hill [16] and was later characterized as the power-duration relationship [34]. The latter authors defined two parameters from this relationship: CP as the asymptote of the power-duration hyperbola which theoretically represents the maximum rate of work that can be maintained for a very long time without fatigue; and *W'* as the finite amount of work that may be performed above CP. Later the CP concept was modified and applied to running [23,37], with critical speed (CS) and *D'* (the maximum distance covered above CS) equivalent to CP and *W'*, respectively (for clarity, CS and *D'* will be used throughout this paper unless otherwise stated). Physiologically, CS demarcates the threshold above which oxygen uptake, inorganic phosphate and hydrogen ions can no longer achieve a steady-state, but instead rise inexorably as the work rate is continued until the limit of tolerance (i.e. defined as the boundary between the heavy and severe exercise intensity domains [28,38]).

For the determination of CS and *D'* linear- and non-linear, two- and three-parameter mathematical models have been used (for review see Jones, et al. [27]). A number of studies have reported that CS differs significantly depending upon the mathematical model used [8,14,35]. For example, Bull, et al. [8] and Gaesser, et al. [14] found differences up to 24% when examining the same data with two non-linear and one exponential model. The exponential model of Hopkins, et al. [19] has been found to result in the highest estimates of CS in both studies whilst the non linear three-parameter model of Morton [35] resulted in the lowest estimates.

According to Jones and Poole [26], CS testing provides a non-invasive, objective, reliable, valid, accurate and sensitive method to assess endurance performance. In addition, for athletes and coaches, it is important to apply a testing method that accurately predicts an athletes' current competition performance. Therefore, the CS concept has been used for performance prediction in various sports such as rowing and swimming [11,30]. However, comparatively few studies have investigated the prediction of running performance. Although, it has been suggested that CS can be maintained for 20-40 min [7,24], strong correlations have also been reported with longer endurance events such as the half-marathon or marathon [13,31]. Kolbe, et al. [31] investigated the relationship between CS and running performance (time) over a range of distances and found correlation coefficients of -0.75 (1 km), -0.85 (10 km) and -0.79 (21.1 km). In addition, a stronger correlation was found between marathon running performance and CS (r = 0.87) compared with $\dot{V}O_{2max}$ (r = 0.71) and the speed at the ventilatory threshold (r = 0.53) [13]. Bosquet, et al. [5] estimated 800-m running speed from two- and three-parameter models of CS and reported good predictive validities (bias 0.0-0.2 $m \cdot s^{-1}$) and strong correlations (r = 0.83-0.94) with actual 800-m speed (5.87 ± 0.49 $m \cdot s^{-1}$). Traditionally CS and D´ were estimated from 3-5 exhaustive runs on separate days. Just recently [15] it was demonstrated that CS determined from a single-visit field test, was not significantly different from a traditional multi-visit test, which improves the applicability in competitive athletes. It remains to be shown however, whether or not running performance can be accurately predicted from three frequently used mathematical models (i.e. the hyperbolic speed-distance model (HYP), the linear distance-time model (LIN) and the linear speed- inverse time model (INV).

It was therefore the aim of this study to evaluate the three mathematical models for the prediction of 5000-m running performance (speed and time). We hypothesized that there would be a good predictive validity from all three models in a cohort of well-trained runners with 5000-m times of approximately 20 min.

Methods

Participants

Sixteen trained, male endurance athletes (mean ± SD: age 30.4 ± 7.3 years; body mass 74.8 ± 7.3 kg; stature 179.6 ± 6.2 cm) volunteered to participate in this study. All athletes had a training history of at least five years, compete regularly in national and international running and triathlon events over various distances and were familiar with treadmill running and exercising to exhaustion. All athletes were informed of the experimental procedures and gave their written informed consent to participate in the study. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and was approved by the institutional review board.

Study Design

After familiarization of the exercise protocol, each participant performed three tests on separate days. All participants were asked to refrain from strenuous exercise, alcohol and caffeine intake and were instructed to follow a carbohydrate rich diet during the 24 hours before exercise testing and to drink at least 4 liters to ensure high glycogen stores and full hydration.

During the first visit, the participants completed a graded exercise test (GXT) on a treadmill to assess maximal- and submaximal indices of aerobic function. During the second visit, CS was determined through a series of three randomly ordered treadmill runs at intensities leading to exhaustion within 2-15 min [17]. Finally, the 5000-m running performance was determined on a 400-m running track.

Laboratory Incremental Graded Exercise Test

The GXT was performed on a motorized treadmill (HP Cosmos Pulsar, Nussdorf-Traunstein, Germany). The incline during all treadmill tests was set at 1% to simulate air resistance in the laboratory [25]. After a 3-min warm up at 5 $km \cdot h^{-1}$ the tests started at a speed of 6 $km \cdot h^{-1}$ and was increased by 0.5 $km \cdot h^{-1}$ every 60 s until exhaustion. If the last step was not completed, maximal speed was calculated according to Kuipers, et al. [33]:

$$S_{max} = SL + t / 60 \times 0.5$$

where SL is the speed of the last completed step and t is the time for the incomplete step.

Oxygen uptake was measured continuously via breath-by-breath open circuit spirometry (MetaMax 3b, Cortex Biophysik, Leipzig, Germany). Before each test, the gas analyzers were calibrated with gases of known concentrations (4.99 Vol% CO_2, 15.99 Vol% O_2, Cortex Biophysik, Leipzig, Germany). Flow and volume were calibrated with a 3-L syringe (Type M 9474-C, Cortex Biophysik, Leipzig, Germany). The participants wore a facemask and breathed through a low-resistance impeller turbine.

Achievement of $\dot{V}O_{2max}$ was taken as the highest 30-s value attained before volitional exhaustion. Determination of ventilatory threshold (VT) followed the criteria of an increase of the ventilatory equivalent of O_2 ($\dot{V}E/\dot{V}O_2$) without a concomitant increase of the ventilatory equivalent of CO_2 ($\dot{V}E/\dot{V}CO_2$) and the first loss of linearity in the relationship between minute ventilation ($\dot{V}E$) and carbon dioxide production ($\dot{V}CO_2$) [1]. Heart rate was measured continuously throughout the test using short-range radio-telemetry (Polar Vantage NV, Polar Electro, Kempele, Finland).

Critical Speed Test

Critical speed was determined through a series of three randomly ordered runs to exhaustion at the Delta70% intensity (i.e. 70% of the difference between VT and S_{max}) and at 110% and 98% of S_{max}. After a 10-min individual warm up, the speed was increased to the criterion intensity and the participants were required to stand with their feet astride the treadmill belt holding onto the handrails. The transitions from rest to running were performed by the participants using the handrails to suspend their body above the belt while they developed the speed required with their legs. The timing for each trial began when the participants released the handrail support and started running. The bout was terminated when the athletes grasped the handrails again, signaling exhaustion. All participants were verbally encouraged throughout the trials. However, to prevent pacing the display of the treadmill was covered and no information on speed or elapsed time was given. A rest period of 30-min [15] was provided between the runs during which the participants were allowed to drink water ad libitum.

The least square modeling procedure was used to fit the data from the critical speed tests. The parameter estimates (CS and *D'*) were resolved from the three two-parameter models using the software GraphPad Prism 5.0 (GraphPad Software Inc., San Diego, CA).

The hyperbolic speed-distance model (HYP) [16] using the nonlinear regression between speed and time:

$$t = D' / (\text{speed} - CS) \quad (1)$$

where t represents the time (s), *D'* is the maximum distance covered above critical speed and CS is the critical speed ($m \cdot s^{-1}$).

The linear distance vs. time model (LIN) [34] using the linear regression between distance (d) and time:

$$d = CS \times t + D' \quad (2)$$

And the linear speed- inverse time model (INV) [41] using the linear regression between speed and the inverse of time:

$$\text{speed} = D' \times 1/t + CS \quad (3)$$

The 5000-m performance was predicted from individual parameter estimates from each model. For models 1 and 3 speeds were predicted from the equations and the durations were calculated as distance divided by speed. For model 2 the duration was predicted and speed was calculated as distance divided by duration.

Field Tests

For determination of 5000-m running performance, the participants were asked to complete the distance as quickly as possible on a 400-m outdoor running track in calm conditions at sea-level, at a temperature and humidity of 15° C and 40-45%, respectively. The participants started individually at staggered intervals of 30 s, and were verbally encouraged throughout the test. The runs were timed and recorded to the nearest second and no information of elapsed time was provided.

Statistical Analysis

All statistical analyses were performed with the software package SPSS Statistics 21 (IBM Corporation, Armonk, NY, USA). Descriptive data are summarized as mean ± standard deviation (SD). The assumption of normality was verified using Kolmogorov-Smirnov's test. Repeated measure ANOVA was used to compare CS and *D'* across the models, as well as the predicted speeds and durations from the three models and the actual performance during the 5000-m run. Significant effects were followed up with pairwise comparisons employing the Bonferroni procedure for multiple testing. The agreement between predicted and actual performance was assessed with the 95% limits of agreement (LOA) [4]. Relationships between variables were examined with Pearson's product moment correlations. In addition, the standard error of estimate (SEE) from linear regressions between predicted and actual performance is provided as a measure of precision. The level of significance was set at $P < 0.05$.

Results

The results from the GXT and the 5000-m run are reported in Table 1 with estimates for the CS and *D'* parameters derived from each model shown in Table 2. The speeds during the prediction trials at the Delta70% intensity, 98% and at 110% of S_{max} were 4.09 ± 0.33 $m \cdot s^{-1}$,

4.55 ± 0.35 m·s^{-1} and 5.11 ± 0.39 m·s^{-1} and resulted in times to exhaustion of 765 ± 109 s, 313 ± 53 s and 126 ± 38 s.

There was a significant main effect of the model on estimates for CS ($F_{2,14} = 43.2$; $P < 0.001$) and *D'* ($F_{2,14} = 33.1$; $P < 0.001$) during treadmill running. Post-hoc tests revealed significant differences across all three models for estimating CS (HYP < LIN < INV; all at $P < 0.001$) and *D'* (HYP > LIN > INV; all at $P < 0.001$).

5000-m running speed was significantly higher than the predicted speeds from all three models ($F_{3,13} = 63.9$; $P < 0.001$) and strongly correlated with HYP (r = 0.857; SEE = 0.19 m·s^{-1}), LIN (r = 0.851; SEE = 0.19 m·s^{-1}) and INV (r = 0.833; SEE = 0.20 m·s^{-1}) (all at $P < 0.001$). The bias and 95% LOA were 0.34 ± 0.20 m·s^{-1} for HYP, 0.31 ± 0.21 m·s^{-1} for LIN and 0.22 ± 0.22 m·s^{-1} for INV (Figure 1).

5000-m running time was significantly faster compared with the predicted times from all three models ($F_{3,13} = 62.2$; $P < 0.001$) and strongly correlated with HYP (r = 0.852; SEE = 64.1 s), LIN (r = 0.844; SEE = 62.3 s) and INV (r = 0.830; SEE = 63.8 s) (all at $P < 0.001$). The bias and 95% LOA were 99.4 ± 63.9 s, 90.3 ± 64.1 s and 62.3 ± 66.6 s for HYP, LIN and INV, respectively (Figure 2).

Discussion

The results of this study showed that predicted speed and duration of 5000-m running performance, estimated from three mathematical models, are strongly correlated but significantly different from actual performance. All models underestimated real performance by approximately 5-9 %. With a bias of 0.22-0.34 m·s^{-1} for speed and 62-99 s for duration, the two-parameter models from a single-visit laboratory test are not considered as strong predictors of 5000-m running performance.

A number of studies have reported that CP or CS differ significantly depending on the mathematical model used [8,14,35]. By examining two linear, two non-linear and an exponential model in both studies [8,14], the exponential model [19] resulted in the highest estimates of CP and the non-linear three-parameter model [35] in the lowest estimates. More recently, Bull, et al. [9] compared CS determined from five mathematical models. To calculate CS, the linear total distance model (Lin-TD), the linear velocity model (Lin-V), the two-parameter hyperbolic velocity time model (Non-2), the three parameter model with the addition of V_{max} (Non-3) and the exponential model which includes V_{max} and an undefined time constant (τ) were used. Again, the Non-3 model resulted in a significantly ($P < 0.05$)

lower CS than the other four models. However, results revealed no other significant differences among the CS estimates. In the present study we used three classical two-parameter models to determine CS and *D'*: the hyperbolic speed-time model, the linear distance-time model and the linear speed-inverse time model. In accordance with previous studies, we also found significant differences ($P < 0.001$) between all three CS estimates. The linear speed-inverse time model produced the highest CS (3.94 ± 0.36 $m \cdot s^{-1}$), followed by the linear distance-time model (3.83 ± 0.34 $m \cdot s^{-1}$) and the hyperbolic speed-time model (3.76 ± 0.35 $m \cdot s^{-1}$). However, differences between the highest and the lowest estimate were only 4.6%, which is much smaller compared to other studies where differences of up to 24% have been reported [14]. Moreover, the goodness of fit of the data from the three models (Table 2) is high and is consistent with the values reported in previous studies [22,32,39]. As additional criteria of the quality of the mathematical models Black, et al. [3] used standard errors < 5 and 10% associated with CS and *D'*, respectively. If these criteria were exceeded after three prediction trials, a fourth trial was performed, which was required in five of ten subjects. Although in the present study the standard error associated with CS was below 3%, the variation of *D'* was > 20% (Table 2) and only in 5 of our subjects was < 10%. It is therefore likely that this error associated with *D'* could impact on performance prediction.

In the present study, it was found that actual 5000-m running performance was significantly better than performance predictions from all three models, indicating that none of the models could accurately predict 5000-m running performance. Kranenburg and Smith [32] compared CS determined from field- and laboratory-tests with a 10-km criterion performance. During the field test, subjects completed three maximal effort runs between 3 and 15 min on an indoor running track. CS in the laboratory was estimated from three constant speed runs until volitional exhaustion within approximately 3, 7 and 13 min. The authors reported strong correlations for both track (293 $m \cdot min^{-1}$) and treadmill (300 $m \cdot min^{-1}$) CS with race speed (293 $m \cdot min^{-1}$) ($r = 0.92$; $P < 0.001$). Whilst track CS speed was very similar to race speed, treadmill CS was ~2% higher than 10-km speed. The results of the present study revealed that 5000-m running speed was 10-12% higher than CS and 5-9% higher than the predicted speed. Relative anaerobic contributions have been reported for 3000-m (14%) [12] and for 5000-m running (7%) [10], indicating a significant anaerobic contribution to the energy turnover for these race distances that could partly explain the prediction errors.

Various authors have pointed out that it is important to select the right range of duration for the trials to determine CS [6,17,18,40]. Whilst classical guidelines for two-parameter models recommend trials not shorter than 3 min and not longer than 30 min [2,40], more recent studies did not use trials longer than 12 min [6] with a minimum difference of 5 min between the longest and shortest trial [21]. This is in accordance with recommendations [17] where the prediction trials are intended to yield times to exhaustion between 2-15 min. The intensities chosen are typically between 75% and 110% of the maximum power output achieved during a GXT. In the current study, we selected the highest intensity at 110% of S_{max}, which presumably would lead to exhaustion within 2-3 min. The two other trials where performed at the Delta70% intensity and at 98% of S_{max}. The results revealed exhaustion times between 126 ± 38 s and 765 ± 109 s and therefore were in agreement with the guidelines stated above.

Finally, the present study employed a single-visit protocol to estimate CS and *D'*, which is in contrast to traditional protocols where exhaustive trials over multiple days were required. However, this is time consuming and disruptive to an athlete's daily training program and, therefore, may limit the compliance of athletes to complete such a protocol. Recently [15], it was demonstrated that CS determined from a traditional multi-visit treadmill test, was not significantly different from single-visit protocols with 30-min and 60-min inter-trial recovery periods. In addition, no difference in critical power was found by Karsten, et al. [29] comparing single-visit time-to-exhaustion trials in laboratory conditions with maximal-effort time-trials during field cycling. However, the single-visit protocol used by Galbraith, et al. [15] was applied in field conditions at fixed distances, whereas the present study used time-to-exhaustion trials on a treadmill. It has been suggested that self-pacing, typically adopted during time-trials, closely reflect competitive performance and therefore increase the ecological validity in comparison with time-to-exhaustion trials [20,36]. In addition, critical power has been shown to increase (~7%) when the prediction trials were self-paced compared with constant-power trials in laboratory conditions [3]. When parameter estimates derived from constant-power trials were used, a ~6% under-prediction of time-trial performance was reported and it was recommended to permit self-paced trials to enhance performance prediction.

Conclusions

The present study demonstrated that the two-parameter models of CS significantly underestimated 5000-m running performance by approximately 5-9%. Despite strong correlations between predicted and actual performance, the bias was 0.22-0.34 $m \cdot s^{-1}$ for speed and 62-99 s for duration. Therefore the single-visit laboratory protocol is not considered to be a valuable test for predicting performance over race distances of 5000 m. It remains to be shown whether or not a single-visit field-test, which in contrast to the present study employ self-paced prediction trials, can further improve the predictive validity for running performance.

Conflicts of Interest and Source of Funding

This research was not supported by external funding. The authors declare no conflict of interest. The results of the current study do not constitute endorsement of the product by the authors or the journal.

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Figure captions:

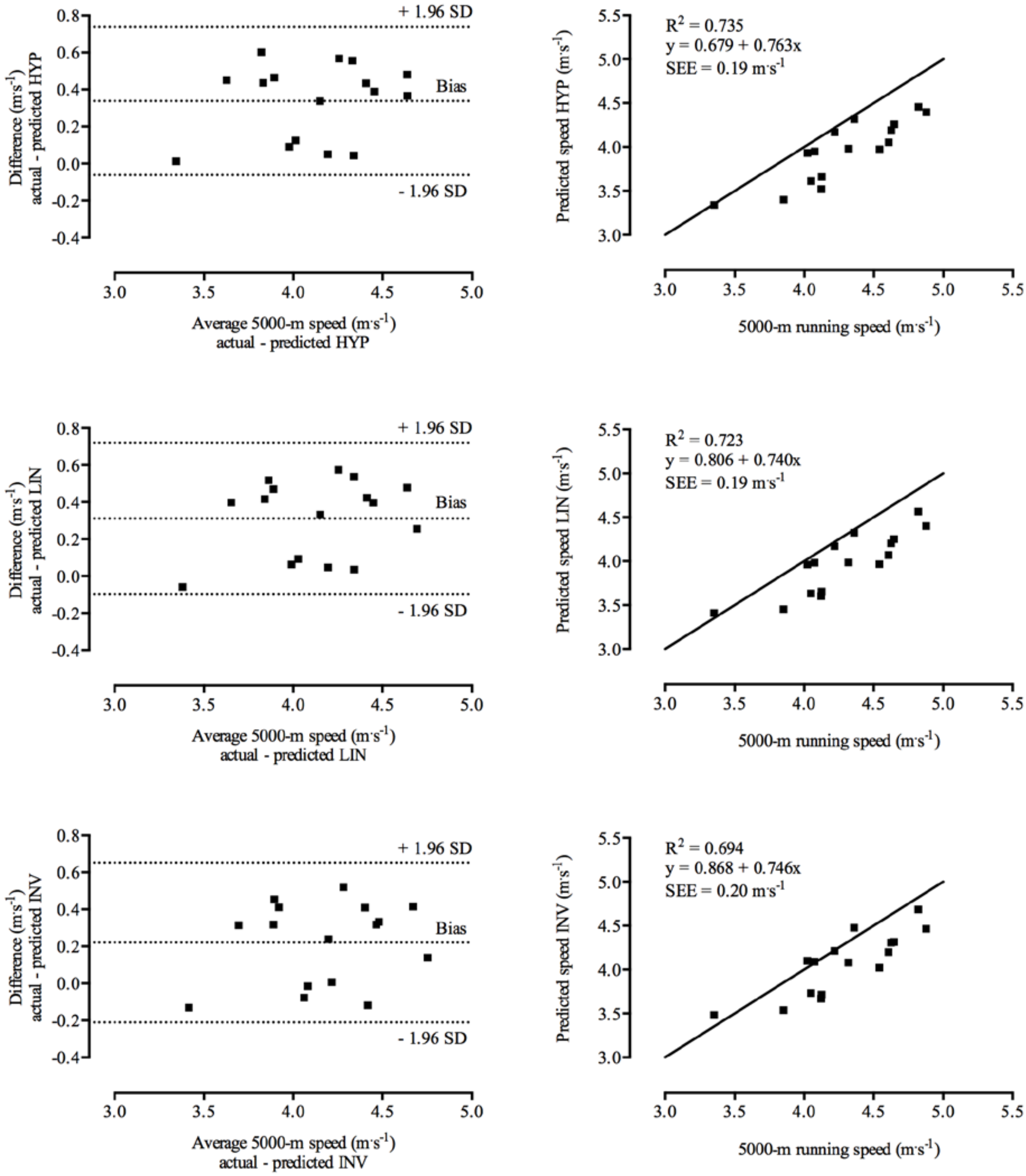

Figure 1: Bland-Altman plots of the differences between the actual and the predicted speed (left panel). Relationships between the actual and the predicted speed (right panel). Solid lines represent the line of identity.

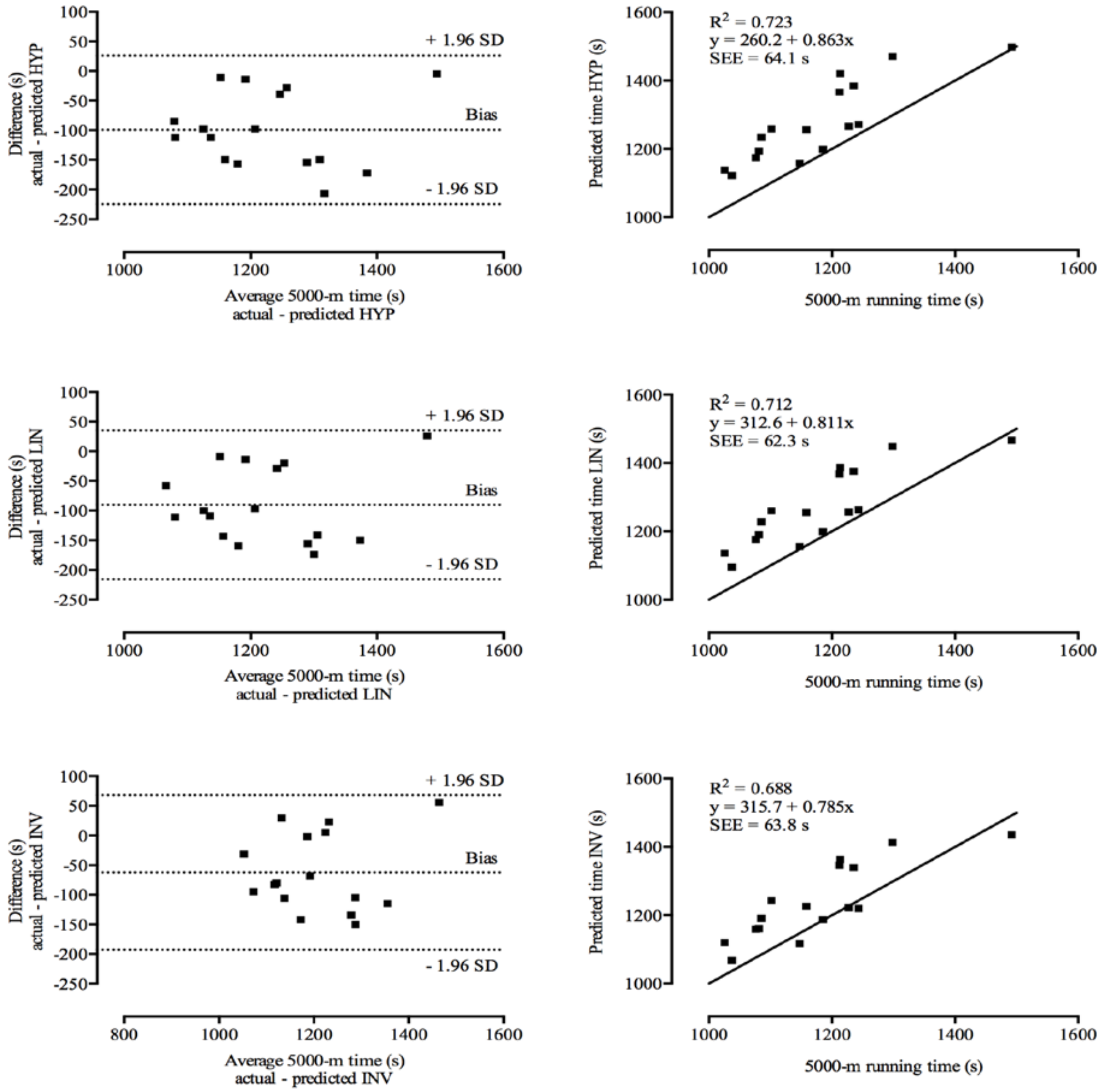

Figure 2: Bland-Altman plots of the differences between the actual and the predicted time (left panel). Relationships between the actual and the predicted time (right panel). Solid lines represent the line of identity.

Table 1: Results from the GXT and the 5000-m run (mean ± SD)

Measure	**Group (n = 16)**
$\dot{V}O_{2max}$ (ml·min^{-1})	4757 ± 613
$\dot{V}O_{2max}$ (ml·min^{-1}·kg^{-1})	63.6 ± 6.9
VT (m·s^{-1})	2.66 ± 0.24
S_{max} (m·s^{-1})	4.63 ± 0.36
5000-m running speed (m·s^{-1})	4.29 ± 0.39
5000-m finish time (s)	1176 ± 117

VT = ventilatory threshold; S_{max} = maximum speed

Table 2: Parameter estimates of CS and *D'* derived from the three models (mean ± SD)

Model	**CS (m·s^{-1})**	**SE (%)**	***D'* (m)**	**SE (%)**	**R^2**
HYP	3.76 ± 0.35*	2.2 ± 1.5*	222 ± 68*	23.3 ± 10.1	0.950 – 0.999
LIN	3.83 ± 0.34*	2.8 ± 1.4*	187 ± 61*	28.2 ± 13.8*	0.997 – 0.999
INV	3.94 ± 0.36*	3.8 ± 1.5*	152 ± 61*	20.5 ± 8.7	0.892 – 0.994

HYP = hyperbolic speed-time model; LIN = linear distance-time model; INV = linear speed-inverse time model; R^2 = goodness of fit; SE = standard error (%); * significantly different at $P < 0.01$